International Conference on Transportation and Development 2024

Transportation Planning, Operations, and Transit

Selected Papers from the International Conference on Transportation and Development 2024

Atlanta, Georgia
June 15–18, 2024

EDITED BY

Heng Wei, Ph.D., P.E.

ASCE

TRANSPORTATION & DEVELOPMENT INSTITUTE

INTERNATIONAL CONFERENCE ON TRANSPORTATION AND DEVELOPMENT 2024

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Preface

It is my great pleasure to present to you the proceedings from the ASCE International Conference on Transportation and Development (ICTD 2024), organized by the Transportation and Development Institute (T&DI) of ASCE. ICTD is ASCE's flagship conference in transportation and development. A special feature of this event was the partnership with Georgia Department of Transportation (GDOT) that helped deliver sessions showcasing their projects as part of the ICTD program. In addition, the 19th International Conference on Automated People Movers and Automated Transit Systems (APM-ATS 2024) was co-located with ICTD 2024 to cater to the technical content needs of the APM-ATS community. The event was held from June 15 to 18, 2024, at the Hilton Atlanta in the heart of the beautiful downtown Atlanta – the capital city of the state of Georgia.

ASCE ICTD 2024's three days of technical program featured three super-plenary sessions, one plenary session, and 42 technical breakout sessions that included leaders from ASCE, government agencies, private industry, and the academic sector, covering key areas of the entire spectrum of transportation and development. Technical sessions were organized by Georgia DOT, and ASCE-T&DI's CAV Impacts Committee, Uncrewed Aerial Systems Committee, MODaaS Committee, Data Sensing & Analytics Committee, AI in Transportation Committee, Transportation Safety Committee, Street and Highway Operations Committee, Active Transportation Committee, Highway Pavements Committee, Highway Construction Committee, Sustainable Transportation Committee, Freight and Logistics Committee, Infrastructure Systems Committee, Economics and Finance Committee, Aviation Planning & Operations Committee, Public Transport Committee, and Rail Transport Committee.

Technical posters divided into 25 different topics areas were on display throughout the conference. The poster program concluded with a dedicated poster reception, providing attendees with additional content to learn about cutting edge research and practice, and have the opportunity to speak directly with the authors. The conference program also included a variety of special events including offsite socials for students and younger members, a welcome reception, a seated awards luncheon, and several networking events in the exhibit hall.

The conference was preceded by two (2) workshops on the following topics as preconference events:

- AI and Emerging Technologies for Integrated Transportation Cybersecurity
- Government Relations and Public Relations University

In addition, the conference featured seven (7) tours on June 18, 2024, including the following:

- Hartsfield-Jackson Atlanta International Airport (ATL) - Behind the scenes
- Automated People Mover (APM) at Hartsfield-Jackson Atlanta International Airport (ATL)
- MARTA Control Center: Behind the Scenes
- Delta Technical Operations

- GDOT Traffic Management Center and Highway Emergency Response Operators (TMC/HEROs)
- Curiosity Labs
- Atlanta Beltline

The co-located APM-ATS 2024 Conference shared three super-plenaries and Awards Banquet with ICTD 2024 and included two separate plenary sessions and 18 technical breakout sessions. Technical sessions covered topics ranging from APM application at airports to APM engineering, design, operations, and maintenance, and from ATS planning to Personal Rapid Transit and Urban Systems and Major Activity Centers. In addition, the conference shared the welcome reception and other social and networking events with ICTD 2024. Last but not least, APM-ATS preceded with an Airport Operations and Maintenance Managers' Workshop and concluded with a technical tour of the Hartsfield-Jackson Atlanta International Airport Automated People Mover Systems.

ASCE ICTD 2024 has followed the great success of past ICTDs and attracted significant interest indicated by the rich technical program. A large number of papers were accepted for publication in the proceedings. Each paper went through a rigorous peer review by technical experts before becoming a publication of ASCE – the world's largest publisher of Civil Engineering content.

The proceedings for this conference have been organized into three (3) volumes based on the topical distribution as follows:

Volume I: Transportation Safety and Emerging Technologies
  - Transportation Safety
  - AI in Transportation
  - CAV Impacts
  - Data Sensing and Analytics
  - Intelligent Transportation Systems
  - Uncrewed Aerial Systems

Volume II: Transportation Planning, Operations, and Transit
  - Active Transportation
  - Freight & Logistics
  - Social Equity, Justice, and Welfare
  - Sustainable Transportation & Urban Development
  - Transportation and Public Health
  - Transportation Economics & Finance
  - Workforce Development, Diversity and Inclusion
  - APM-ATS
  - Public Transport
  - Rail Transport
  - Street & Highway Operations

- Volume III: Pavements and Infrastructure Systems
  - Airport Pavements

- Highway Construction
- Highway Pavements
- Infrastructure Systems

All these accomplishments were due to the incredible efforts of ASCE ICTD 2024 Conference Co-Chairs, Mr. Russell R. McMurry, and Ms. Marsha Anderson Bomar, the Conference Steering Committee, and the terrific support from ASCE staff. I would also like to express my sincere gratitude to all the authors and conference participants for their significant contributions. I am also grateful to all paper reviewers for their outstanding volunteer efforts. I would extend my special thanks to the T&DI technical committee volunteers, conference sponsors, exhibitors, moderators, and speakers for their help in making ASCE ICTD 2024 a great success!

Our unique integration of private, government, and academic leaders makes ASCE ICTD event series an excellent platform for information exchange, experience sharing, and professional networking. I hope you found ASCE ICTD 2024 to be a wonderful and rewarding experience, and I sincerely hope that ASCE ICTD becomes a 'can't miss' conference in each year that follows. On behalf of the conference leadership and committee, and ASCE T&DI, I wish you all the best in your professional endeavors and hope to see you at the ICTD 2025 and the co-located Pavements 2025, scheduled to be held at the Renaissance Resort in Glendale, Arizona from June 8 to 11, 2025.

ASCE ICTD 2024 Proceedings Editor

Heng Wei, Ph.D., P.E., F.ASCE
The University of Cincinnati

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Counting Bicyclists and Pedestrians on a Rural Highway in New Mexico

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ABSTRACT

This paper details challenges, opportunities, and lessons learned while seeking to count the number of people walking and bicycling along US 180 in southwest New Mexico. Findings show people are walking and bicycling along this corridor, with at least 2 to 6 people bicycling, one-way, on an average day, and at least 9 to 11 people walking, one-way, on an average day. Those using an existing sidewalk and multi-use pathway appear to be doing so for utilitarian purposes, particularly during weekdays. Bicyclists on the roadway and those walking and bicycling on the weekends appear to be for more recreational purposes. The researchers used the best available tools for the count. However, from this effort, there was a demonstrated need to provide methods, guidance, and tools regarding best practices for counting those walking and bicycling in the rural context.

INTRODUCTION

In southwest New Mexico, 13.25 miles of U.S. 180 connects the mining communities of Silver City, Arenas Valley, Santa Clara, Bayard, and Hurley (Figure 1).

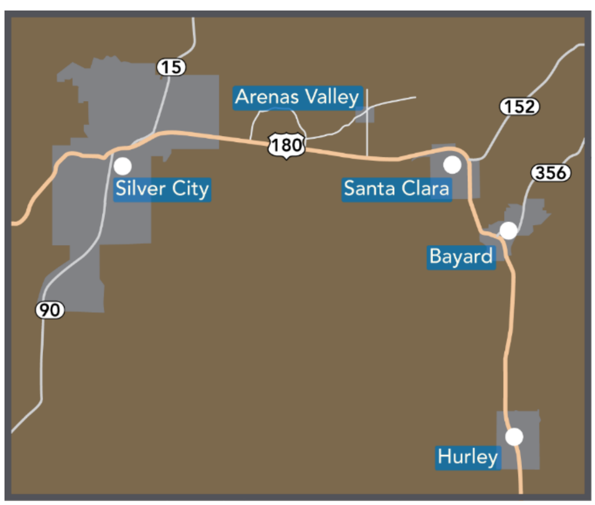

Figure 1: U.S. 180 Communities of Silver City, Arenas Valley, Santa Clara, Bayard & Hurley

With the volatility of mining in today's economy, these communities, with the help of the Southwest New Mexico Council of Governments (SWNMCOG), are seeking to diversify their economies by capitalizing and investing in services and infrastructure that support outdoor recreation. The Tour of the Gila, an annual cycling event, and other similar races (e.g., Gran Fondo) are examples of activities that bring economic benefits to the region ((Tour of the Gila 2023); (Chavez 2012)). Bicyclists can be found training for the Tour of the Gila along the corridor. Those connecting to the Continental Divide Trail (CDT) may also use the corridor (Figure 2).

Figure 2: Bicyclist Riding Along U.S. 180, Potentially Connecting to the CDT

Furthermore, locals walking and biking, particularly on the newly implemented Copper Trail connecting Santa Clara and Bayard, are known to use the corridor. In fact, images within Google Street View showed people walking and bicycling throughout the corridor. Another local effort, the “Five Points Initiative” (American Institute of Architects' Communities by Design 2021), aims to connect these five communities along U.S. 180 via bicycle and walking trails and pathways to allow locals and visitors safe opportunities to actively explore the region and its natural assets. As a result, SWNMCOG was interested in quantifying the existing use of the corridor by pedestrians and bicyclists. Hence, this paper details how counts were collected and why these counting tools were chosen. It also describes challenges of the methods, identifying many opportunities available as well as lessons learned to improve quantifying active transportation users on rural roadways.

METHODOLOGY FOR COUNTING BICYCLES & PEDESTRIANS

This corridor includes a high-speed rural highway, a separated multi-use pathway between Santa Clara and Bayard, and sidewalks in Silver City and Bayard, all of which presented unique challenges when considering how to quantify the corridor’s use by bicyclists and pedestrians.

With a qualitative understanding that people were walking and bicycling in the corridor, the *Guidebook on Pedestrian and Bicycle Volume Data Collection* (National Academies of Sciences, Engineering, and Medicine 2014) was consulted to obtain recommendations regarding considerations and best practices for counting people walking and bicycling. The guidebook noted that bicycle and pedestrian counts are more variable when compared with those for motor vehicles. In particular, the number of people walking and bicycling tend to be lower, the effects of the environment (e.g., rain) are more pronounced, and the time of day and season are often more impactful. Motor vehicles, in contrast, tend to be confined to a guideway. Bicycles, and more so pedestrians, can be provided with a defined space (e.g., sidewalk), although they may not follow it as closely (e.g., a pedestrian crosses mid-block (Figure 3)). Most of the current bicycle and pedestrian counting tools are intended for "screenline" counts, meaning that if someone walks or bicycles past an imaginary line, they are counted. Four to seven days of counts were recommended to reduce the annual estimated volume to less than twenty percent. Summer was identified as the best time to perform counts.

Figure 3: Pedestrians Crossing U.S. 180 Mid-Block

The researchers had considered other counting tools, such as video recordings, which can enable long-term counting at intersections or screenline locations. While the New Mexico Department of Transportation (NMDOT) possesses some video technology as a part of their counting program (New Mexico Department of Transportation 2021), this option was not available for use at the time of this research effort, in part because of the geographic challenges of transporting the equipment to the study area. The U.S. 180 corridor is more than four hours away from NMDOT headquarters in Albuquerque, and the tools are most often kept in Sante Fe, about another hour north. As technology advances, more advanced tools that can more comprehensively document the number of bicycle and pedestrian users in a location may become available.

Based on what was learned from the guidebook, two automated counting tools were leveraged to document the number of pedestrians and bicyclists along the U.S. 180 corridor: Mobile MULTI Eco-Counters (referred to hereafter as Eco-Counters) and JAMAR Trax Cycles+ counters (referred to hereafter as JAMAR). Seven JAMAR counters were leveraged as part of NMDOT's Bicycle Counter Lending Program (New Mexico Department of Transportation 2021); however, it should be acknowledged that this style of counter is no longer sold by JAMAR, suggesting that the tool may not be as desirable. The researchers' entity owned the two Eco-Counters. JAMAR counters can only count bicycles; they were used to quantify the number of road bicyclist users. The Eco-Counters can count bicycles and pedestrians, where a passive-infrared and precision lens combined with pneumatic tubes categorize both pedestrians and bicyclists (Eco-Counter 2019). Therefore, there exists a gap in the ability to count people walking along U.S. 180. The Eco-Counters were installed along the Copper Trail pathway and on a sidewalk on U.S. 180 near Hilltop Road in Silver City where the researchers had observed people walking and bicycling while on-site (recall from the guidebook, it is desirable to count where "high" counts may be expected).

The seven JAMAR counters were installed at four locations along the corridor (at three locations, two were needed for each direction); the Eco-Counters were installed at two locations along the corridor (Figure 4). Two people worked to install both types of counters.

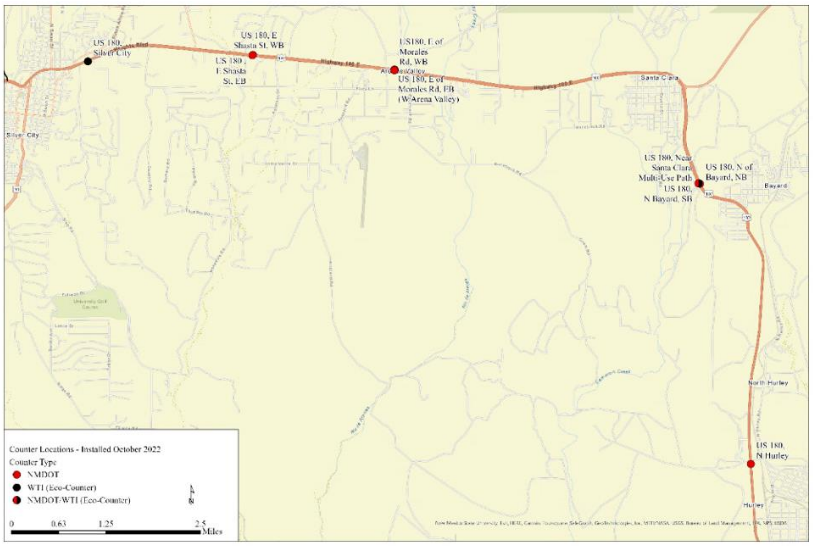

Figure 4: Location of JAMAR and Eco-Counter Installations Along U.S. 180

JAMAR counters were installed in tangent roadway sections (e.g., no horizontal curves), as horizontal curvature can result in erroneous counts. The Eco-Counters were installed in locations where the passive infrared beam did not face traffic or have bushes or shrubs in the background, as both can result in erroneous counts. While the Eco-Counter has remote access capability, cellular reception in the U.S. 180 corridor can be limited, and there is an extra fee to enable this capability. Considerations like these and others (e.g., being able to properly secure the counters) should be considered when choosing where the counters can be installed. The counters were installed between September 27-28, 2022, and removed between October 17-18, 2022. Data was analyzed from September 30 through October 16, 2022, to ensure consistency across counts. In total, more than two weeks of data was available for analysis, as recommended by the guidebook (National Academies of Sciences, Engineering, and Medicine 2014). While the guidebook recommended summer, fall was chosen in favor of more temperate weather, as southwest New Mexico can get very hot in the summer, even at altitude. Overall, the weather was partly cloudy, with temperatures ranging from about 52 to 68 degrees Fahrenheit. As is typical of the desert southwest, precipitation was reported on only a few days, most notably the weekend of October 6-8, 2022, the weekend of the Gran Fondo (Tour of the Gila 2023).

In addition to the automatic counters, the researchers also conducted four, short-term (e.g., two hours) manual counts at intersections, as the automatic counters are intended to collect screenline counts, not intersection counts (Figure 5). Two of the locations (U.S. 180 and Maple

Street; U.S. 180 and N. Hurley Avenue) saw no pedestrians or bicyclists pass the location at the time of the count.

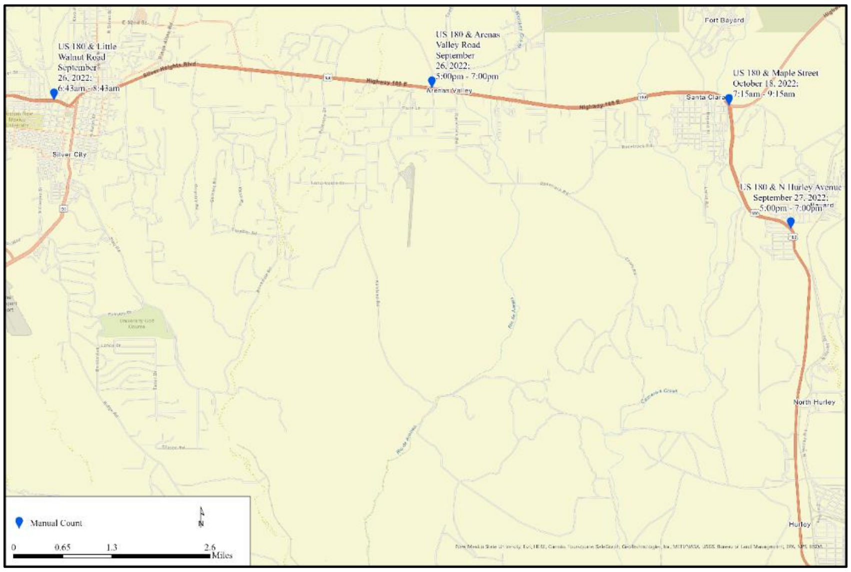

Figure 5: U.S. 180, Manual Count Locations

The researchers were told that the corridor was used by all-terrain vehicles (ATVs); however, while on-site, they did not observe any ATVs traversing the corridor. Therefore, this reflects a gap in what the counts can achieve.

RESULTS

This section presents the results of both the automated and manual counts.

Automated

Table 1 shows the number of bicyclists and pedestrians counted at each location, as applicable, by day. (Note: No data is shown for the location east of Morales Road because the pneumatic tubes for that counter were cut on October 4, 2023.)

The average daily bicycle counts by direction are slightly greater on the sidewalk and pathway (Figure 6). While only slightly greater, within the context of small numbers to start with which can be expected in rural areas with smaller populations and therefore potentially less people bicycling and walking, a small amount greater can be impactful.

When looking at pedestrian counts, the two locations where data was available suggest higher numbers than the number of bicyclists (Figure 7).

This is consistent with other information from rural areas, where walking seems to be more accepted and accessible, and consequently, infrastructure supporting walking is preferred (Villwock-Witte and Clouser, Mobility Mindset of Millennials in Small Urban and Rural Areas 2016). Furthermore, there are less barriers to walking. It removes the need to own a bicycle (rates believed to be as low as 37% in the U.S.) and to know how to bicycle (rates believed to be 69% in the U.S.), both of which remain a barrier to participation, particularly in the rural context ((Villwock-Witte and Clouser 2022); (Ipsos 2022)).

Table 1: Bicycle and Pedestrian Counts by Location

Date	Location						
	Silver City		Santa Clara			E. Shasta Street	N. of Hurley
	Bike*	Ped*	Bike (path)*	Ped*	Bike (road)	Bike (road)	Bike (road)
9/30/22	14	20	7	31	4	9	7
10/1/22	10	14	21	23	4	9	7
10/2/22	3	23	6	22	1	6	2
10/3/22	5	28	17	20	3	15	5
10/4/22	14	29	6	37	5	11	9
10/5/22	2	17	11	26	6	13	8
10/6/22	5	12	6	18	4	12	5
10/7/22	8	7	5	15	12	8	6
10/8/22	13	16	6	9	3	19	3
10/9/22	5	13	12	19	4	2	7
10/10/22	16	9	12	34	10	8	3
10/11/22	12	20	14	22	4	8	4
10/12/22	12	28	21	17	8	8	7
10/13/22	14	17	10	16	7	3	10
10/14/22	11	19	8	20	5	1	7
10/15/22	20	20	15	15	5	0	7
10/16/22	1	16	3	3	3	0	20
TOTAL	172	358	180	347	88	132	117

*These counts were from the Eco-Counter; the other counts were from the JAMAR counter.

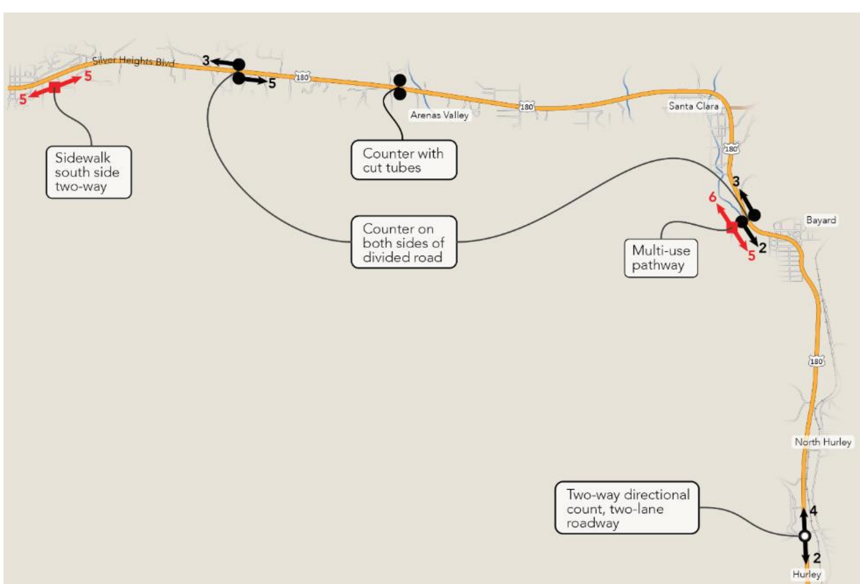

Figure 6: U.S. 180, Average Daily Bicycle Counts by Direction

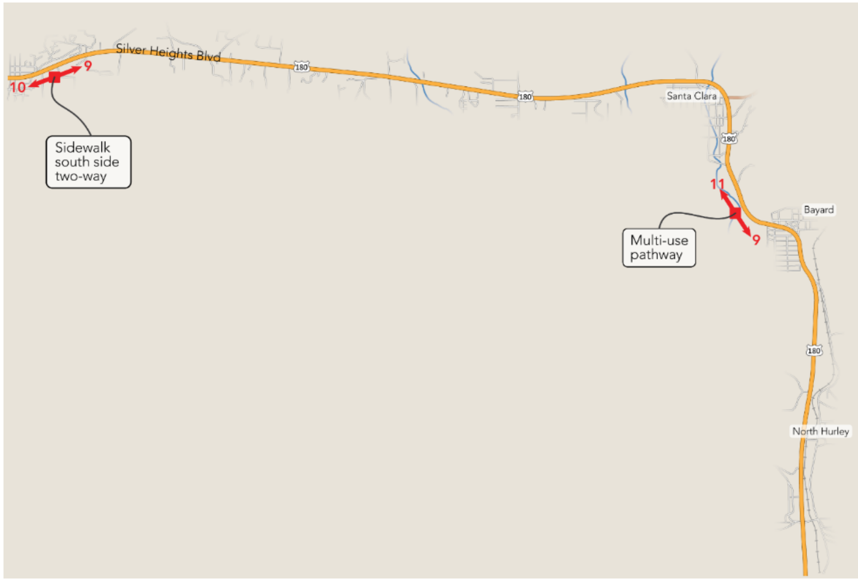

Figure 7: U.S. 180, Average Daily Pedestrian Counts by Direction

The researchers also reviewed the data by average hour. The data was not further disaggregated by direction due to the smaller sample sizes. When looking at the hourly data, the Eco-Counter locations (e.g., the sidewalk and pathway) typically exhibited more utilitarian travel (see Figure 8 for an example), as suggested by the patterns showing two peaks, as noted from the guidebook (National Academies of Sciences, Engineering, and Medicine 2014). The counts stemming from the JAMAR counters, on the other hand, tended to suggest more recreational travel (see Figure 9 for example), as suggested by the single-peak pattern, as noted from the guidebook (National Academies of Sciences, Engineering, and Medicine 2014). Overall, a more recreational pattern of travel tended to be observed for the weekend when compared with weekday travel.

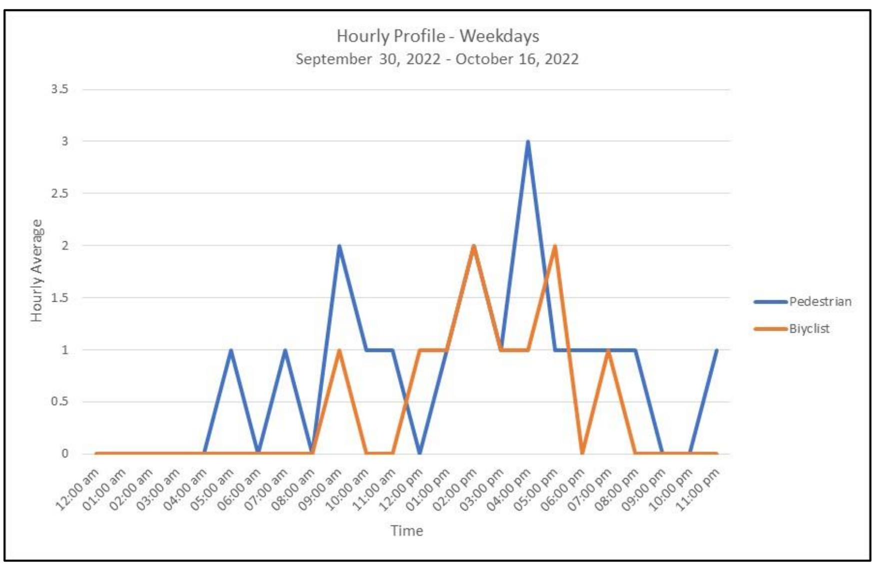

Figure 8: Example of Utilitarian Pattern (Silver City Eco-Counter)

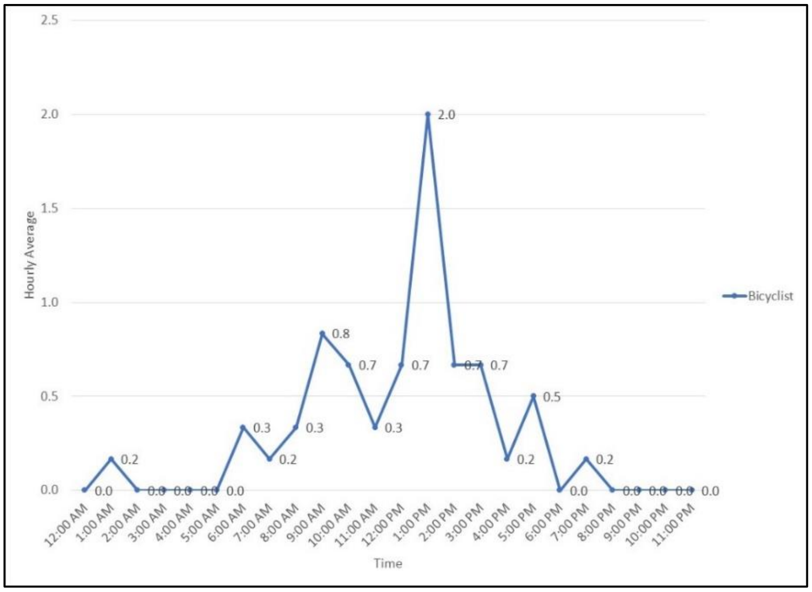

Figure 9: Example of a Recreational Pattern (JAMAR Counter Near E. Shasta Road)

Two validation counts were conducted, one at the JAMAR counter near Hurley and one at the Eco-counter between Santa Clara and Bayard. The comparisons were not intended to be a full analysis of the reliability of the counters. One bicyclist northbound and one bicyclist southbound were recorded by the JAMAR device, whereas the human observer recorded none. For the Eco-Counter, during the hour and a half observation, the count matched the automatic counter. This even included a child that was pushed in a stroller. The results suggest some concerns with at least one tool, in that the counts may not well match reality. However, the comparison period was minimal. Therefore, the researchers are assuming the counters function as intended, yet it highlights a need for validation of tools for the rural context, where mixed traffic facilities are commonplace.

Manual

In a two-hour count at U.S. 180 and Little Walnut Creek, five bicyclists and thirteen pedestrians were observed moving through the intersection. The users ranged from a young girl who appeared to be walking to school, bicyclists with panniers suggesting utilitarian travel, a bicyclist appearing to be going for a training ride, and two ladies out for a morning walk. Hence, a variety of ages and purposes brought people out on foot and on bike.

Three bicyclists were observed during the two-hour count at the U.S. 180 and Arenas Valle Road intersection.

CHALLENGES, OPPORTUNITIES, & LESSONS LEARNED

The following sections detail the challenges, opportunities, and lessons learned.

Challenges

The rural context presents challenges when trying to quantify the number of people walking and bicycling.

Cell phone connectivity remains limited in rural areas, including the U.S. 180 corridor. The Eco-Counters can potentially transit data via cellular connection, but with limited cell phone connectivity, rural areas may not always be able to support the use of this feature. Furthermore, this feature comes with an additional cost. The JAMAR counters are not believed to have this feature available. If the researchers could have remotely connected to the counters, they could have identified when issues occurred (e.g., when the pneumatic tube was cut for one counter) to the local partner who could have repaired the tube so that the data would not have been lost.

Rural areas, like the U.S. 180 corridor, can be very remote. Therefore, even if equipment is provided by a state department of transportation (DOT), leveraging these tools can be a challenge. If these tools are available, there may not be enough staff to leverage them (e.g., ensure their safety by having at least two users install the counters in mixed traffic). The vehicles in the U.S. 180 corridor are traveling at high rates of speed and there are many large trucks.

Bicycle and pedestrian counters remain a relatively new tool. Therefore, while regional or local entities may be more familiar with installing vehicular counters, they may not be as familiar with tools that can be used to quantify bicycle and pedestrian use.

Many facilities for people walking and bicycling in rural areas are often mixed-traffic situations (e.g., a bicyclist is expected to ride just inside the fog line on a signed bicycle corridor). Yet tools available to accurately count in such a scenario remain limited or expensive to deploy. The Eco-Counters utilized for this research effort provided a solution to count both bicyclists and pedestrians; however, the sensor which is used to count pedestrians cannot be pointed in the direction of motor vehicle traffic. So, this type of counter could not be utilized in areas where people are potentially walking on the shoulder of a roadway, which can be common in rural areas.

Opportunities

The rural context also has a lot of opportunities. As shown by this example, and others, people are walking and bicycling in the rural context. How can designers incorporate facilities into rural design to ensure the safe mobility of people walking and bicycling?

People were reported to be using ATVs in the U.S. 180 corridor. In some instances, ATVs may be used on facilities intended for those bicycling and walking (e.g., pathways). Tools designed to count ATVs or similar vehicles (e.g., golf carts) are needed. Furthermore, recommendations are needed as to whether or not these users should be accommodated on such facilities (e.g., concerns with speed differentials). If ATVs are restricted from pathways, what strategies can mitigate or eliminate their use of these facilities so as not to inhibit the provision of pathways out of concerns for bicyclist and pedestrian safety?

The researchers used tools that were readily available (e.g., owned by their agency or could be borrowed from the state DOT). Other regional or local entities could quantify those walking and bicycling in their area by identifying if their state DOT has a program that loans out similar tools.

The existing guidance separates out utilitarian and recreational bicycle and pedestrian travel. Yet, when designing for vehicles, utilitarian and recreational trips are not as explicitly separated. There is a need to stop suggesting that travel by bike and on foot should be separated into utilitarian and recreational travel.

Lessons Learned

This effort identified some lessons learned that can be shared. A significant challenge that remains is the ability to count people walking and bicycling in a mixed context.

The JAMAR Trax Cycles+ counter should be further evaluated to determine its effectiveness, or preferably, its updated offering evaluated.

The data suggested that higher quality facilities (e.g., pathways) were supportive of enabling more people to walk and bicycle as compared with more traditional facilities (e.g., in the roadway). Providing spaces for people to walk and bicycle in the rural context can enable them to move to attain health benefits as well as to allow them to safely get to where they need to go (e.g., jobs, school).

While the guidebook (National Academies of Sciences, Engineering, and Medicine 2014) recommended summer implementations, as more entities desire to quantify bicycle and pedestrian use, understanding if other time periods (e.g., fall) are preferable. As more information is gained, updating guidance that reflects a myriad of climates and contexts would be of value.

CONCLUSIONS

People are walking and bicycling along the U.S. 180 corridor, with a slightly greater number found where infrastructure specific to those walking and bicycling (e.g., pathway, sidewalk) is provided. More people walking than bicycling were recorded when comparing the maximums of all the locations. A primary conclusion is that people are walking and bicycling in the rural context. Consequently, designers should ensure that their designs facilitate the safe travel of pedestrians and bicyclists, as many rural infrastructure projects will remain as designed for an extended period of time.

There is no perfect method to quantify active transportation users. This research effort utilized two automated counting tools and manual counts to gain an understanding of bicycling and walking in the U.S. 180 corridor. However, these methods each have opportunities and drawbacks. These devices were able to be deployed in a relatively remote rural corridor. The JAMAR counters utilized could not count pedestrians who were potentially walking on the shoulder of the roadway. While there are some opportunities for mixed traffic deployment, as a whole, the Eco-Counters best counted bicyclists and pedestrians on dedicated active transportation infrastructure. Thus, they miss bicyclists riding within the roadway or bicycle lane. The Eco-Counters require a line of site not obstructed by objects like bushes, shrubs, and vehicles, which can result in erroneous counts. Both styles of counters are also best deployed in a location where horizontal curvature is not present. An additional challenge occurred where pneumatic tubes for a counter were cut; however, since the researchers had to be onsite to download the counter data (automated data retrieval was not accessible as cellular service was sparse), this issue was not identified until it was too late to fix. While people were observed walking and bicycling here, the researchers had safety concerns with installing counters across the roadway where there were large vehicles traveling at high rates of speed. These safety concerns may limit more people who live in the corridor from connecting between the communities on foot or bike. Finally, manual counts are time consuming and in rural environments, which may require the individual conducting the count to be on the roadside, these can present a safety challenge. Ideally, a variety of methods should be utilized to count bicyclists and pedestrians.

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Subjective Walkability and Bikeability: Analysis of the Built Environment and Safety at a Campus Area

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ABSTRACT

With a growing interest in promoting sustainable and healthy modes of transportation within academic settings, this study aimed to identify factors that influence the campus community's preferences for walking and bicycling. To assess the perceptions of the campus walking and bicycling environments, two subjective indices were developed based on the input from university campus members. The analysis involved studying campus members' walking and bicycling habits, and further utilized structural equation modeling (SEM) to examine the relationships between different variables. The results indicated notable gender disparities in the frequency of active transportation on campus, with male students showing a higher inclination to ride bicycles compared to female students. This discrepancy was primarily attributed to the safety and security concerns encountered by female students. The present study also focused on the influence of built environment characteristics on walkability and bikeability scores. Clear and unobstructed pathways, well-marked bike lanes, appropriate lighting conditions, and the presence of visible traffic control devices emerged as significant factors impacting the perceived walking and bicycling conditions on campus. The SEM analysis also highlighted a positive correlation between walkability and bikeability scores, indicating that improvements in one domain have a beneficial impact on the other.

INTRODUCTION

For the past 70 years, the prevalence of the automobile has increased and generated an auto-centric lifestyle in the United States. After decades of car-centric policies, the consequences that have emerged include traffic congestion, pollution, high gas prices, fiscal constraints, and a steady reduction in physical activity contributing to adverse health outcomes such as obesity among all age groups (Balsas, 2003; Horacek et al., 2012). Similarly, many universities in the United States have been significantly impacted by the use and dependence of the automobile. Therefore, universities across country are becoming increasingly concerned with the consequences that have emerged due to the heavy dependency on the automobile (Rybarczyk & Gallagher, 2014; Akar & Clifton, 2009).

Previous research has found a decrease in the levels of physical activity reported by students and faculty members on university campuses in the United States (King et al., 2020; Bopp et al., 2011). Furthermore, less than half of college students in the United States meet the recommended physical activity guidelines provided by American Heart Association (Bailey et al., 2022). The longer students attend university, the more their total physical activity decreases. Therefore, college students are susceptible to a sedentary lifestyle when young adulthood is a critical time to develop lifelong habits (Irwin, 2004).

There is an increasing interest in promoting walking and bicycling as active modes of transportation among universities. Several studies have discussed promoting active transportation on university campuses as one of the most suitable locations to increase utilitarian walking and bicycling for students, faculty, staff, and residents living nearby (e.g., Zhang et al., 2020). The university campus members generally have better access to an integrated roadway network, including walkways, bikeways, and roadways. Since university campus environments are typically more conducive to active transportation, promoting walking and bicycling in campus settings could lead to an increased number of university campus members engaging in a more active and healthier lifestyle.

While promoting active transportation in a campus environment has many benefits, implementing the policies and strategies to promote walking and bicycling come with several challenges. Determinants that influence the adoption of active transportation among members of university campuses include overall travel behavior, travel distance, time, convenience, presence of infrastructure, sociodemographic factors, age, current physical activity level, self-efficacy, access to a bicycle and skills, prevailing attitude towards walking and bicycling among the campus members, social and cultural support, the characteristics and appearance of the built environment and the campus' location (Balsas, 2003; Akar & Clifton, 2009).

Many studies have previously attempted to evaluate and measure active transportation through developing different indices. For example, walkability and bikeability indices are the two frequently used measurements to quantify how conducive the selected environment is to walking and bicycling (e.g., Wahlgren & Schantz, 2011). Nevertheless, although several walkability and bikeability indices have been developed and modified to measure different neighborhood areas, cities, workplaces, route environments, and street segments, few present studies have assessed the walkability and bikeability of university campuses. The purpose of the present study is to examine campus travel behavior and perceptions of the current walking and bicycling conditions among the university campus population through a survey distributed at California State University, Sacramento (CSUS). Furthermore, this study seeks to create two subjective indices by gauging the perceptions of the university campus population regarding the current conditions for bicycling and walking. The aim is to understand how favorably the campus community views the walking and bicycling environments on campus..

LITERATURE REVIEW

Researchers have defined walkability and bikeability differently in the existing literature on walking and bicycling. Therefore, there are no universally accepted definitions of walkability and bikeability. However, the prevalent definition of walkability in the literature is the certain features within a place that encourage people to walk, and it is a measure of how conducive the built environment is to walking (Li et al., 2018). The term walkability encompasses the ability to quantify the perceived friendliness, safety, and desirability of walking routes in a specific environment (King et al., 2020; Zhang et al., 2020). Kellstedt et al. (2020) explained that bikeability is the extent to which the studied environment is conducive and safe to bicycling. Bikeability integrates terms such as bicycle comfort, bicycle suitability, bicycle friendliness, and bicycle accessibility (Reggiani et al., 2021).

Measuring the qualities of the studied environment to determine walkability and bikeability can mainly be done objectively and subjectively. Objective tools measure the physical attributes of the built environment by including direct observations, using audits or extraction of geospatial data such as census-based geographic information system (GIS) (Kellstedt et al., 2020; Maghelal

& Capp, 2011). However, subjective measures are designed to assess the individual's perception of the quality of their environment including motivators and barriers for walking and bicycling, attitude, willingness, and overall user satisfaction through interviews, self-reported surveys, and discussions (Reggiani et al., 2021). Subjective tools that are frequently mentioned in the literature are the surveys Neighborhood Walkability Scale (NEWS), Active Commuting Environment Scale (ACRES), and Assessing Levels of Physical Activity and Fitness (ALPHA) (Wahlgren & Schantz, 2011; Saelens et al., 2003; Spittaels et al., 2009). Another notable questionnaire that assessed motivators and deterrents of bicycling is "Cycling in Cities" by Winters and Teschke (2010). The authors of the study used the findings from the survey to identify environmental factors that influence bicycling together with travel behavior analyses and focus group sessions and developed a bikeability index later.

However, few studies have established indices with scoring systems to assess both walkability and bikeability, specifically in university campus environments. For example, King et al. (2020) examined how campus environments influence university members' choices of being physically active by administering a campus walkability survey and creating an environmental scan audit. The authors found that both campus members' perceptions and observations of the walking environment could influence physical activity levels among the campus population.

Different researchers examined demographical, psychological, travel behavior (e.g., most frequent mode of transportation used to commute to campus and travel distance), attitudes towards walking and bicycling, perception of environmental factors, and perceived motivators and barriers for walking and bicycling on campus (Rybarczyk & Gallagher, 2014; Akar & Clifton, 2009; Bopp et al., 2011). For example, Akar and Clifton (2009) performed a web-based survey on attitudes regarding travel characteristics and reasons that prevent or promote bicycling around the University of Maryland campus. They found that time and cost of travel are important factors that influence mode choice among university campus members. More people are likely to bicycle if the travel time decreases. Furthermore, the results showed also that the lack of bike lanes and proper lighting, presence of vehicular traffic, and feeling unsafe at night prevent people from bicycling on campus. Similarly, Rybarczyk and Gallagher (2014) conducted an attitudinal survey in a university campus environment. The authors found that students, faculty, and staff would bicycle more if safer bicycle routes and improved lighting, and more bicyclists on the roads were present on campus.

While campus walkability and bikeability have been assessed subjectively earlier, this study contributes to the present literature on active transportation in campus environments by establishing two subjective indices that evaluate both walkability and bikeability based on measurement tools that have been developed previously.

METHOD

Survey Development

Previous walkability and bikeability measurement tools were reviewed in the process of the survey development to identify the most common components and items used. Furthermore, studies related to bicycling and walking on and around the university campus environments were reviewed to identify components that encourage walkability and bikeability in campus settings. Earlier studies that conducted surveys on perceptions of walking and bicycling in a campus setting, also included personal characteristics and travel behavior to learn how these correlates to the perception of the studied environment. The purpose of this survey was to assess the university campus members' (students, faculty, staff, and others) attitudes and perceptions about walking and bicycling on and around the CSUS campus. The web-based survey was developed by using Qualtrics Survey Software. The survey was divided into four sections:

- Section 1: Housing Situation and Travel Behavior
- Section 2: Walking
- Section 3: Bicycling
- Section 4: Personal Characteristics

Sections 2 and 3 used a five point-Likert response scale (strongly disagree, disagree, neutral, agree, and strongly agree) to evaluate the university campus members' perceptions towards walking and bicycling on and around CSUS. Perception items were self-selected based on previous subjective measurement tools and slightly modified to capture the features of walkability and bikeability in a university campus setting. The statements included in the survey were based on mainly two subjective measures, Neighborhood Environment Walkability Scale (NEWS) and Active Commuting Route Environment Scale (ACRES) (Wahlgren & Schantz, 2011; Saelens et al., 2003). These studies were developed and established more than ten years ago, replicated several times, and modified. Furthermore, a few items were either modified to be applicable to this study or added. For instance, "sufficient bicycle parking on campus" was included since previous studies on active transportation in campus settings considered bicycle parking as an important factor to encourage bicycling (Balsas, 2003; King et al., 2020).

Study Setting and Participants

This study is conducted at the large and urban campus of CSUS that spans 305 acres on the main campus. The university campus is located in the central part of Sacramento in California. After the survey was prepared and approved by the Sacramento State Institutional Review Board (IRB) (IRB protocol number: Cayuse-22-23-149), the online survey was administered to over 5,000 students, faculty, and staff members at CSUS, in February 2023. Data collection took place over the course of two weeks, and the data were compiled through Qualtrics Survey Software. The population sample of this survey did not cover everyone at CSUS, as the survey link was emailed to those who were subscribed to the College of Engineering and Computer Science (ECS) mailing list.

A total of 331 responses were received, from which 283 participants completed the entire survey. The other 46 respondents did not complete the survey and left at least 29% of the survey incomplete upon submittal. Therefore, their responses have been filtered out from the results to ensure the analysis of complete data. Overall, 72.9% of the survey sample respondents were male and 24.3% female. The majority of the respondents were between the ages of 18 to 24 (69.6%). Also, the survey respondents' primary roles at the university were 90.5% students and 9.5% non-students. The participants identified themselves with different ethnic backgrounds, with a majority of White or Caucasian (37.8%), Asian (32.9%), and Hispanic or Latino (26.5%).

RESULTS

Walking and Bicycling Habits

Table 1 shows all the respondents that reported either walking and/or bicycling among their top two modes of travel to CSUS, separated by gender. As shown in this table, walking frequency is similar between female and male participants (24.6% vs. 26.1%). However, more male participants (15.9%) bicycle to the campus compared to the survey respondents that identified themselves as female (8.7%). This is in line with the trends observed across the United States. Walking mode share is almost the same for male and female pedestrians. However, data from the 2018 benchmarking report for biking and walking in the U.S. (The League of American Bicyclists, 2018) shows that while women represent 50.8% of the population of the U.S., they only represent 30.3% of all bicycling trips.

TABLE 1. Walking and Bicycling among Top Two Modes of Travel

Mode to campus	Group	N	Sample Total	(%) Mode
Walking	Male	51	207	24.6%
	Female	18	69	26.1%
	Other	3	7	42.9%
	All Groups	72	283	25.4%
Bicycling	Male	33	207	15.9%
	Female	6	69	8.7%
	Other	0	7	0.0%
	All Groups	39	283	13.8%

Respondents were asked the reasons why they bicycle and walk to, on, and around campus. This question considered walking and bicycling as a mode of transportation when commuting to CSUS from their own residence, but also when they are on campus. The respondents could select multiple choices. A total of 861 answers were received from 283 survey participants. Table 2 shows counts and percentages of the possible reasons why the university campus members (students vs. non-students) walk and/or bicycle to and on/around the CSUS campus. Overall, among all the 283 respondents, 61.8% stated, “supports my physical and mental health,” which is the primary reason among all groups. The second most common reason among the overall population is “convenient” which was selected by 60.1% of the respondents, followed by 53.4% of the overall population considering walking and bicycling “affordable”.

TABLE 2. Main Reasons for Walking and Bicycling

Reasons	Students	Non-Students	All (N)
Affordable	55.8%	28.0%	151 (53.4%)
Time efficient	42.2%	40.0%	119 (42.0%)
Convenient	63.8%	32.0%	170 (60.1%)
Enjoying walking/bicycling	46.5%	48.0%	132 (46.6%)
It is good for the environment	41.1%	32.0%	114 (40.3%)
Supports my physical and mental health	61.6%	64.0%	175 (61.8%)
Other reasons	8.9%	4.0%	24 (8.5%)

Walkability and Bikeability Indices

Structural Equation Modeling (SEM) is a series of statistical methods that allow for the analysis of complex relationships between one or more independent variables and one or more dependent variables. It can be viewed as a combination of factor analysis and regression or path analysis. SEM can encompass observed or measured variables (also known as manifest variables) as well as theoretical constructs that are not directly measured (also known as latent variables). SEM is often visualized by a graphical path diagram in which observed variables are represented by rectangle boxes and latent variables are represented by ellipses. Single-headed arrows are used to define causal relationships, and double-headed arrows indicate covariance (Hox & Bechger, 1998).

In this study, SEM was used to systematically investigate the simultaneous construct of walkability and bikeability by developing four latent variables from survey questions representing walking/bicycling conditions and walking/bicycling safety perceptions at and around the CSUS campus. Table 3 shows definitions and summary statistics for the selected variables in the final model. SEM was applied in this study using R software (version 3.3.1) package lavaan.

TABLE 3. Variable Description and Summary Statistics

Variable	Variable description	Response frequency
Walking Conditions (*latent variable*)	To what extent do you agree or disagree with the following statements? [1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree]	
WC1	The levels of air pollution and noise are low for walking	1: 4.2% | 2: 11.0% | 3: 23.3% | 4: 47.3% | 5: 13.1%
WC2	There are many destinations to go within easy walking distance (e.g., restaurants, coffee shops, grocery stores, gym, library and green space)	1: 4.9% | 2: 12.0% | 3: 17.7% | 4: 48.1% | 5: 17.0%
WC3	It is easy to walk to a public transit stop	1: 4.6% | 2: 9.9% | 3: 32.5% | 4: 37.1% | 5: 15.5%
WC4	The pedestrian signs, markings, and signals are clearly visible	1: 2.5% | 2: 9.9% | 3: 22.3% | 4: 47.3% | 5: 17.7%
WC5	The pedestrian facilities are clear from obstructions	1: 2.5% | 2: 8.1% | 3: 21.6% | 4: 50.5% | 5: 17.3%
WC6	The pedestrian facilities have a proper lighting system	1: 4.2% | 2: 16.3% | 3: 27.9% | 4: 38.2% | 5: 13.4%
Walking Safety (*latent variable*)	To what extent do you agree or disagree with the following statements? [1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree]	
WS1	The occurrence of conflicts between pedestrians and other road users are low	1: 4.6% | 2: 15.2% | 3: 24.7% | 4: 40.6% | 5: 14.8%
WS2	Pedestrians are visible to other road users	1: 1.8% | 2: 10.6% | 3: 21.2% | 4: 49.8% | 5: 16.6%
WS3	It is safe to walk on the sidewalks along the moving traffic	1: 2.8% | 2: 5.3% | 3: 19.4% | 4: 54.4% | 5: 18.0%

Variable	Variable description	Response frequency
WS4	It is safe to cross the intersections	1: 1.1% | 2: 8.1% | 3: 29.0% | 4: 47.7% | 5: 13.8%
WS5	It is safe to walk at night	1: 9.9% | 2: 19.4% | 3: 35.7% | 4: 29.0% | 5: 6.0%
Bicycling Conditions (*latent variable*)	To what extent do you agree or disagree with the following statements? [1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree]	
BC1	The levels of air pollution and noise are low for bicycling	1: 4.6% | 2: 8.5% | 3: 32.5% | 4: 42.4% | 5: 12.0%
BC2	There are many destinations to bicycle within a short distance (e.g., restaurants, coffee shops, convenience stores, gym, library, and green space)	1: 0.7% | 2: 4.6% | 3: 27.2% | 4: 43.8% | 5: 23.3%
BC3	It is easy to bicycle to a public transit stop	1: 1.1% | 2: 4.6% | 3: 34.6% | 4: 38.9% | 5: 20.1%
BC4	The bicycle signs, markings, and signals are clearly visible	1: 2.1% | 2: 5.7% | 3: 39.6% | 4: 35.0% | 5: 16.6%
BC5	There are enough bicycle parking spaces	1: 3.2% | 2: 4.9% | 3: 40.6% | 4: 30.0% | 5: 19.8%
BC6	The bikeways are clear from obstructions	1: 2.5% | 2: 13.1% | 3: 38.9% | 4: 31.4% | 5: 13.4%
BC7	The bicycle facilities have a proper lighting system	1: 2.1% | 2: 10.6% | 3: 45.9% | 4: 29.0% | 5: 11.7%
Bicycling Safety (*latent variable*)	To what extent do you agree or disagree with the following statements? [1: Strongly disagree; 2: Disagree; 3: Neither agree nor disagree; 4: Agree; 5: Strongly agree]	
BS1	The occurrence of conflicts between bicyclists and other road users are low	1: 4.6% | 2: 17.7% | 3: 38.2% | 4: 30.0% | 5: 9.2%
BS2	Bicyclists are visible to other road users	1: 2.5% | 2: 10.6% | 3: 30.0% | 4: 48.1% | 5: 8.5%
BS3	It is safe to bicycle on bikeways that are not separated from other traffic	1: 9.2% | 2: 23.3% | 3: 36.0% | 4: 25.1% | 5: 5.3%
BS4	It is safe to bicycle through the intersections	1: 2.1% | 2: 14.1% | 3: 44.2% | 4: 32.5% | 5: 6.7%
BS5	It is safe to bicycle at night	1: 7.4% | 2: 20.8% | 3: 44.5% | 4: 20.8% | 5: 5.7%
Walkability Index	[1: very bad; 5: very good]	Mean: 3.83 | SD: 0.94
Bikeability Index	[1: very bad; 5: very good]	Mean: 3.14 | SD: 0.95

Figure 1 depicts a graphical representation of the final SEM with the standardized path coefficients (loading factors). The final structure was achieved through an iterative modeling process. Several SEM structures were investigated, and the one that was found to be the most descriptive of identified conceptual objectives and demonstrated the best statistical fit of the data was chosen. There are two models within the larger model of the final SEM: one to examine the construct of walkability, and the other to examine the construct of bikeability. SEM also makes it possible to investigate the covariance between walkability and bikeability.

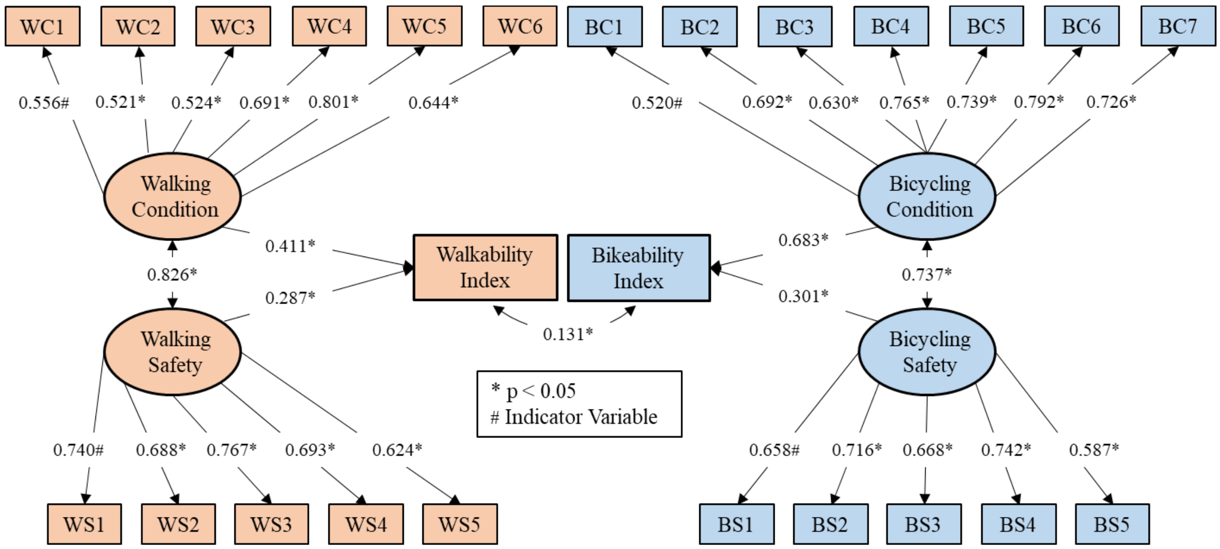

Figure 1. SEM Path Diagram with Standardized Coefficients

Two of the widely reported Goodness-of-Fit indices used in SEM analysis are Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). According to Hooper et al. (2008), a value less than 0.08 for these parameters could indicate an acceptable fit. The results of SEM estimation suggest a value equal to 0.074 for RMSEA and 0.066 for SRMR, both of which confirm an acceptable fit for the final structure.

To evaluate the walking index, two latent variables were constructed, and their direct effect on walkability was evaluated through simultaneous regression models. All latent variables were unobserved, unitless constructs. As such, to define a unit of measurement, a non-zero coefficient was assigned to each latent variable as an indicator. These reference variables were given the value of 1 (non-standardized) and are shown with # in Figure 1. The latent variable "Walking Condition" had the most significant positive impact on walkability (loading factor = 0.411). "Walking Condition" was developed from six observed variables that analyzed the CSUS built environment from a pedestrian frame of reference. These observed variables were coded such that a higher value represented a better walking environment. While all the feeding manifest variables had a positive impact, walkways free of obstruction (WC5) and proper lighting system (WC6) had the most significant impact, as shown by the loading factors (WC5 loading factor = 0.801 and WC6 loading factor = 0.644). "Walking Safety" was the second effective latent variable to describe walkability (loading factor = 0.287). While all the feeding manifest variables had a positive impact, walking on sidewalks along the traffic (WS3) and the occurrence of conflicts between bicyclists and other road users (WS1) had the most significant impact, as shown by the loading factors (WS3 loading factor = 0.767 and WS1 loading factor = 0.740).

To evaluate Bicycling index, two latent variables were constructed and their direct effect on bikeability was evaluated through simultaneous regression models. The latent variable "Bicycling Condition" had the most significant positive impact on bikeability (loading factor = 0.683). "Bicycling Condition" was developed from seven observed variables that analyzed the CSUS built environment from a bicyclist frame of reference. Similar to walkability measurement, the observed variables were coded such that a higher value represented a better bicycling environment. While all the feeding manifest variables had a positive impact, bike lanes free of obstruction (BC6) and visibility of bicycle signs, markings, and signals (BC4) had the most significant impact, as shown by the loading factors (BC6 loading factor = 0.792 and BC4 loading factor = 0.765). In a similar relationship observed in walkability, “Bicycling Safety” was the second effective latent variable to describe bikeability (loading factor = 0.301). While all the feeding manifest variables had a positive impact, bicycling through the intersection (BS4) and visibility of bicyclists to other road users (BS2) had the most significant impact, as shown by the loading factors (BS4 loading factor = 0.742 and BS2 loading factor = 0.716).

Covariance estimates among these developed latent variables showed that “Walking Condition” and “Walking Safety” were directly correlated (loading factor = 0.826). Same results were obtained for “Bicycling Condition” and “Bicycling Safety” (loading factor = 0.737). As shown in the final SEM model, walkability and bikeability were reported to be directly correlated, meaning that those who reported a higher subjective walkability index also reported a higher subjective bikeability index, and vice versa (loading factor = 0.131).

While several different structures were tested, none of the variables in section 1 (e.g., travel time and driver’s license) and section 4 (e.g., GPA and BMI) of the survey were found to be statistically significant. As such, they were not included in the final SEM.

CONCLUSION

The role of gender in walking and bicycling behaviors is evident from the differences observed between male and female participants in their preferences, performance, and perceptions of safety and comfort. Studies have shown that male and female road users exhibit distinct preferences for walking and bicycling and display differing performance levels on the road (e.g., Tilahun et al., 2007). For women, perceptions of safety and comfort play a crucial role in influencing their inclination to use bicycles as a mode of transportation. As shown in Table 1, for every two male students, there is only one female student who reported bicycling among their top two modes of travel. This is further supported by the survey responses from participants around the CSUS campus, where female respondents consistently reported lower scores on measures of walking and bicycling conditions and safety issues compared to their male counterparts. For instance, female students provided on average 19% lower safety scores for walking at night (WS5 – 2.56 vs. 3.17) and 11% lower scores for bicycling at night (BS5 – 2.69 vs. 3.02), highlighting their heightened concerns about safety in both activities. The statistical significance of these safety-related issues is confirmed by the final SEM analysis, which underscores the impact of safety and security in shaping perceptions of walkability and bikeability scores. For example, proper lighting condition was found statistically significant in the construct of both walking and bicycling indices (WC6 and BC7). Understanding and addressing gender-specific concerns are imperative for promoting active transportation and ensuring equitable and safe mobility options for all.

Table 2 provides insights into the reasons why individuals are willing to walk or ride a bike on campus. The primary motivations include supporting their physical and mental health and finding walking or biking a convenient mode of transportation within the campus grounds. These factors highlight the importance of promoting health and emphasizing the accessibility and convenience of walking and bicycling options to attract more individuals towards adopting these modes of travel. To encourage the growth of walking and bicycling in such cases, the SEM analysis underscores the significance of several factors. One key aspect is the creation of walking and bicycling pathways that are free of obstructions. By ensuring clear and unobstructed paths, individuals are more likely to feel safe and encouraged to walk or bike, making the campus more pedestrian and bicyclist-friendly. Furthermore, the SEM findings emphasize the importance of implementing visible and informative traffic control devices, such as colored pavement markings, to enhance the bicycling conditions on campus (e.g., BC4 and BS2). These measures can help reinforce the right of way for bicyclists and increase their visibility to drivers, thereby reducing potential conflicts and enhancing safety.

The observed correlation between walkability and bikeability indices, as revealed by the SEM analysis, indicates that individuals who reported higher scores for walking also tended to report higher scores for bicycling. There are several potential reasons for this positive relationship. Firstly, the presence of well-designed and user-friendly infrastructure, such as wide sidewalks, well-marked crosswalks, and separated bike lanes, can contribute to both walkability and bikeability. When walking conditions are improved, it is likely that the same improvements extend to bicycling, making it safer and more convenient for bicyclists as well. Secondly, a campus environment that prioritizes active transportation and fosters a culture of walking is likely to extend the same emphasis to biking, promoting the use of bicycles as a viable and preferred mode of transportation. Moreover, the factors influencing walkability, such as safety, accessibility, and proximity of amenities, also play a role in enhancing bikeability. For instance, well-lit and safe pathways that are conducive to walking are equally beneficial for bicyclists. The shared factors contributing to both walkability and bikeability create a positive feedback loop, where improvements in one domain inadvertently lead to improvements in the other, thus reinforcing the correlation between the two indices. Overall, this correlation signifies the interconnectedness of walking and bicycling experiences, and underscores the importance of adopting integrated approaches to promote and support active transportation on campus.

In conclusion, our study underscores the critical role of the built environment in influencing walkability and bikeability scores on campus. Various characteristics of the built environment, such as the presence of obstructions, adequacy of lighting, appropriate traffic control devices, and designated spaces for walking and bicycling, significantly impact the overall walkability and bikeability of the campus. Investing in well-designed and user-friendly infrastructure can lead to improvements in both walking and bicycling conditions, making active transportation more appealing and feasible for all campus members. Integrating safety-enhancing features will not only enhance the campus experience for pedestrians and bicyclists but also contribute to fostering a culture of sustainable and healthy transportation choices. Overall, our findings underscore the importance of adopting gender-sensitive and environment-focused strategies to create a more walkable and bikeable campus that caters to the diverse needs and preferences of its community members.

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Improving the Efficiency of Traffic Outside Intermodal Facilities: A Proof of Concept of Operations

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ABSTRACT

Intermodal facilities, including port terminals, play a significant role in the economic framework of the United States by making substantial contributions to the country's GDP, but face challenges managing increased freight volumes. However, increased transportation time within port facilities leads to higher costs, emissions, and impacts on efficiency and sustainability. This research aims to develop a concept of operations (ConOps) for improving the efficiency of heavy truck movement outside port facilities, with goals of reducing congestion, considering greenhouse gas (GHG) emissions, and addressing truck drivers' satisfaction. The study proposes integrating technological solutions to streamline heavy truck traffic at intermodal port facilities, including scheduled truck arrivals and departures, truck stop and rest areas, real-time traffic information, implementation of dedicated truck lanes, and autonomous truck platooning. The focus is improving communication, efficiency, and safety for trucking companies, operations managers, and truck drivers. Using microsimulation modeling a traffic impact study is also conducted, focusing on a case study near the port of Miami. Different traffic scenarios are implemented to evaluate different strategies, such as dedicated and exclusive truck lanes, freeway lane restrictions, and autonomous truck platooning. Simulation findings emphasize the positive impact of these strategies on travel times and delays, and forecast scenarios account for increased truck volumes. Dedicated truck lanes and truck platooning demonstrate promising results in improving overall traffic flow. This research supports decision-making for government officials and logistics service providers in sustainable and efficient intermodal freight planning.

Keywords: Intermodal facilities, concept of operations (ConOps), traffic impact study, dedicated lane

INTRODUCTION

Intermodal facility is intended to facilitate the efficient movement of a shipment from one mode of transportation to another as it travels from origin to destination [1]. In the United States, ports serve as key entry points for international trade operations. Also, the transportation industry contributes significantly to the U.S. economy. In the United States, approximately 72.5% of the nation's total freight by weight, or 10.93 billion tons, is transported by trucks. And the trucking industry is expected to experience substantial growth in the coming years, resulting in an anticipated increase in revenue [2]. U.S. ports serve as important engines of the national economy, functioning as crucial nodes in the global supply chain. On the other hand, truck operation is critical to port operations, whose efficiency directly influences port productivity and overall economic performance. However, high transportation costs and increased times can increase operational expenses for wholesale organizations, indirectly affecting the economy through increased inventory costs and opportunity losses. Moreover, long queues of trucks at terminal gates can significantly add to emissions, noise, and traffic jams in and around ports [3].

Heavy truck operations also have environmental implications and equity considerations. The transportation sector is a significant contributor to greenhouse gas (GHG) emissions, which contribute to global warming. Heavy-duty trucks, rail, and marine transportation account for a substantial portion of CO2 emissions in the United States. Furthermore, heavy truck operations at ports can have impacts on air pollution, affecting the health of nearby communities. The lack of sufficient truck parking areas further complicates matters, necessitating additional trips between the port and supplementary truck service areas, increasing greenhouse gas (GHG) emissions [4]. The population is currently concerned about global warming, and greenhouse gas (GHG) emissions are a major contributor. Heavy-duty trucks comprise a significant part of port traffic and contribute about 40% of a port's total greenhouse gases, accounting for 3% of global carbon emissions [5].

In the context of port operations, long lines and delays for loading and unloading can increase fatigue risk for heavy truck drivers if it extends their working hours or limits their opportunities for rest [6]. Sometimes the truck drivers pay the price for overcrowded ports, with long wait times. They have been waiting for hours outside ports, and drivers who regularly pick up loads from ports have reported lines as long as five/six miles long and wait times of up to eight hours. Congestion leads to long waiting times and increased fuel consumption, impacting port efficiency and traffic management. The increased heavy truck movement around the port creates bottlenecks, leading to increased congestion, long queues outside the intermodal terminal gate, and a lack of available truck parking areas, further worsening the situation. Currently, various technologies and strategies aim to improve port efficiency in general and heavy truck movement, such as truck automation, truck electrification, and truck platooning systems. So, the study proposes guidelines considering the environmental impact of heavy truck operation for the community living near the port and truck driver satisfaction.

RELATED WORK

Worldwide, the transportation infrastructure for transferring cargo to and from ports and the regions they service is challenging to keep up with current cargo quantities. These numbers are projected to increase higher. Port logistics includes a wide range of activities, including cargo handling, loading, and unloading, customs documentation, monitoring, and more. Thus, success in global trade and transactions necessitates efficient port logistics operations. Containers accumulate at various U.S. port terminals due to transportation bottlenecks, resulting in costly delays and more significant fuel expenses for rescheduling and compensating for lost time. A problem in one place can affect everything from ports to transport carriers all over the supply chain, making things cost more for everyone [7]. So, several research studies have been conducted, focusing on different studies related to concepts of operation, traffic impact studies, port truck operation, truck scheduling problems, truck parking, and bottleneck situations. This study reviews various research efforts to gain a deeper understanding of previous work conducted on this specific topic. Firstly, Concept of Operations (ConOps) is important in systems engineering as it defines operational and system-level requirements by facilitating a shared understanding of a future system. It is a crucial element in the systems engineering process, acting as a solid foundation upon which the entire system is built and operated. It is essential that this document remains accessible and relevant to all stakeholders involved, regardless of their backgrounds or roles within the system [8]. The Federal Highway Administration (FHWA) defines the Concept of Operations for a Freight Advanced Traveler Information System (FRATIS) intending to provide a complete understanding of its goals, functions, user classes, and operational policies. ConOps describes different FRATIS applications, such as freight-specific travel planning, dynamic routing, performance monitoring, and drayage optimization [9]. A study conducted by Shaw & Quigley states that the Concept of Operations consolidates vital issues, methodologies, and duties for implementing, managing, and operating Intelligent Transportation System (ITS) deployments on Florida's limited-access highways. These strategies are rooted in established ITS practices and developed by involved agencies [10]. Kaisar et al have developed in their research guidelines and criteria known as the concept of operation, and this is intended to assist transportation agencies in implementing signal priorities based on specified decision factors along specific corridors [11].

By optimizing journey planning and ensuring compliance with transportation regulations, the aim is to enhance commercial vehicle operations and improve industry efficiency [12]. Truck scheduling systems are commonly employed to address issues such as high truck volumes and long queues at container terminals. A study by Jovanovic introduced a novel approach to developing a truck appointment system (TAS) for container terminals. The research demonstrated that it is possible to enhance driver satisfaction while maintaining the benefits for the port. By considering factors such as daily truck visits, driver working hours, and dray transfer distances, the proposed method effectively reduced gate waiting times. Terminal gate congestion, a prevalent form of container port congestion, creates bottlenecks that hinder port productivity and restrict truck movement [13]. With the increasing demands of the global economy, truck drivers spend extended periods on the road, making adequate rest facilities essential for their well-being and road safety. However, a pressing issue arises as many states as possible in the United States struggle with a shortage of these vital services. Truck drivers heavily rely on designated parking spaces like truck stops and rest areas to rest, fulfill personal needs, and comply with legal rest regulations. These facilities typically provide amenities such as restrooms, food options, showers, and sometimes additional spaces for relaxation or entertainment [14,15]. A study conducted by Bunn et al found that there is a higher likelihood of crashes when the nearest rest facilities are located 20 miles or more from the crash site, especially on parkways and during nighttime hours. According to the U.S. Department of Transportation, 36 states are currently experiencing shortages in rest areas, which directly impacts truck drivers' ability to comply with working hour regulations [16].

CONCEPT OF OPERATION

The proposed system aims to enhance heavy truck traffic flow outside intermodal facilities, such as ports, by reducing truck waiting times. The proposed system focuses mainly on three primary user groups such as dispatchers and operation managers, truck drivers and people living near the port area. The system incorporates various features and functions to achieve its objectives: Implementing a smart queuing system outside the terminal gate and proper truck scheduling system can reduce truck waiting time. Also, Real-time reliable data sources are used to predict truck arrival times and prioritize them for route planning system.

Technology plays an important role in improving efficiency. Intelligent transportation systems, such as real-time traffic monitoring and communication technologies can optimize traffic flow and reduce truck idling time, gas emissions, and fuel consumption. Also encouraging the use of alternative fuels and technologies, such as automated, electric, and hybrid vehicles, can mitigate the environmental impact.

Prioritizing infrastructure development, introducing truck parking areas and rest areas which can provide safe and secure truck stops and rest areas for drivers, reducing waiting times and increasing overall efficiency. Collaboration among stakeholders, such as trucking companies, port authorities, and public and private agencies involved in the supply chain can ensure coordinated and efficient traffic operations.

Also, the system's essential features, capabilities, and functions can be categorized into three functional areas:

Scheduled appointments and truck parking availability: Truck appointment systems involve providing specific time slots for specific trucks to take entry and exit at the terminal gate. By implementing this system truck queuing and waiting times can be reduced. Also, adequate truck parking spaces near the terminal prevent illegal parking and ensure smooth cargo loading and unloading. The parking lots should be conveniently positioned and easily accessible, with amenities such as restrooms, overnight resting areas, showers, food, and fuel stations. Implementing Dedicated Separate Truck Lane: This involves implementing special truck treatments on the road, developing a truck road network, and making recommendations for implementing a pilot system. Trucks can utilize only specific lanes that are designated only for their use. Sometimes no other vehicles are allowed to use the exclusive lane just to reduce the car-truck interaction. These exclusive lanes can be physically separated from other lanes, or sometimes other vehicles can access those lanes [12].

Automated Truck Platooning: Autonomous Truck Platooning (ATP) allows trucks to travel in closely spaced convoys using V2V communication and autonomous driving systems. Trucks can be completely automated or partially automated. Also, multiple trucks can be connected based on requirements or freight carried by trucks. The truck platoon has the right to choose specific lanes, and they can travel through the highways. However, they can get separated whenever they travel through any intersection, and after passing the intersection, they can choose their specific route [17].

By addressing the challenges and focusing on the needs of the primary user groups, the proposed system aims to increase overall efficiency and mitigate negative impacts on the environment and the community. The system's foundation can be constructed as a primary application package to be incorporated into any existing public sector computer application systems connected within a port community region. Transportation authorities in both the public and private sectors will take the initiative and oversee the system installation process, preparing the website and smartphone app, overall maintenance, and managing the system operation, and ensuring smooth integration and effective operation. Figure 1 illustrates the key relationships and connections within the concept and provides a conceptual representation of the proposed system, incorporating Freight-Specific Dynamic Travel Planning developed by USDOT.

METHODOLOGY

In this study, the objective is to conduct a traffic impact study, enhance current freight mobility and prevent worsening traffic congestion in the overall network. The methodology begins with a detailed explanation of the problem. Next, the method used to solve the problem and the resulting outcomes are analyzed. At first, a case study area is selected, and required data, such as vehicle volume, speed distribution, vehicle classes, etc., are collected to develop the simulation model network. The study focuses on a case study area in Miami-Dade County, Florida, which experiences significant congestion near freight facilities, particularly the Port of Miami. Following data collection, the microsimulation platform VISSIM is used to create the base network, and the model is calibrated by modifying the model's default parameters. The model then develops seven distinct strategies, including dedicated truck lanes, truck platoons, vehicle platoons, etc. Then, for current traffic conditions such as AM Peak Hour (7-9 AM), Normal Hour (12-2 PM), and PM Peak Hour (4-6 PM), each scenario model is developed and run for ten replications with a random seed increment. Each model is executed for traffic forecasting scenarios with 10% increased truck volumes. Traffic forecasting entails anticipating future traffic conditions based on current and historical data. According to the literature, traffic volume is predicted to increase yearly, and the study intends to analyze the operational movement of truck flow. Based on recent data from the U.S. Department of Transportation, there was a more than 10% increase in the total number of registered trucks from 2019 to 2021. So, because this study includes adding methods such as dedicated truck lanes and truck platoons, we are making assumptions about increased truck numbers for our simulation network and seeing how they behave in the simulation network compared to present traffic conditions. After that, the vehicle travel time and delay results for each scenario are compared.

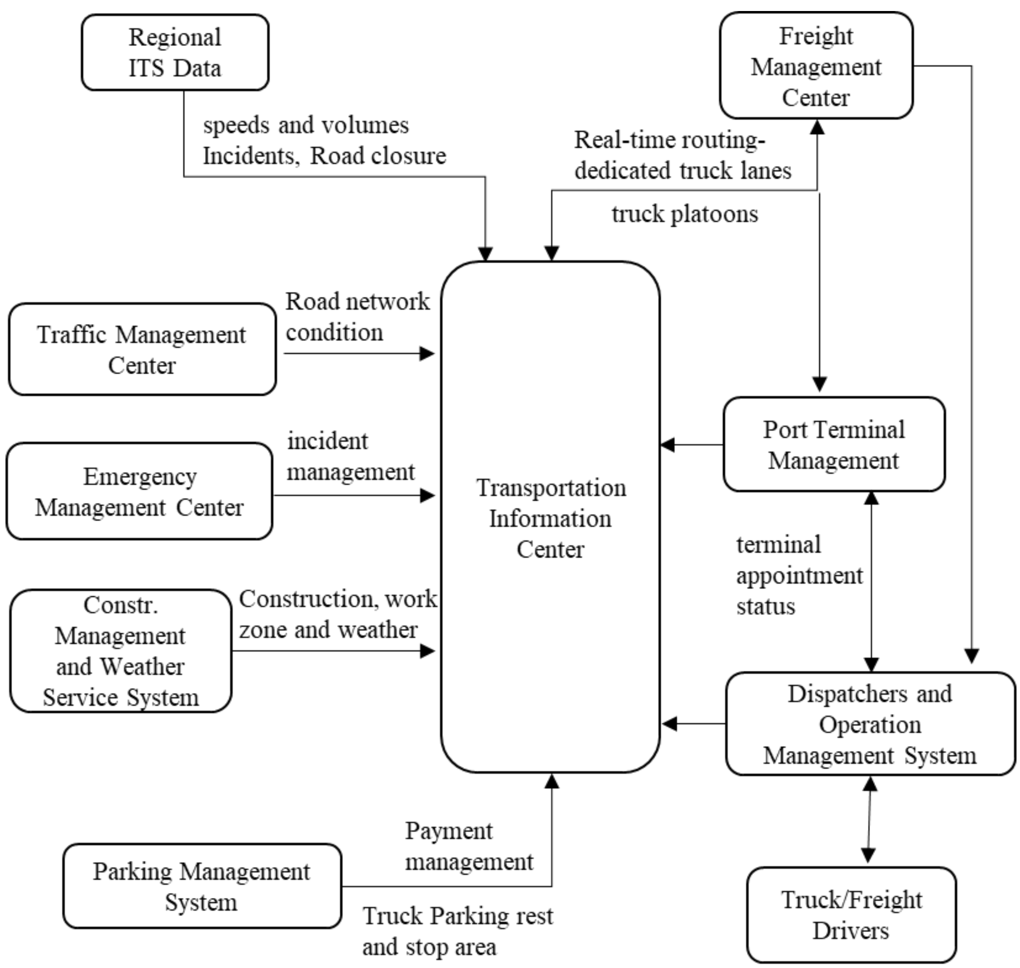

Figure 1: Proposed System Concept

The development of the microsimulation model is done using PTV VISSIM, a widely used traffic flow simulation software. It allows users to simulate real traffic conditions, model different geometries, and analyze traffic flow impacts. A total of eight road segments are considered in the model as shown in Table 1. The model calibration process involves adjusting various parameters to accurately represent the real-world roadway network conditions. Parameters related to link behavior, driving behavior, vehicle routing, vehicle speed distributions, and vehicle composition are modified. The calibration ensures that the model replicates the actual traffic conditions in the study area. After calibrating the model, a total of eight scenarios are developed and implemented as shown in Table 2.

First, a base scenario is created that replicates the network's present traffic conditions. The base scenario offers a general understanding of the road network's operation and how trucks interact with other vehicles.

Each scenario is evaluated based on its impact on traffic flow and compared to the base scenario and other scenarios. Scenario II focuses on the implementation of a dedicated truck lane strategy along major routes such as the Dolphin Expressway and I-395, commonly used by trucks heading to the Port of Miami Tunnel. The dedicated truck lane is designed at the left side of the freeway to reduce interactions between trucks and cars, improving traffic flow and road safety. The lane is designated on the left side of the road and extends approximately 4 miles. Trucks are restricted to this lane, and other vehicles are prohibited from using it. The dedicated truck lane aims to prioritize freight transport and enhance efficiency for both trucks and general traffic. Due to the high levels of congestion typically found in the Port of Miami area, dedicated truck lanes are exclusively implemented on the freeway, avoiding residential areas. As per the FDOT Open Data Hub, it is estimated that in 2022, more than 5400 trucks traveled in both directions using the I-395 corridor before proceeding to the Port of Miami via the tunnel, as shown in Figure 2.

In Scenario III, lane restrictions are implemented on the freeway. The left lane is restricted for truck use, while other vehicles are allowed to share any lane with trucks. There are no lane restrictions for trucks entering or exiting the freeway, providing flexibility for their movement.

Scenario IV introduces a truck-exclusive lane, where trucks have a separate lane isolated from the mainline traffic. On the Dolphin Expressway, a truck-exclusive lane is provided on the left side of 1 mile, serving as a toll route for trucks heading towards the Miami tunnel.

Scenario V explores the utilization of truck platoons on the freeway. Platooning involves groups of trucks traveling closely together, which can enhance traffic flow and fuel efficiency. The microsimulation model considers aggressive driving behavior for automated truck platoons, with a maximum of seven trucks in each platoon. Platoons are formed on the freeway, and trucks disperse when they need to take an exit.

Scenario VI combines the truck platooning concept from Scenario V with a dedicated truck-only lane. Truck platoons exclusively use the left lane, enhancing both the benefits of platooning and the segregation of trucks from general traffic.

Scenario VII combines truck platooning with lane restrictions. Truck platoons are confined to the left lane, while other vehicles have lane choice. This scenario aims to examine the impact of platooning while maintaining flexibility for other vehicles.

Scenario VIII introduces vehicle platoons, including both trucks and a percentage of autonomous cars. Platooning is simulated on the freeway, with the assumption that 10% of the cars form platoons. This scenario explores the behavior of car platoons and their effect on the overall network condition.

Each scenario is run for different time periods, including peak hours and regular hours. The microsimulation model accounts for various driving behaviors, lane restrictions, and lane-changing dynamics. The results of these scenarios are analyzed and compared to the base scenario and other scenarios to evaluate their impact on traffic flow, freight mobility, and environmental factors.

Table 1: Road Network Segments

Segments	Directions
1	Dolphin Expy-Tunnel (EB)
2	Dolphin Expy-Tunnel (WB)
3	Port Blvd (EB)
4	Port Blvd (WB)
5	I-95-Biscayne Blvd (NB)
6	I-95-Biscayne Blvd (SB)
7	I-95-Tunnel (EB)
8	I-95-Tunnel (WB)

Table 2: Implementation of Strategies

Scenarios	Descriptions
1	Base Scenario
2	Truck Only Lane
3	Lane Restrictions
4	Truck Exclusive Lane
5	Truck Platoons
6	Truck Platoons-Dedicated Lane
7	Truck Platoons-Lane Restrictions
8	Vehicle Platoons

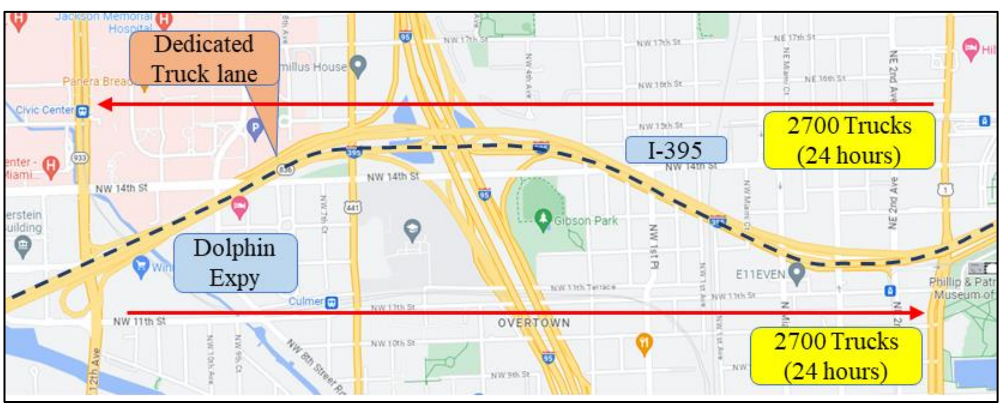

Figure 2: Dedicated Truck Lane

RESULTS

The findings of the study are intended to shed light on the effects and potential implications of employing various techniques in a congested area near the port. The findings from the analysis are reported separately for each scenario and the entire traffic network. The goal of the analysis is to demonstrate that introducing a range of scenarios to enhance truck movement efficiency provides efficient transportation connectivity and has a favorable impact on overall crowded circumstances. To evaluate the effects of the different scenarios being studied, two main performance measures are considered: average delay and total travel time for different road segments for all vehicles. The simulations are conducted during different time periods: the A.M. peak morning hour, the Normal hour during the day, and the P.M. peak evening hour. Each scenario runs ten times with consistent random seed sequences, and the results are averaged and categorized.

The results of the simulations are reported separately for each scenario and the entire traffic network. The analysis revealed that introducing strategies such as dedicated truck lanes and truck platooning led to significant improvements in travel time and reduction in delays. These strategies showed positive impacts on traffic flow, road safety, and overall transport efficiency. The findings highlight the potential benefits of dedicated truck lanes and truck platooning in reducing travel times, mitigating congestion, and improving freight movement efficiency. The study emphasizes the positive impacts of these strategies, especially when combined with other measures, and their potential environmental benefits.

Overall, the study's results contribute to the understanding of how different strategies can enhance truck operations near ports and congested areas. The findings provide valuable insights for decision-makers and transportation planners in evaluating and implementing effective measures to optimize traffic conditions and improve overall transport performance.

Travel Time

The analysis conducted in this study focused on measuring travel times in the network segments near the port of Miami using the VISSIM Microsimulation model. The average travel times for different scenarios are calculated for eight directions for both current traffic conditions and for traffic forecasting conditions. The analysis has yielded a range of results, with some scenarios showing promising improvements and others demonstrating less favorable outcomes. The results are shown in Figure 3.

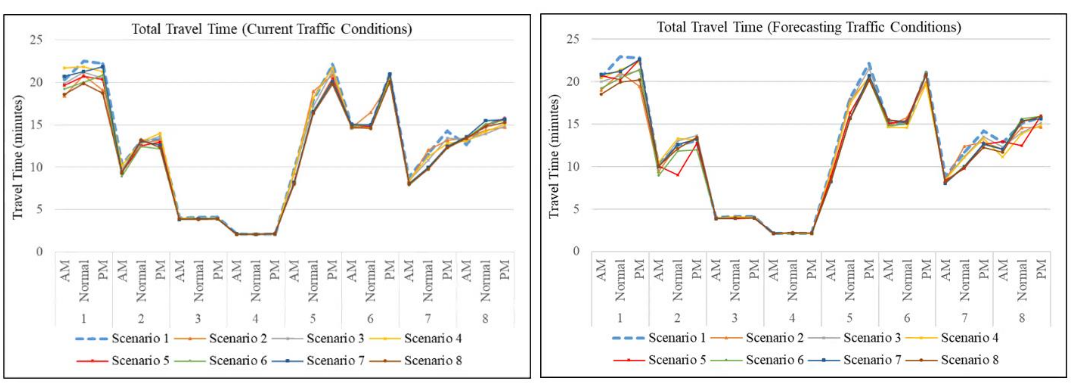

Figure 3: Average Total Travel Time – Current and Forecasting Traffic Conditions

Figure 3 illustrates how implementing different strategies change vehicle travel times for current operational traffic conditions: such as implementing a dedicated truck lane can reduce travel times ranging from 3.1% to 16.3% (EB) and from 1.05% to 8.5% (WB). When trucks are using the dedicated truck only lane it improves the traffic condition with a maximum travel time reduction of 16% in the EB direction compared to the lane restrictions and exclusive lane. A truck platoon strategy on the freeway reduces vehicle travel times from 1.7% to 12.6% in the EB direction and a maximum of 16.1% in the WB direction when vehicles use Dolphin Expressway through I-395. And using a truck platoon reduces vehicle travel times by a maximum of 17.9% in the EB when vehicles are traveling using I-95. When truck platoons use a dedicated truck-only lane, it provides better than a dedicated lane shared with other vehicles. Additionally, using the vehicle platoon strategy results in a maximum travel time reduction of 18.4% in the EB direction and 10.8% in the WB direction. These Scenarios demonstrate neutral results for vehicles traveling on Port Blvd and Biscayne Blvd, due to the changes targeting freeways, specifically those using the Miami tunnel. The Truck Platoon formation offers advantages when vehicles are using i-95 to Biscayne Blvd, with benefits of 8% to 10% in the NB direction for normal and PM traffic conditions and a maximum of 17% for the AM peak hour. The combined implementation of Truck Platoons and Car Platoons significantly improves travel times over any individual strategy.

For road segments 3 and 4, the outcomes appear neutral across the strategies. In some instances, the changes indicated are minimal, demonstrating neutral impacts, while in others, no significant improvements are detected. Vehicle travel time results of different scenarios for forecasting traffic conditions with increased truck volumes. It indicates how implementing strategies can reduce travel time across different traffic scenarios and times of the day. Implementing a dedicated truck lane, for example, can reduce vehicle travel times from 2.1% to 17.2% (EB) and 2.5% to 9.8% (WB) when vehicles use Dolphin Expressway. Dedicated truck lanes improve the traffic condition compared to the lane restrictions and exclusive lanes maximum of 17.2% in EB and 9.8% in WB directions. In the forecasting scenarios, truck volume increases, so using a truck-only lane reduces the interaction between trucks and other vehicles.

In some cases, when trucks use the dedicated truck lane for the forecasting traffic condition, it provides benefits by reducing the travel time compared to the current operational traffic condition. Using Truck Platoon on the freeway reduces vehicle travel times by 13.9% in the EB, and 39% in the WB direction when vehicles are using Dolphin Expressway, and using Truck Platoon reduces vehicle travel times by a maximum of 19.9% in the EB and 21.6% in the WB directions when vehicles are traveling using I-95. Using a dedicated lane for truck platoons shared with other vehicles reduces travel time by 17.3% in the EB and 7% in the WB direction, while vehicle platoons on the road reduce travel time by up to 19.9% in the EB direction and 9.8% in WB direction when vehicles are using I-95 through Miami Tunnel.

The comparison of maximum average total travel time reduction in percentages for different scenarios in EB and WB directions when vehicles are using Dolphin Expressway, are illustrated in Figure 4 for current operational traffic conditions and forecasting traffic. For current traffic conditions, truck only lane, truck platoons, and truck platoons with dedicated lane result in a significant reduction in travel time in the eastbound (EB) direction compared to other scenarios. However, in the forecasting scenario, vehicle platoons demonstrate better performance. Truck platoons provide superior results for the WB direction under the current traffic conditions and the forecasting scenario. Also, vehicle platoons show better results in forecasting traffic conditions.

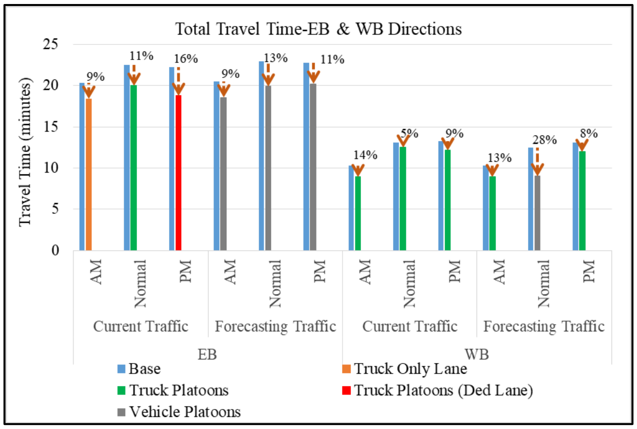

Figure 4: Total Travel Time for Current & Forecasting Traffic - EB & WB Directions

Delay

The analysis of delays is a standard measure used to assess the benefits of improving the efficiency of vehicle movement. In the study, different scenarios, such as implementing dedicated truck lanes and using truck platoons, showed positive impacts, while specific scenarios reported neutral impacts in vehicle delays. Compared to the base scenario, for current traffic conditions, some of the scenarios tested demonstrated promising results, suggesting that these strategies could improve the overall traffic flow. These scenarios successfully reduce delay times, offering a potentially potent strategy for managing heavy traffic. Figure 5 represents a detailed overview of the average delay times in minutes for each scenario, considering current and forecasting traffic conditions, thereby offering a comprehensive dataset for future traffic management and infrastructure planning research.

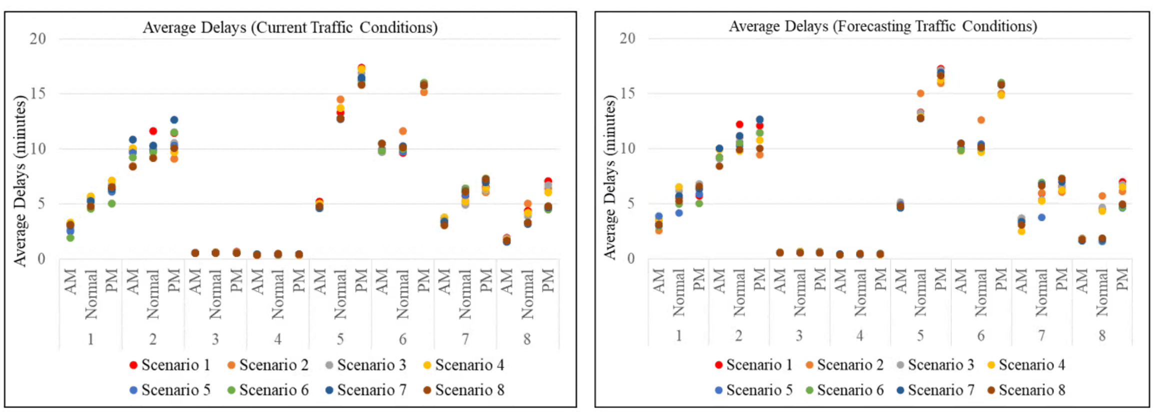

Figure 5: Average Delay – Current and Forecasting Traffic Conditions

Figure 5 shows the average delay measurements in minutes for each strategic approach for analyzing the current traffic situation and forecasting traffic conditions with increased truck volume. The review reveals that some scenarios have improved average delays for all vehicles compared to the base model. Implementing the Dedicated Truck Lane strategy within the current traffic condition results in substantial decreases in vehicle delays by 16.76% in the EB direction and 20.41% in the WB direction. This positive impact is amplified when trucks use dedicated lanes solely or share these lanes with other vehicles, reducing delay compared to truck-exclusive lanes. Truck exclusive lane is not showing any improvements because it is only implemented on a very short length of the Dolphin Expressway. Truck Platoon on the freeway reduces vehicle travel delays by 18% to 39% in the EB and 11% to 16% in the WB direction when vehicles use Dolphin Expressway. Furthermore, when vehicles travel WB on I-95, this strategy reduces delay times by 36%. However, these scenarios have limited impact on Port Blvd and Biscayne Blvd, as enhancements are predominantly targeted at freeway systems, notably benefiting vehicles traveling towards the Miami tunnel. The delay results remain unchanged in segments 3 and 4. Using vehicle platoon shows a 12% to 21% reduction in both EB and WB direction when vehicles use Dolphin Expressway and 10% to 31% when using I-95.

For forecasting traffic conditions, the deployment of a Dedicated Truck Lane under this forecasted traffic scenario has resulted in a reduction of vehicle delays from 9.62% to 28.46% in the EB direction and from 19.34% to 21.56% in the WB direction when vehicles are using Dolphin Expressway. When trucks use the dedicated truck lane for the forecasting traffic condition, it provides benefits in delay reduction compared to the current operational traffic condition. Additionally, implementing a Truck Exclusive Lane has only proven beneficial, reducing delays by 19.7% in the WB direction when vehicles use Dolphin Expressway. Truck Platooning on the freeway also decreased vehicle delays by 25% in the EB and 16% in the WB on the same roadway. Furthermore, using vehicle platoons has reduced delays by 11% to 18% in both directions. Still, it yielded notable reductions in vehicle delays, by a maximum of 14% in the EB and 59% in WB when vehicles are traveling using I-95. Despite these improvements, the strategies have limited impact on Port Blvd and Biscayne Blvd, where most changes focus on freeway systems, particularly benefiting vehicles using the Miami tunnel.

The comparison of maximum average delay reduction for different scenarios in EB and WB directions when vehicles are using Dolphin Expressway is illustrated in Figure 6 for both current operational traffic conditions and forecasting traffic. Implementing Truck Platoons with dedicated truck lanes results in a considerable reduction in delays in the EB direction compared to other scenarios for both current and forecasting traffic conditions. For the WB direction, truck-only lane and vehicle platoons show a significant reduction for current traffic conditions, and for the forecasting traffic implementing truck-only lane, lane restrictions, and vehicle platoons show significant reductions in delays.

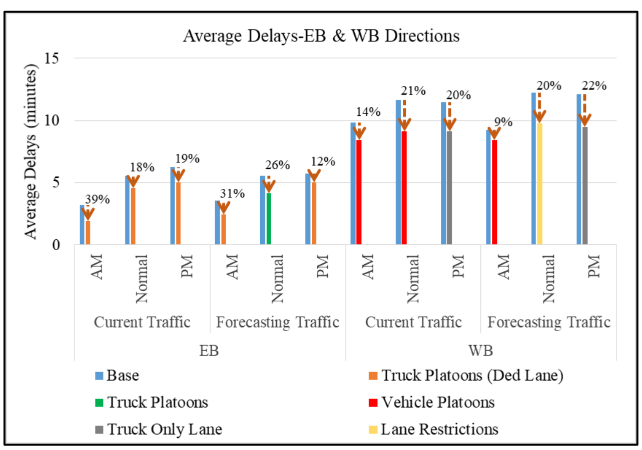

Figure 6: Average Delay for Current & Forecasting Traffic - EB & WB Directions

CONCLUSIONS

Intermodal facilities, in which various modes of transportation converge to facilitate the transfer of products, play a crucial role in U.S. commerce. These facilities include ports, rail yards, and transport terminals, constituting essential nodes in the global supply chain. Ports are crucial to the economy and trade of the United States, accounting for practically all international trade. However, they are having difficulty managing increased freight volumes, causing delays and increased expenses. Trucks, responsible for moving 72.5% of all U.S. freight by weight, face longer wait times and consume more fuel due to port congestion. This issue also has significant environmental implications, as heavy-duty trucks contribute significantly to greenhouse gas emissions and local air pollution. The communities that surround these areas suffer health and quality of life consequences. Additionally, port congestion affects truck drivers' earnings, as they're commonly paid per trip rather than hourly. Rising truck traffic due to increased port activity also leads to broader traffic congestion and elevated pollution levels. Hence, there's a need for effective management of truck movements and parking strategies to alleviate these issues, improve port operations, and maintain U.S. competitiveness in global trade.

This study develops a concept of operation to enhance the truck movement around intermodal facilities and conducts a traffic impact analysis to improve the heavy truck operation efficiency around a specific port area based on traffic data using microsimulation platform. The proposed concept suggests implementing a flexible, technology-oriented system at port intermodal facilities. It includes scheduled truck appointments, proper truck parking stops and rest areas, real-time information on road conditions and route planning, dedicated truck lanes, and the introduction of autonomous truck platooning. These changes aim to reduce congestion, waiting times, and environmental impact while ensuring equal access for all stakeholders. The traffic impact study, conducted using microsimulation, focuses on the Port of Miami area. Different traffic management strategies are evaluated, such as dedicated truck lanes, lane restrictions, and truck platooning. The simulations show that these strategies can significantly improve travel times, reduce congestion, and alleviate vehicle delays.

The key contributions of this research lie in providing practical solutions and insights for improving freight movement and saving time. The microsimulation model developed for the Port of Miami showcases its application to real-world traffic scenarios and helps mitigate environmental impacts. The research also contributes to reducing traffic congestion and increasing freight movement in densely populated areas.

The proposed concept and microsimulation model have potential for future extensions. They can be implemented through applications and websites for efficient information transfer. The concept can be expanded to optimize terminal operations, integrate sustainable last-mile delivery solutions, and incorporate emerging technologies like truck automation and electrification. The microsimulation model can be further developed to analyze traffic scenarios inside and outside the port area, including rail freight networks.

In summary, this research provides valuable guidelines for improving freight planning, optimizing truck operations, and mitigating the negative impacts of port congestion. By incorporating innovative technologies and strategies, it aims to enhance the efficiency of freight transportation, reduce environmental impact, and improve safety. The findings contribute to creating resilient and efficient supply chains while ensuring equitable access to resources and opportunities.

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Vehicle Miles Traveled and Environmental Impacts from On-Demand Delivery: A Literature Review

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ABSTRACT

The boom of e-commerce and the increasing demand for fast and reliable delivery services have led to the thriving of on-demand delivery (ODD), which provides delivery services to food takeout, grocery, pharmacy, and other light-weighted goods. The operational efficiency of ODD is subject to many factors—access to curbside, delays at the pick-up and drop-off locations, order dispatching mode, vehicle routing schedule, and vehicle refueling needs. The fast-growing delivery orders coupled with operational inefficiencies of ODD may lead to higher vehicle miles traveled (VMT) and pollutant emissions. Policymakers as well as practitioners need to evaluate the VMT and emissions impact of ODD, given the consumer behavior, operational paradigm, and business models. This paper conducted a systematic review of the existing literature to synthesize and summarize the impacts of ODD with a specific focus on VMT and emissions. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guideline was employed to systematically search for related studies in multiple databases and to crystallize the review scope. The impact evaluation was delved into three aspects: customer shopping behavior (online shopping vs. in-store shopping), ODD operational strategy (truck/van vs. green vehicles, professional delivery vs. crowdsourcing), and business models (home delivery vs. depot/collection point). Overall, this study found that online shopping with coordinated ODD can achieve significant VMT and emissions reduction compared with in-store shopping. The reduction extent depends on the customer trip chaining, travel mode choice, residential area type, and the ratio of product return. The use of zero-emissions vehicles in ODD, such as electric van/truck/vehicle, cargo-bike, UAV, provides relatively higher emissions reductions, but also brings new issues such as charging needs or capacity limits. Collection points (e.g., parcel locker, retailer store, postal service point) can reduce the VMT and emissions if they are optimally distributed, and customers visit them in zero-emissions modes or through trip chaining.

Keywords: On-demand delivery, Vehicle-Miles-Traveled, Emissions, Systematic Review.

INTRODUCTION

Online shopping has been continuously reshaping customer shopping behavior. Nowadays, people could obtain almost everything needed (e.g., meal, grocery, clothing, electronics) via online shopping. In the U.S., the retail e-commerce sales were 958.7 billion in 2021 accounting for 14.6 % of total sales which represents a growth of 17.1% compared to 2020 (US Census Bureau 2023). During the pandemic, over 60% of Americans younger than 35 would shop online once a week or more, as reported in a study (Ecola et al. 2020).

Along with the increasing online shopping demand, customers have higher expectations to receive the purchased items with shorter delivery time and lower/no delivery cost (Qi et al. 2018), which boosts the proliferation of On-Demand Delivery (ODD) service within the realm of Urban Freight System; especially, during the COVID-19 pandemic (Bezirgani and Lachapelle 2021; Gao et al. 2020; Roggeveen and Sethuraman 2020). ODD service is designated to meet the increasing online shopping demand and the ever-growing customer expectations by providing timely, transparent, and convenient delivery services. Typically, a customer places an order via an online platform, i.e., a website or a smartphone application, and selects the delivery preferences (drop-off location, delivery time slot, etc.). The order is then picked up and delivered to the customer location by the delivery driver to complete the order. The customer can receive notifications about the order status in real-time (Pourrahmani and Jaller 2021).

In the last mile sector, ODD typically performs low-volume and high-frequency short trips to complete the orders within the required time window, thus representing more than 25% of the total logistical costs (Goodman 2005). Many factors could lead to inefficiencies – high volume of daily orders, inefficient order dispatching, lead time in preparation of the order at pick-up points, delays at the drop-off locations, diversity of items, driver overtime, vehicle recharge, and refueling needs, among others. Increased delivery orders coupled with operational inefficiencies of individual deliveries made by internal combustion engine vehicles may lead to higher VMT and emissions. On the other hand, new operation paradigms and new technologies such as vehicle electrification and robot/UAV delivery are unfolding great potential in lowering the VMT and emissions. Previous studies have shown a 20%-93% reduction potential on VMT and greenhouse gas emissions for grocery delivery (Durand and Gonzalez-Feliu 2012; Motte-Baumvol et al. 2022; Nock et al. 2022; Siikavirta et al. 2008). Given the evolving nature of ODD, it requires further studies to fully understand the potential impacts of ODD in the urban freight system under the modern operational era.

To fill the research gaps in understanding the negativities stemming from ODD services under the evolving service models, and to facilitate the efficient and sustainable development of ODD in the future, this paper provides a comprehensive literature review on the impacts of ODD in terms of Vehicle Miles Traveled (VMT) and Greenhouse Gas (GHG) emissions and aims to identify the operation strategies to support the operation of ODD. The main contributions of this paper include: 1) identifying the existing and upcoming operation paradigms and business models of ODD by providing a clear categorization considering the parcel size, time urgency, and service sector. 2) conducting a systematic literature review to synthesize the impacts of ODDS related to VMT and GHG. 3) highlighting existing issues and research gaps in ODD.

REVIEW SCOPE

This review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines to systematically search for related studies in multiple databases and to crystallize our review scope (Moher et al. 2015). PRISMA is an evidence-based minimum set of items for reporting in systematic review and meta-analysis, which has been widely used in systematic literature reviews.

We relied on the following databases: Web of Science (WOS), Scopus, and TRIS, to search for related research without any limitations publication time. The peer-reviewed journal papers, conference proceedings and other gray literature such as research reports and policy briefs were included in the review. The search string is the logical combination of the following terms: "On-demand delivery", "Online delivery", "Online-to-offline delivery", "Shared Delivery", "Crowdsourced delivery", "VMT", "travel distance", "emission", "GHG", "sustainability". The searching and screening process is shown in Figure 1.

After the fast screening via reading the titles and abstracts of 521 records, we reduced the potential inaccuracies stemming from keyword searches and formed an initial pool of 87 records. Then, we applied the exclusion criteria to exclude papers categorized as review papers, those that did not discuss the on-demand delivery in the last-mile setting and those lacking evaluation of VMT and emissions. Finally, we identified 31 papers for our systematic literature review.

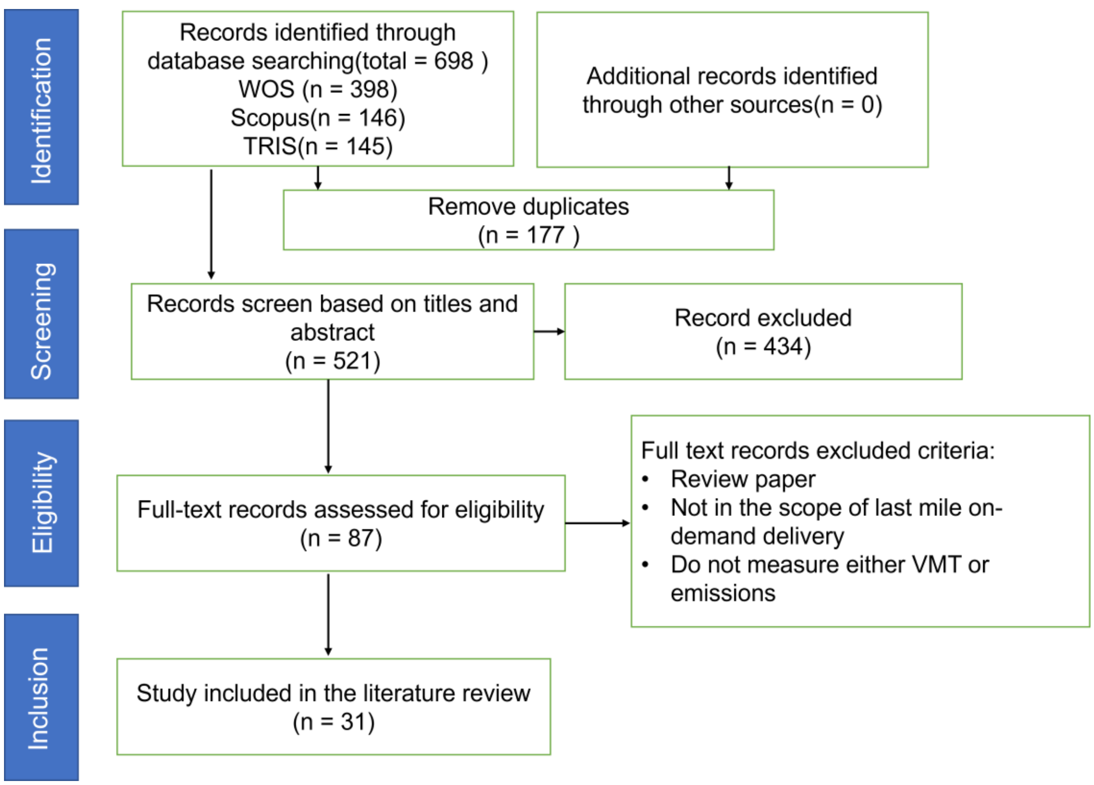

Figure 1. PRISMA flow diagram for literature review for on-demand delivery

SYSTEMATIC LITERATURE REVIEW

Overview of On-Demand Delivery

In the literature, On-Demand Delivery (ODD) is also termed as online delivery, online-to-offline delivery, shared delivery, or crowdsourcing delivery, etc. However, there exists a lack of a clear definition of ODD regarding the service scope. Thus, we proposed a categorization of on-demand delivery based on three primary dimensions (parcel size, industry, and time urgency), as shown in Figure 2. Meal delivery is an example of instant delivery, wherein cooked meals from restaurants are transported quickly, typically involving small-sized parcels and an urgency for instant delivery, often within an hour. Conversely, grocery delivery includes a spectrum of small to medium-sized parcels, usually aiming for same-day delivery. This service is extensively provided by numerous grocery stores and third-party platforms in the U.S., such as Walmart, Amazon Fresh and Instacart. Moreover, for the delivery of general retail items, the parcels vary in size from small to large, and the delivery date is predetermined at the time of customer order placement. This broader category extends beyond immediate perishable goods, catering to a range of consumer products with differing sizes and delivery timelines.

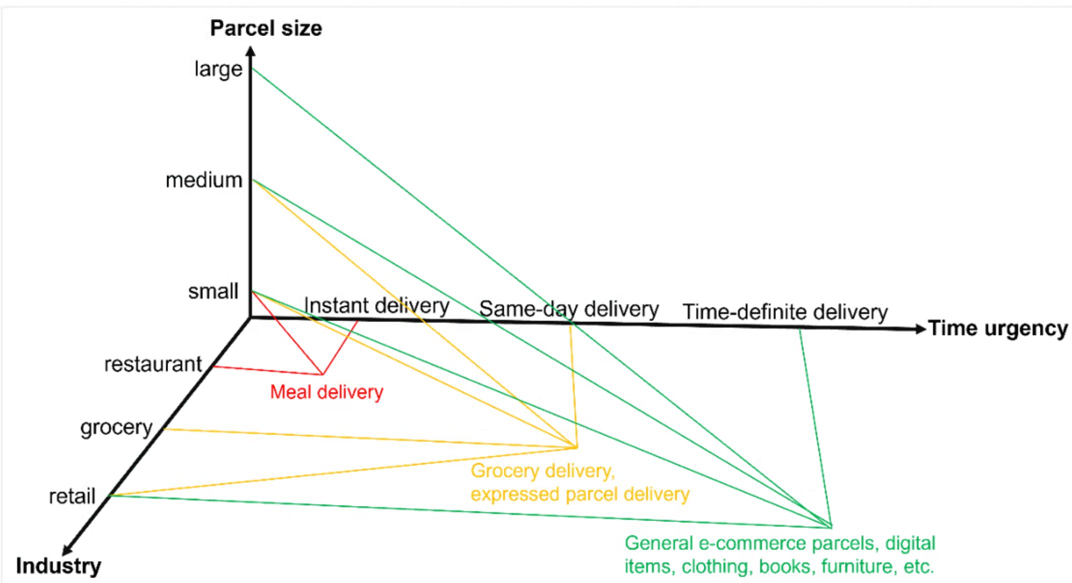

Figure 2. The scope and categorization of On-demand delivery

The collected studies on on-demand delivery and its effects on Vehicle Miles Traveled (VMT) and environmental impact can be categorized into two main streams. The first stream (48% of the collected papers) studied the potential negative or positive externalities of on-demand delivery to serve the boost of e-commerce compared to traditional in-store shopping. Regarding the in-store shopping behavior, researchers have considered the key factors that define the VMT and emission impact of in-store shopping trips. The factors are customer trip chaining, travel mode, and customer resident area type. The other stream (52% of the collected papers) has been focused on comparing different on-demand delivery business modes and operation strategies that are beneficial in saving VMT and emissions. Based on our collected papers, the research can be delved into two aspects 1) Business model comparison: home delivery versus collection point delivery and 2) ODD operation strategies: delivery vehicle comparison (truck/van versus electric van, UAV, unmanned robot), professional delivery versus crowdsourcing delivery in which local neighbors can participate in the delivery process. In the following sub-sections, we presented the key results and findings with the systematic literature review.

Online-shopping versus In-store Shopping

E-commerce has reshaped households' shopping behaviors with an online platform to provide diverse products, transparent prices, and convenient digital payment which allows customers to shop with only a click of mouse. Normally, the ordered goods will be delivered to the home location by delivery companies. Along with the rise of e-commerce, researchers have contributed to studying the potential impact of e-commerce home delivery compared with traditional in-store shopping. To identify which way of shopping is more beneficial at reducing VMT and emissions impact, most research adopted the substitution hypothesis, assuming that customers will substitute their shopping trips to visit the brick-and-mortar store with buying the same items online. The conceptual comparison of in-store shopping and on-demand delivery is shown in Figure 3, where multiple factors were discussed in the literature when comparing the environmental impacts and vehicle miles traveled between the two shopping choices.

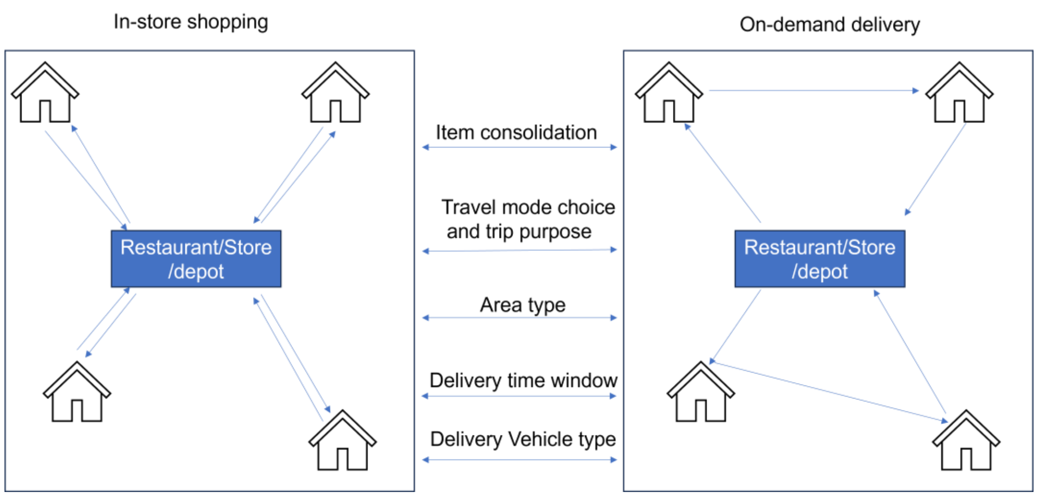

Figure 3. Illustration of in-store shopping and on-demand delivery

Many studies have been focusing on to what extent the substitution of in-store shopping trips could help to reduce the VMT and emissions. The advantage of ODD is to consolidate orders together and perform organized delivery to the customer location, instead of multiple individual trips. The consolidation level depends on the penetration level of on-demand delivery, spatial distribution of the orders, and the delivery time window requirements. As modeled by (Siikavirta et al. 2008), with 100% substitution, the GHG emissions in food and production system in Finland depend on the home delivery model used, order delivery time slot, and vehicle type, and it is possible to achieve 18%-87% of GHG reductions. With a shorter delivery time slot (within 1 hour), the delivery driver needs to make more trips in the delivery area to meet the promised delivery time, which only achieves the lower bound of GHG reduction (17%). The upper bound of GHG reduction (87%) is achieved by better consolidating orders in the same area and delivering orders to the unattended box. Meanwhile, the VMT is decreased by 53%-92% with delivery service compared to individual travel to the supermarket. (Carling et al. 2015) developed a method to measure the CO_2 footprint from the entry point to a region to the consumer's residence. Results demonstrated a substantial reduction (84% reduction) in CO_2 emissions by switching from in-store shopping for electronics products to buying the same product online. This is due to the fact that professional carriers are capable of transporting goods in bulk which is more efficient than individual shopping trips. (Stinson et al. 2019) found that the VMT reduction and emission benefits is sensitive to the e-commerce penetration level. With the household e-commerce rate of three orders per week, a 15% net VMT reduction occurs along with a 40%-50% energy consumption reduction depending on vehicle electrification technologies. An 80% VMT reduction was found when all customers choose to shop online, owing to the fact that adding a new stop to a delivery route only increases a small portion of Medium Duty Vehicle's VMT, but it can replace a much longer Light Duty Vehicle trip. (Motte-Baumvol et al. 2022) points out that for the United Kingdom, online grocery contributes to a 30% trip reduction along with an overall 37% household emissions, although the exact reduction extent depends on whether the household has a private car or not. (Nock et al. 2022) studied online grocery shopping in Seattle and showed that the start location of deliveries has a significant impact on congestion and emissions. If the grocery is not delivered from the closest store, then no beneficial impacts can be achieved. This is partly because only 36% of individual trips are two-way grocery trips and the other customers also tend to optimize the grocery trips themselves by adding a stop in their daily routine trip.

The performance of ODD also depends on other factors. One factor several researchers paid attention to is the delivery location, whether in the urban area or rural area. Customers in the rural area need to travel a longer distance compared to the residents in the urban area, which provides a high potential to reduce the delivery distance by replacing individual trips with coordinated on-demand delivery service. (Goodchild et al. 2014) found a dramatic difference in VMT and CO_2 emissions between Seattle and its rural area. In Seattle, the VMT reduction is 20% when in-store shopping was replaced by on-demand delivery services. In most rural areas, the VMT reduction reached up to 85%. (Mommens et al. 2021) further divided the service area into three types: urban, urbanized (with a population density falling between that of urban and rural areas), and rural and demonstrated the area type has an impact on the sustainability of home delivery. Based on the calculation of transport-related external costs, this research concludes that delivery to the home location via a well-established on-demand delivery service (from a warehouse) in urbanized and rural areas is more sustainable. While in the urban area, collection point delivery is more beneficial.

E-commerce also causes the issue of frequent product returns. Customers return items for different reasons, i.e., wrong product, product damaged during delivery, or unsatisfactory items. Product return will lead to extra travel trips and emissions. The impact of return depends on the way to return the products, either the unwanted item is collected on a subsequential delivery round or customers return to a high-street store. (Edwards et al. 2010a) found that the latter option is the worst case in terms of CO_2 emission. However, customers could reduce CO_2 emissions by trip chaining, e.g., returning items as part of a routine trip. (Wiese et al. 2012) studied the return effect in clothing e-retailing. CO_2 emission per transaction increases with higher return ratios. But online shopping has a lower increasement compared to in-store shopping and can cover a larger service area.

Home Delivery versus Collection Point Delivery

Conventional ODD service usually delivers the ordered goods to customers' home locations. This delivery type requires customers to receive the parcel right at the delivery time, which may cause failed delivery due to the customers not being present. The delivery companies need to perform extra delivery trials or drop the parcel at depots that allow customers to pick up later. Collection point delivery is proposed to avoid failed deliveries and reduce delivery VMT costs. Typical collection points can be divided into two types: unattended and attended. One commonly used unattended collection point is a parcel locker, which can be operated the entire day and provides high flexibility for customers to pick-up. Amazon, a large-scale retail provider in the US, also provides the self-service parcel delivery service where customers can retrieve the orders after receiving the delivery confirmation message (Amazon 2023). Attended collection points have several options: retailer store, postal service point, 'neighborhood relay', etc. The VMT and emission impacts of the collection point delivery are the sum of truck delivery to the collection points and from collection points to customer locations, which closely depend on the distribution of collection points, travel trip purposes, and travel modes to visit the collection point.

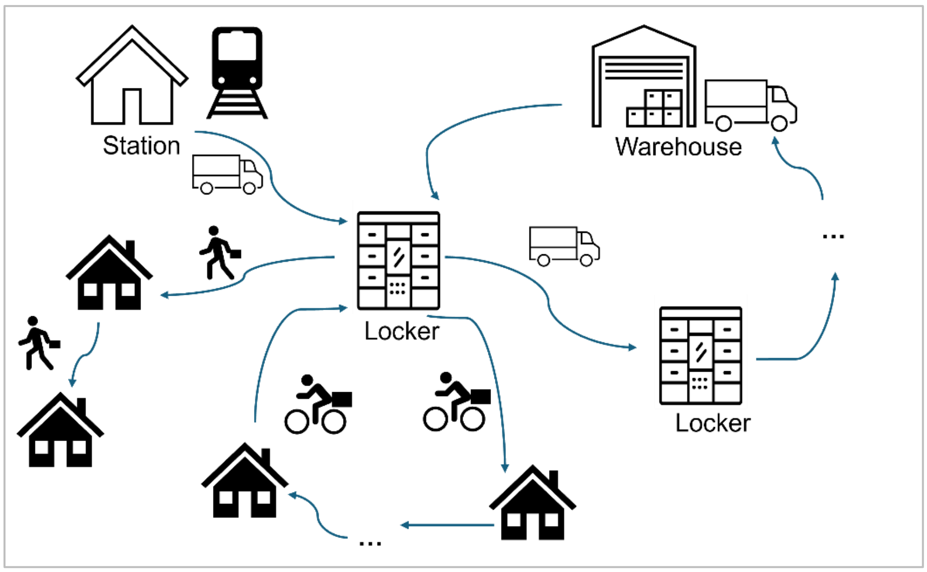

Figure 4. Illustration of on-demand delivery with parcel lockers combined with occasional couriers, referenced from (dos Santos et al. 2022).

In the collection point delivery paradigm, the sizing and sitting of collection points are crucial to support the order delivery. Some researchers studied the collection point optimal location problem with objectives to select collection points that are accessible for all customers with minimal total travel cost for customers' pick-up trips, which is a classical vehicle routing problem (VRP). A two-phase algorithm with Ant Colony was proposed by (Hong et al. 2019) to solve the collection point selection problem. They conducted a sensitivity analysis regarding the influence of service radius of collection point and the capacity. Numerical experiments showed a negative relationship between the total cost and the service radius of each delivery point as well as its capacity. (dos Santos et al. 2022) further proposed a comprehensive last-mile delivery system in which collection points can be used as transshipment nodes in a 2-echelon delivery system and allows a customer who picks up orders individually to work as an occasional courier to make delivery to another customer along their pick-up trip to the collection point (shown in Figure 4). However, both Hong's and Santos' studies only evaluated the scenarios with the generated datasets without considering the real-world networks which fail to quantify the realistic VMT and emission impacts. (Carotenuto et al. 2022) developed a cluster-first-route-second approach to compare the two delivery options, home delivery and locker delivery, incurred total travel distance and CO_2 emission. The authors also investigate the impact of dedicated trips for customers to visit the locker. An empirical study was conducted in the town of Dolo, Italy, consisting of 65 user zones, 2 depots and 19 lockers. The CO_2 emissions were reduced by 9%-32% depending on the delivery vehicle size, but the emissions benefit of locker delivery is offset if there are 20%-30% dedicated trips to the lockers.

There are several studies utilized agent-based simulation to model the real-world collection point delivery. (Calabrò et al. 2022) proposed an agent-based model to simulate both home delivery and collection point delivery including the possible matching customers and collection points with a minimum detour from the routine trip. The authors highlighted the importance of locker density and customers' willingness to make a detour to visit the collection point. The results illustrated that the percentage of customers choosing collection point delivery goes up from 26% to 58% with the increasing density of lockers. But the total travel distance did not show a clear decreasing trend. When the customer willingness to detour increases from 6 min to 10 min, the average transport intensity(km/parcel) reduces slightly. (Edwards et al. 2010b) studied the real-world scenario where failed delivered parcels will be dropped at alternative locations, such as supermarkets, post offices and railway stations. The results suggest that the alternative location has great capability to reduce CO_2 emissions of failed deliveries. In their case study, they found the post office was the most environmentally favorable choice since a package left there only accounts for 13% of CO_2 generated by a collection from local depot. (Mommens et al. 2021) utilized the agent-based freight transport model TRABAM to investigate the sustainability of collection point and home delivery in Belgium. They specifically studied the area type difference in terms of the two delivery options and found that collection point delivery is sustainable in the urban area. (Wygonik and Goodchild 2018) instead employed regression models to study the factors that influence the impact of last-mile good movements. The high road density can reduce the VMT and emission impacts.

Electric Vehicles, UAV/Robot and Crowdsourcing Delivery

With the development of new technologies, some researchers also focused on the transformation of delivery fleets to decrease the environmental impact of urban logistics. This transformation is mainly introducing green vehicles, such as electric van/truck, cargo-bike, UAV, to partially substitute the traditional truck/van. (Perboli et al. 2021) studied the economic and environmental benefits of introducing cargo bikes into the on-demand parcel delivery. A numerical study is conducted within the city of Turin (Italy). Compared to traditional van delivery, with cargo-bike, the VMT-related economic cost and CO_2 emissions are reduced by 20% and 17% respectively. (Llorca and Moeckel 2021) exclusively investigated the potential of cargo bikes for last-mile delivery through agent-based simulation. Their results showed that due to the speed and capacity limitations of cargo bikes, the total time required time for delivery increased by 6% and VMT doesn't reduce compared to van delivery. However, the use of cargo bike in all cases represents a reduction of CO_2 emissions, even considering the emissions related to electricity production. With 100% of cargo bikes delivering light-weighted goods, CO_2 emission can be reduced by around 23%. Besides, with van electrification, the total CO_2 emission of parcel delivery presents significant reductions. Considering the performance of electric vehicles (EVs) and internal combustion engine vehicles (ICEVs) in the urban last-mile scenario, (Siragusa et al. 2022) conducted a life cycle assessment of EV and ICEV to compare their emission and efficiency performance in last-mile delivery in B2C e-commerce. The assessment results showed that EV can save 17%-54% of GHG emissions compared to ICEV. The substitution of an ICEV with an EV allows a saving of 2700 tonnes of CO_2 emissions per year. Another factor discussed in this paper is the battery autonomy. It turns out that battery autotomy does not represent a barrier to EVs in last-mile delivery because most EVs' travel range can cover the delivery distance per day. (Goodchild and Toy 2018) evaluated the VMT and CO_2 impact of unmanned aerial vehicles (UAV) delivery compared to truck delivery. Experimental results illustrated that drones' CO_2 efficiency depends on the average energy required to charge a drone. If the energy cost of the drone is less than 20 Wh/mi, then drone delivery can reduce around 20% of CO_2 emissions. On the other hand, if the delivery address is far away from the depot, then truck is favorable. Drones only tend to have emissions advantages over trucks when the service zones are close to the depot, or the number of orders is small. This research concluded that a blended system would perform best, with drones serving nearby addresses and trucks serving far destinations.

The prevalence of information and communication technology has catalyzed many new shared mobility services. Crowdsourced delivery is one of the emergent services provided by online platforms, i.e., UberEATS, DoorDash. The online platforms outsource the delivery tasks to crowds of local non-professional agents to finish the delivery tasks and the agent will receive a delivery fee as compensation. Crowdsourced delivery has attracted much attention given its capability to provide fast and low-cost service. On the other hand, crowdsourced delivery could also contribute to sustainable efforts by using the excess capacity of vehicles and existing routing trips. The operational challenges and opportunities are well summarized in (Pourrahmani and Jaller 2021). In urban parcel delivery, (Perboli et al. 2021) evaluated a scenario with the crowdsourced driver. Compared to professional van delivery, crowdsourced delivery reduced the VMT-related economic cost by 21% and saved 16% CO_2 emissions. The identified most environmentally friendly strategy with high service quality is combined crowdsourced delivery with green vehicles (e.g. cargo bikes), which reduces the economic cost and CO_2 emission by 44% and 46% respectively. (Devari et al. 2017) modeled and evaluated the benefits of exploiting customer's social network for last-mile delivery with friendship modeling and agent-based transportation simulation. Crowdsourced drivers can reduce the truck delivery miles by 57% and bring substantial savings in NO_x, $PM_{2.5}$, PM_{10} by 55%. CO and THC emissions increase because gasoline cars emit more CO and THC compared to diesel engines powering trucks. (Liu et al. 2023) investigated the VMT and emissions impacts of food delivery with a comprehensive framework to quantify those impacts with the consideration of COVID-19 Pandemic. With the optimized delivery results, on-demand food delivery (ODFD) shows great potential to curb dinning-related VMT and emissions. The VMT was estimated to be reduced by 38% during the pandemic and 6% - 9% after the pandemic depending on the penetration level of ODFD in the future scenario. Besides, the author also conducted the emission sensitivity analysis with the delivery fleet electrification. With a fully electrified delivery fleet, the ODFD service can reduce 14% - 22% of emissions in the post-COVID period.

GAP ANALYSIS

On-demand delivery (ODD) has reshaped people's shopping behaviors by offering reliable, faster, and affordable delivery services. To form an efficient and sustainable urban freight system, it is necessary to understand the impact of ODD from the perspective of vehicle miles traveled and emissions. While there have been attempts to evaluate those impacts under multiple scenarios, several areas still need extensive research and standardization to enable fair comparison and a better understanding of ODD. Firstly, a clear and well-structured taxonomy for classifying the ODD services is yet established, resulting in multiple vague synonyms in the ODD system. Secondly, more innovative delivery modes need to be evaluated, such as combining delivery with human rides, truck and drone delivery, truck and robot coordination, etc. Thirdly, more realistic traffic network settings and emission models should be integrated into the evaluation process instead of simply assuming the static traffic speed, euclidian travel distance and simple emission rate. Fourthly, more research is needed to understand customer's behavior and preferences when choosing delivery options, which will be valuable in designing the ODD delivery strategies.

CONCLUSIONS

The paper conducted a systematic literature review to understand the VMT and emission impacts of on-demand delivery (ODD). We have delved into three perspectives: Online-shopping versus In-store Shopping, Home Delivery versus Collection Point Delivery, and emerging new technologies including Electric Vehicles, UAV/Robot and Crowdsourcing Delivery. Related studies were reviewed in each subsection. Finally, we identified the potential gaps and pointed out future research directions in ODD. The extensive literature review shows that online shopping with coordinated ODD can achieve significant VMT and emissions reduction compared with in-store shopping. The reduction extent is influenced by multiple factors: customer trip chaining, travel mode choice, residential area type, delivery time window, delivery vehicle type, etc. Collection points (e.g., parcel locker, retailer store, postal service point) can reduce the VMT and emissions if they are optimally distributed and customers visit them in zero-emission modes or through trip chaining. The use of zero-emission vehicles in ODD, such as electric van/truck/vehicle, cargo-bike, UAV, provides relatively higher emissions benefits, but also brings new issues such as charging needs or capacity limits.

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Inadequate Safe Truck Parking: Impacts on Pandemic Response Supply Routing and Delivery

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ABSTRACT

Inadequate truck parking along major US highways, a national crisis, worsens road safety and leads to hours of service (HOS) violations due to trucks parking in unauthorized areas. This study, focusing on challenges during pandemics and similar disruptions, used a survey revealing 85% of truck drivers struggled to find parking during the pandemic. Employing a random-parameters bivariate ordered probit model (RPBOPM), the study identified factors affecting parking availability and HOS compliance both before and during pandemic events. These findings highlight the severity of the truck parking issue and provide a basis for developing targeted programs and policies to alleviate these challenges, particularly during critical times like pandemics, thus enhancing overall highway safety.

1. INTRODUCTION

The COVID-19 pandemic not only intensified the long-standing issue of inadequate truck parking on America's major highways, affecting all states and regions, but also led to severe shortages of essential goods like non-perishable foods, cleaning products, and medical supplies (Boggs et al. 2019; Bunn et al. 2019; FHWA Freight Management and Operations 2020; FHWA Office of Operations 2020; Hernández and Anderson 2017; Mahmud et al. 2020; McNally 2021). This surge in consumer demand strained supply chains and increased the demand for truck parking services, exacerbating the already critical nationwide shortage of truck parking spaces. Recognizing this, the Federal Highway Administration (FHWA), Federal Motor Carrier Safety Administration (FMCSA), and various state Departments of Transportation (DOTs) implemented measures to aid motor carriers and truck drivers. The FMCSA issued a National Emergency Declaration, allowing vehicles delivering essential goods to bypass regulations such as the mandatory 30-minute break and the standard 34-hour restart, with continual updates to meet the evolving needs of essential services. Additionally, DOTs eased truck size and weight limits for larger shipments during the health crisis, and the FHWA permitted food trucks to operate at rest areas, providing crucial support to truck drivers and travelers, highlighting the need for immediate solutions to the truck parking deficit.

In 2019, the Federal Highway Administration (FHWA) and the National Coalition on Truck Parking identified approximately 313,000 truck parking spaces in the United States, with a 6% increase in public and an 11% increase in private parking facilities from 2014 to 2019, including 40,000 at public rest stops and 273,000 at private truck stops (FHWA Office of Operations 2020). However, state Departments of Transportation (DOTs) struggled with developing new public parking facilities, facing challenges in planning, funding, and provisioning. This was exacerbated by a significant ratio of truck drivers to parking spaces, as reported by the American Trucking Associations (ATA), which found that 98% of drivers struggled to find adequate parking, spending an average of 56 minutes daily in their search and suffering an approximate annual wage loss of $5,500, or a 12% reduction in earnings. Furthermore, 58% of drivers often resorted to unauthorized parking spots (McNally 2021). The COVID-19 pandemic intensified these issues, with increased demand for essential goods delivery and pandemic-related restrictions like shelter-in-place orders, further straining the already limited parking availability and underscoring the urgent need for solutions to the truck parking crisis in the United States.

In terms of related research, the American Transportation Research Institute (ATRI) and the Owner-Operator Independent Drivers Association (OOIDA) Foundation, conducted a critical examination of the operational disruptions faced by the trucking industry during the onset of the COVID-19 pandemic. In the early onset of the pandemic, ATRI monitored truck activity in several states from February to April 2020, finding an initial surge in truck movements due to increased demand for essentials (American Transportation Research Institute 2020). This spike, however, was followed by a decline in April as economic activities slowed due to the pandemic. Later both ATRI and OOIDA designed a survey to further understand changes in trucking operations, encompassing delivery, travel times, detention, and parking (The American Transportation Research Institute and The OOIDA Foundation 2020). Results from over 5,100 respondents painted a mixed picture: nearly half reported lower freight volumes, while others saw no change or increases. The pandemic notably shifted operations towards local trucking, with short trips doubling and detention times lengthening for some. Traffic congestion eased considerably, but parking remained a challenge, with nearly half of the drivers finding it more difficult, though a similar proportion reported no change. Overall, the survey highlighted the significant yet diverse impacts of COVID-19 on the trucking sector. This research highlights the diverse and substantial impacts of the pandemic on trucking operations, and the industry's resilience and adaptability in the face of global pandemic.

Therefore, this study extends existing research into truck parking by exploring factors that impact a driver's compliance with hours-of-service (HOS) regulations, with a particular focus on pandemics or similar widespread disruptions. Given the strict HOS rules that dictate driving hours and rest periods, drivers are forced to plan to meet these requirements and maintain job performance. The study aims to deepen understanding of the relationship between the availability of safe and adequate truck parking and adherence to HOS regulations. It includes an analysis of a stated-preference survey from the COVID-19 pandemic period and employs a random-parameters bivariate ordered probit model (RPBOPM) to investigate the parking challenges drivers face, a first. Applications of the random-parameter bivariate ordered probit models in transportation are not new (Chen et al. 2019b; Mannering et al. 2016), however it provides a mechanism to better understand the diverse responses collected from individuals during various stages of the pandemic. Additionally, the study seeks to identify factors that contribute to these challenges both prior to and during the pandemic. Identifying these factors will shed light on the parking shortage in the US and help develop programs or policy initiatives to support truck drivers in need.

2. EMPIRICAL SETTING

This study utilized a stated preference survey targeting truck drivers across the nation, conducted during the COVID-19 pandemic. The survey aimed to gauge truck drivers' perspectives on operational changes before and amid the pandemic and to identify factors influencing their ability to find safe and adequate parking while complying with hours-of-service (HOS) regulations. Conducted from May 25th to June 1st, 2020, the survey was facilitated by the University of Arkansas and distributed via Qualtrics, an online survey platform, to large truck operators (Hernandez et al. 2020). Participation was voluntary, with eligibility criteria including being at least 18 years old, holding a Commercial Driver's License (CDL), having over a year of experience in operating a commercial motor vehicle, and active driving during the pandemic. Out of the respondents, 521 truck drivers met these criteria and completed the survey.

The survey comprised of 67 questions, divided into nine sections: socioeconomic background, business details, driver demographics, driving characteristics, safety perceptions, time-of-day operations, management of driving, and truck configuration. To comprehensively assess drivers' opinions on the changes pre-and-during the pandemic, Likert scale questions were utilized. Notably, the proportion of drivers who never faced parking issues was double during the pandemic compared to before.

Both Tables 1 and 2 summarize key characteristics and behaviors of truck drivers before and during the COVID-19 pandemic, established through the truck driver survey. Before the pandemic, a majority of drivers were aged between 30 and 49 (57%), and a significant proportion (79%) received hazard pay. Most drivers had more than a year of experience, with only 4% being less experienced. During the pandemic, 66% of the drivers were male.

3. METHODOLOGY

In undertaking the diverse responses collected from individuals during various stages of the pandemic, this study proposes the use of a bivariate random parameter ordered probit model. This advanced econometric model is essentially a hierarchical system composed of two interconnected equations, designed to simultaneously analyze the relationship between two distinct yet related response variables. Utilizing this model facilitates a more nuanced understanding of the dynamics at play, allowing for the identification of significant factors that influence parking availability. Moreover, it enables the quantification of the impact these factors have on the frequency with which drivers encounter a lack of parking—a critical part in addressing this issue in the trucking industry (Xiao et al. 2021).

The bivariate random-parameter ordered probit model assumes that two ordered dependent variables, y_j (j = 1 before pandemic, 2 during pandemic) result from a joint decision-making process. These decisions are influenced by the individual characteristics unique to each probit equation, and there is a correlation between the errors of the two equations. Consequently, the model can be characterized as follows (Xiao et al. 2021):

$$y_{i,j=1} = k, \;\; if\; \mu_{j=1,k-1} < y^*_{i,j=1} < \mu_{j=1,k} \tag{1}$$

$$y_{i,j=2} = 1, \;\; if\; \mu_{j=2,l-1} < y^*_{i,j=2} < \mu_{j=2,l}$$

where $\mu_{j,k-1}, \mu_{j=1,k}, \mu_{j,l-1}, \mu_{j,l}$ are thresholds or cut-off values used to determine the reported frequency lack of parking caused HOS adherence problems before and during the pandemic, their values are relative to their corresponding influencing factors in driver i. Additionally, k (k = 0, 1, 2,..., K) and l (l = 0, 1, 2,..., L) represent ordinal categories of the frequency lack of parking caused HOS adherence problems reported by each driver. $y^*_{i,j=1}$ and $y^*_{i,j=2}$ serve as thresholds for the conditions and can be calculated using real data as follows:

$$y^*_{i,j=1} = \beta'_1 X_{i,j=1} + \varepsilon_{i,j=1} \tag{2}$$

$$y^*_{i,j=2} = \beta'_2 X_{i,j=2} + \varepsilon_{i,j=2}$$

where $y^*_{i,j=1}$ represents latent, unobserved variables denoting a boundary for choosing one alternative to the other, in which *i* = *1,...n*, is the number of observations; $X_{i,j}$ represents individual specific covariates; β_j denotes the regression coefficients, and $\varepsilon_{i,j}$ represents the random components in the errors that are attempted to be captured by the unobserved factors associated with two involved parties, which are assumed to be exogenous and follow a bivariate normal distribution as follows (Chen et al. 2019a):

$$\begin{pmatrix} \varepsilon_{i,j=1} \\ \varepsilon_{i,j=2} \end{pmatrix} \sim \mathrm{N}\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{3}$$

where ρ is the estimated correlation parameter between $\varepsilon_{i,j=1}$ and $\varepsilon_{i,j=2}$. If significant, provides evidence that the bivariate approach is appropriate. Therefore, $y^*_{i1}$and y^*_{i2} denote the frequency in lack of parking causing HOS adherence problems for drivers before and during the pandemic, respectively, and x_{i1} and x_{i2} include various influencing factors, such as socioeconomic, business, and driver characteristics captured in the survey.

The observed ordered dependent variable follows the rule by the following equation:

$$y_{ij} = \begin{cases} 0 \; if \; y^*_{ij} = Never \\ 1 \; if \; y^*_{ij} = Sometimes \\ 2 \; if \; y^*_{ij} = About\ half\ the\ time \\ 3 \; if \; y^*_{ij} = Most\ of\ the\ time \\ 4 \; if \; y^*_{ij} = Always \end{cases} \tag{4}$$

While bivariate ordered probit can address the problem of factors correlation between the two conditions, this method assumes the parameters β'_1, β'_2 to have a certain value neglecting the effect of unobserved heterogeneity of observations. The random-parameter approach is designed to manage unobserved heterogeneity by permitting parameters to differ among observations. Consequently, the random parameters in a bivariate ordered probit model are established by configuring the following settings:

$$\beta'_i = \beta + \gamma_i \tag{5}$$

where β'_i is the vector of specific parameters and is estimated by the maximum likelihood method with Halton draws; $\gamma_i$is the randomly distributed term which is normally distributed with a zero mean value and variance σ^2.

4. ESTIMATED RESULTS AND DISCUSSION

To determine the significant factors affecting a driver's ability to locate adequate and safe parking during pandemics or comparable system disruptions, a bivariate random parameter ordered probit model was estimated. This model estimated the probabilities of five distinct outcomes—never, sometimes, about half the time, most of the time, always—across 28 variables that were found to be statistically significant at the 10% level (See Tables 2 and 3).

Table 1. Summary Statistics of Model Parameters (Before)

Variable Before Pandemic	Frequency	Percentage
Socioeconomic Characteristics		
Driver age (1 if between 30 and 49, 0 otherwise)	295	57%
Compensation (1 if received hazard pay, 0 otherwise)	411	79%
Driver experience (1 if less than one year, 0 otherwise)	23	4%
Business Characteristics		
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	163	31%
Driver Characteristics		
Participation in team driving (1 if never, 0 otherwise)	87	17%
Participation in team driving (1 if sometimes, 0 otherwise)	178	34%
Participation in team driving (1 if about half the time, 0 otherwise)	135	26%
Participation in team driving (1 if most of the time, 0 otherwise)	69	13%
Time of Day Operations		
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	132	25%
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	184	35%
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	132	25%
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	78	15%
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	21	4%
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	124	24%
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	125	24%
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	130	25%
Driving Management		
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	196	38%
Real time parking availability tools used (1 if none, 0 otherwise)	40	8%
Drive while tired (1 if rarely, 0 otherwise)	96	19%
Drive while tired (1 if never, 0 otherwise)	35	7%
Driver's most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	203	39%

Table 2. Summary Statistics of Model Parameters (During)

Variable During Pandemic	Frequency	Percentage
Socioeconomic Characteristics		
Driver gender (1 if male, 0 otherwise)	343	66%
Driver Characteristics		
Participation in team driving (1 if sometimes, 0 otherwise)	121	23%
Participation in team driving (1 if never, 0 otherwise)	82	16%
Time of Day Operations		
Normal driving start time (1 if mid-day, 0 otherwise)	121	23%
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	120	23%
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	125	24%
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	128	25%
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	117	23%
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	136	26%
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	91	18%
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	69	13%
Driving Management		
Drive while tired (1 if very often, 0 otherwise)	78	15%
Real time parking availability tools used (1 if websites, 0 otherwise)	196	38%
Real time parking availability tools used (1 if none, 0 otherwise)	40	8%

The overall model fit was tested by using the chi-square distribution and Akaike information criterion (AIC), which are calculated using equations (6) and (7) below, where the likelihood ratio tests are conducted to statistically assess if these models on the frequency of lack of parking are significantly different across the fixed-parameter model and the random-parameter model:

$$X^2 = 2\left[LL\ (\beta_{random}) - \ LL\ \left(\beta_{fixed}\right)\right], \tag{6}$$

$$AIC = 2k - 2\ln(L) \tag{7}$$

where $\mathrm{LL}(\beta_{random})$ is the log-likelihood at convergence of the random-parameter ordered probit model and the $LL\ \left(\beta_{fixed}\right)$ is the log-likelihood at convergence of the fixed parameter ordered probit model. The likelihood ratio is chi-square distributed with degrees of freedom equal to the number of estimated random parameters. K is the number of parameters of the model. The smaller the AIC and the higher the chi-square values, the better the model fits the data.

Table 3 presents the results of the random parameters bivariate ordered probit models. The finding of normally distributed random parameters in both models explicitly demonstrates the existence of heterogeneity in the effects of influencing factors. The following subsections describe the changes in the trucking industry found to be most influential on the frequency of lack of parking causing HOS adherence problems. The marginal effects that were used to assess the effect of the estimated parameters in the models are shown in Tables 4 and 5, respectively.

Table 3. Results of Random-Parameter Bivariate Ordered Probit Models

Variable	Mean	t-Stat
Before Pandemic		
Constant	2.067	8.39
Driver age (1 if between 30 and 49, 0 otherwise)	0.179	1.78
Compensation (1 if received hazard pay, 0 otherwise)	0.438	3.5
Driver experience (1 if less than one year, 0 otherwise)	-0.458	-1.95
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	-0.275	-2.63
Participation in team driving (1 if never, 0 otherwise)	-1.07	-4.76
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	0.371	3.21
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	0.329	3.03
Participation in team driving (1 if sometimes, 0 otherwise)	-0.742	-3.76
Participation in team driving (1 if most of the time, 0 otherwise)	-0.541	-2.42
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.646	-3.15
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	-0.353	-2.63
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.91	3.39
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	0.332	-2.51
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	0.261	-3.49
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	-0.277	2.95
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	0.243	-2.29
Real time parking availability tools used (1 if none, 0 otherwise)	-0.532	-2.66
Drive while tired (1 if rarely, 0 otherwise)	-0.375	-2.84
Drive while tired (1 if never, 0 otherwise)	-0.899	-4.53
Driver’s most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	0.219	2.15
mu1	1.105	16.98
mu2	2.043	32.76
mu3	2.996	37.05
During Pandemic Model		
Constant	1.666	8.09
Driver gender (1 if male, 0 otherwise)	0.366	2.33
Participation in team driving (1 if sometimes, 0 otherwise)	-0.563	-3.53
Participation in team driving (1 if never, 0 otherwise)	-1.034	-4.66
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	0.551	3.54

Drive while tired (1 if very often, 0 otherwise)	0.521	2.8
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	0.378	2.24
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	0.296	1.94
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.384	-2.35
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	-0.286	-1.9
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	0.318	1.92
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	-0.878	-4.07
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	1.446	1.98
Real time parking availability tools used (1 if websites, 0 otherwise)	0.373	2.46
Real time parking availability tools used (1 if none, 0 otherwise)	-0.951	-2.23
Normal driving start time (1 if mid-day, 0 otherwise)	0.293	1.78
mu1	0.989	9.91
mu2	1.909	21.51
mu3	2.891	26.72
rhow (correlation parameter)	0.475	5.42
No. of Observations	521	
Log likelihood at convergence	-580.69	
Log likelihood at zero	-608.99	
McFadden Rho-squared	0.05	

Table 4. Estimated Marginal Effects for Ordered Probit Model of Before Model

Variable	Never	Sometimes	About half the time	Most of the time	Always
Driver age (1 if between 30 and 49, 0 otherwise)	-0.0016	0.0000	-0.0060	-0.0062	0.0000
Compensation (1 if received hazard pay, 0 otherwise)	-0.0048	0.0000	-0.0195	-0.0217	0.0000
Driver experience (1 if less than one year, 0 otherwise)	0.0085	0.0000	0.0348	0.0404	0.0000
Trips conducted (1 if completed fewer number of trips during pandemic than before, 0 otherwise)	-0.0004	0.0000	-0.0014	-0.0015	0.0000
Participation in team driving (1 if never, 0 otherwise)	0.0077	0.0000	0.0305	0.0361	0.0000
Most difficult time of day to locate safe truck parking (1 if early morning, 0 otherwise)	-0.0009	0.0000	-0.0034	-0.0036	0.0000
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	-0.0023	0.0000	-0.0082	-0.0083	0.0000
Participation in team driving (1 if sometimes, 0 otherwise)	0.0099	0.0000	0.0418	0.0490	0.0000
Participation in team driving (1 if most of the time, 0 otherwise)	0.0084	0.0000	0.0326	0.0379	0.0000
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0036	0.0000	-0.0134	-0.0134	0.0000
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	0.0060	0.0000	0.0265	0.0290	0.0000

Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.0055	0.0000	-0.0171	-0.0158	0.0000
Service disruptions encountered at public truck stops (1 if fuel services, 0 otherwise)	-0.0041	0.0000	-0.0134	-0.0132	0.0000
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0016	0.0000	-0.0058	-0.0059	0.0000
Service disruptions encountered at public truck stops (1 if restrooms, 0 otherwise)	0.0030	0.0000	0.0115	0.0120	0.0000
Real time parking availability tools used (1 if communications with other drivers, 0 otherwise)	0.0019	0.0000	0.0072	0.0075	0.0000
Real time parking availability tools used (1 if none, 0 otherwise)	0.0538	0.0000	0.1361	0.1017	0.0000
Drive while tired (1 if rarely, 0 otherwise)	0.0050	0.0000	0.0210	0.0232	-0.3038
Drive while tired (1 if never, 0 otherwise)	0.0238	0.0000	0.0862	0.1254	0.0000
Driver's most commonly driven truck configuration (1 if single unit truck, 0 otherwise)	-0.0035	0.0000	-0.0126	-0.0122	0.0000

Table 5. Estimated Marginal Effects for Ordered Probit Model of During Model

Variable	Never	Sometimes	About half the time	Most of the time	Always
Driver gender (1 if male, 0 otherwise)	-0.0025	0.0000	-0.0040	-0.0007	0.1102
Participation in team driving (1 if sometimes, 0 otherwise)	0.0037	0.0000	0.0054	0.0010	-0.1593
Participation in team driving (1 if never, 0 otherwise)	0.0075	0.0000	0.0119	0.0016	-0.2989
Most difficult day of the week to locate safe truck parking (1 if Monday, 0 otherwise)	-0.0032	0.0000	-0.0066	-0.0021	0.1555
Drive while tired (1 if very often, 0 otherwise)	-0.0023	0.0000	-0.0047	-0.0014	0.1141
Service disruptions encountered at public truck stops (1 if vending machine access and supply, 0 otherwise)	-0.0033	0.0000	-0.0063	-0.0019	0.1531
Service disruptions encountered at public truck stops (1 if take out and/or drive thru food services, 0 otherwise)	-0.0025	0.0000	-0.0047	-0.0013	0.1146
Service disruptions encountered at private truck stops (1 if vending machine access and supply, 0 otherwise)	0.0022	0.0000	0.0036	0.0006	-0.0953
Service disruptions encountered at private truck stops (1 if showers, 0 otherwise)	0.0026	0.0000	0.0044	0.0010	-0.1132
Service disruptions encountered at private truck stops (1 if truck wash stations, 0 otherwise)	-0.0020	0.0000	-0.0038	-0.0011	0.0922
Service disruptions encountered at private truck stops (1 if facility closed, 0 otherwise)	0.0060	0.0000	0.0093	0.0008	-0.2286
Service disruptions encountered at private truck stops (1 if other, 0 otherwise)	-0.0061	0.0000	-0.0168	-0.0104	0.3566
Real time parking availability tools used (1 if websites, 0 otherwise)	-0.0017	0.0000	-0.0032	-0.0009	0.0782
Real time parking availability tools used (1 if none, 0 otherwise)	0.0538	0.0000	0.1361	0.1017	-0.3038
Normal driving start time (1 if mid-day, 0 otherwise)	-0.0023	0.0000	-0.0046	-0.0015	0.1093

4.1 Socioeconomic Characteristics

Table 4 shows that before the pandemic, young drivers aged 30-49, who constitute 56.6% of surveyed drivers and align with the national median age of 46, experienced more frequent HOS adherence issues due to parking shortages. In contrast, drivers with less than a year of experience faced fewer such issues, possibly due to their use of real-time parking tools and decision-making regarding parking locations. Drivers receiving hazard pay, often involved in emergency relief, also faced more parking challenges before the pandemic, likely linked to decreased freight movement in various industries and reduced demand from businesses that slowed or shut down production. The Bureau of Labor Statistics reported a loss of 140,000 truck driver jobs by December 2020. Additionally, traffic congestion significantly decreased, with 87% of respondents in an ATRI and OOIDA survey reporting shorter congestion times. Post-pandemic, a higher proportion of male drivers, about two-thirds of those surveyed, reported increased difficulties in finding adequate parking. (Cheeseman Day and Hait 2019; U.S. Bureau of Labor Statistics 2020; The American Transportation Research Institute and The OOIDA Foundation 2020).

4.2 Business Characteristics

Concerning business characteristics, the only significant factor identified was the reduced number of trips taken during the pandemic compared to before. Consequently, drivers who took fewer trips experienced fewer instances of parking shortages leading to HOS adherence issues.

4.3 Driver Characteristics

Negative coefficient values indicate that team driving before and during the pandemic led to a decrease in parking-related HOS adherence issues. Tables 5 and 6 show that before the pandemic, drivers who never engaged in team driving had a lower likelihood (probability 0.0077) of experiencing HOS issues. However, during the pandemic, these drivers were more likely (probability 0.0075) to avoid HOS issues, while those who sometimes participated in team driving faced the highest risk of problems (probability 0.0037). Team drivers who stayed together during the pandemic, likely part of the same social bubble or family, were more efficient at finding adequate parking.

4.4 Time of Day Operations

Time-of-day factors significantly influenced the frequency of parking shortages causing HOS adherence issues both before and during the pandemic. Mondays were found particularly challenging for finding parking (increased). Attempting to park on Mondays reduced the likelihood of avoiding HOS problems by 0.0032 in both periods. Moreover, a shift in drivers' normal start times to mid-day during the pandemic, with 34% fewer starting in the morning and increases of 50% and 140% for mid-day and afternoon starts respectively, also affected parking availability. This shift likely relates to decreased passenger traffic and changes in delivery schedules for essential goods, as indicated by the ATRI and OOIDA survey findings.

Facility closures significantly impacted parking issues. Closed private truck stops or those with limited amenities reduced parking challenges before and during the pandemic. During the pandemic, shower access at private facilities decreased HOS issues, whereas truck wash stations increased them, influenced by the popularity of stops with certain amenities. Conversely, restrooms at public facilities decreased parking issues before the pandemic, but fuel services and vending machine access increased them. During the pandemic, vending machine and food service availability continued to exacerbate parking challenges.

4.5 Driving Management

In terms of driving management, using websites as real-time truck parking availability tools did not effectively reduce HOS regulation adherence problems due to parking shortages. Before the pandemic, website use slightly decreased the likelihood of avoiding HOS issues (probability of 0.0017), while not using these tools significantly increased the probability of never experiencing HOS issues (probability of 0.0538), a trend consistent during the pandemic. Additionally, communicating with other drivers was unreliable for finding parking before the pandemic, leading to more HOS issues.

Fatigued driving also impacted parking-related HOS problems. Before the pandemic, rarely or never driving while tired helped nearly all respondents avoid difficulties in finding parking. However, during the pandemic, frequently driving tired increased the challenges in adhering to HOS regulations.

4.6 Truck Configuration

Before the pandemic, truck configuration characteristics emerged as a significant factor, with single unit trucks more likely to face HOS adherence problems due to parking shortages. Although 39% of surveyed drivers operated single unit trucks, they represent 77.6% of all registered trucks nationally. This higher occurrence of issues among single unit trucks aligns with the American Trucking Associations (ATA) survey findings, which reported more than 11 truck drivers for every parking space and 98% of drivers facing difficulties in finding safe parking. Additionally, nearly half of the drivers in this survey admitted to willingness to park illegally, highlighting the severe impact of the national truck parking shortage. (Bureau of Transportation Statistics 2019). (McNally 2021)

5. CONCLUSION

This study sheds light on the pandemic's impact and the truck parking shortage. It used a random parameters bivariate ordered probit model to analyze how lack of parking affects HOS adherence issues, revealing a correlation in unobserved factors before and during the pandemic. The findings highlight the pandemic's adverse effects on trucking industry characteristics and service availability at rest stops. Disruptions in amenities like vending machines, takeout services, and truck wash stations have led to increased parking and HOS compliance challenges for drivers. The importance of rest stop services, including restrooms, fuel, and showers, emerged as critical for drivers seeking parking. Additionally, the study found that fatigued driving and driving during mid-day or on Mondays heightened parking-related HOS issues. This research offers valuable insights for policy formulation and management regarding HOS regulations, truck parking, and road safety, addressing the national parking shortage. Future studies should focus on modeling based on facility type and geographic region, aiding state agencies, planners, and engineers in crafting effective policies for resilient supply chains and infrastructure.

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Understanding Characteristics of Crowdshipping Trip Production: Evidence from Atlanta

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ABSTRACT

The rapid growth of e-commerce has significantly increased last-mile deliveries in cities, leading to heightened greenhouse gas emissions. Crowdshipping (CS) offers a sustainable alternative by leveraging shared deliveries. However, due to its novelty and limited data, understanding CS characteristics remains a challenge. This study, based on the CS trips in Atlanta from 2015 to 2018, revealed the trip patterns and factors influencing trip production. Machine learning techniques highlighted those areas with concentrated food and home appliance stores, limited access to transit, and higher proportions of low-income, educated, or younger populations tend to experience more CS activities. The findings shed light on how to promote CS services in disadvantaged areas and encourage partnerships with businesses for last-mile delivery.

INTRODUCTION

The advent of e-commerce has revolutionized the purchasing habits of urban residents, leading to an increased frequency of deliveries in the cities. Consequently, this heightened delivery activity escalates the energy consumption and emissions in urban areas (Hidayatno et al. 2019). In this regard, the prevalence of e-commerce and the corresponding surge in last-mile delivery traffic pose significant challenges for cities globally (Khojastehpour et al. 2022). These challenges primarily revolve around issues of congestion, emissions, and road safety (Fessler et al. 2023).

The increasing prominence of e-commerce and customers' demand for express delivery have led metropolitan areas to actively explore innovative and sustainable urban freight transportation for last-mile delivery (Ballare and Lin 2020). In this regard, CS is emerging as a notable innovation in urban logistics, garnering attention for its promising attributes related to sustainability, flexibility, and cost-effectiveness (Wicaksono et al. 2022). CS, stemming from the concept of the sharing economy, has been defined in various ways within the literature.

To predict CS trip production, Shen and Lin (Shen and Lin 2020), worked with a unique set of real-world CS data and utilized deep learning models to predict the delivery trip production;

their study focused on the trip prediction for five zip codes with high trip production in Atlanta city. Nevertheless, it is important to acknowledge that their study did not take into account the features and characteristics of each area and important factors that may impact CS. Accordingly, Le and Ukkusuri (Le and Ukkusuri 2019), investigated decision-making of senders for different products in a logistics market where both CS and traditional carriers are available. To reveal the factors that influence senders' decision-making, they collected data from a survey conducted in the United States (U.S). Their findings indicated that shipping costs play a significant role in senders' choices. However, it's important to note that the researchers used Stated Preference data, which may not reflect the actual behavior of the service users. Moreover, Punel et al.(Punel et al. 2018) did another study to identify factors that influence the generation of CS trips. They found that CS is more commonly used by men, young individuals, and those who are employed full-time. They conducted a web-based survey for both CS users and non-users. In their dataset, they had a total of 35 CS users and 496 non-users. As a result, due to the relatively low number of actual users in their sample, their findings may not be generalized to a broader population.

Overall little is known about the significant characteristics of CS trip production and the existing studies lack either sufficient socio-demographic and the built environment factors (e.g., Shen and Lin 2020) or real-world CS data (e.g.,Punel et al. 2018). To the best of our knowledge, this study represents the first of its kind in addressing the effects of the socio-demographic and the built environment factors on the trip production of CS at the census tract level. It provides greater insights into the popularity and characteristics of areas where CS is more prevalent. In this work, we analyze the Atlanta CS trips between 2015 and 2018. As Georgia is one of the states that the has the most CS users (Punel et al. 2019), the study findings will provide crucial understanding for policymakers and CS businesses to optimize last-mile delivery sustainability and efficiency.

Data

In this study, we utilized a dataset of four districts in Atlanta, GA to understand the spatial patterns, social demographics, built environmental factors, and business presence, all contributing to the use and popularity of CS.

Georgia is among the states that exhibit a high rate of CS usage in the United States (Punel et al. 2019). The study analyzes a dataset from 24,784 CS trips in Atlanta from 2015 to 2018. The dataset contains trip detail (pickup and delivery locations), timestamp (pickup and delivery time windows), package size, and sender type (business vs. individual). Spatial analysis indicates significant spatial heterogeneity, with over 30% of the census tracts having fewer than 5 CS trips. This prompts an investigation into identifying the census tract features influencing the production of CS trips.

The study incorporates the American Community Survey (ACS) dataset, focusing on socio-demographic information at the census tract level in Atlanta from 2012 to 2016. This dataset, covering 200 census tracts, offers insights into population characteristics, socioeconomic indicators, and demographic variables. A third dataset from the Environmental Protection Agency (EPA) provides information about the built environment attributes such as population density, job density, transit service frequency, and walkability. Understanding the relationship between these factors and CS trip production contributes to a better comprehension of how the built environment influences CS utilization. Lastly, the study employs a Business Locations Dataset, utilizing the Google API to collect coordinates of various businesses in the Atlanta area, aiding in identifying areas where CS is popular and determining contributing features, particularly for the business-to-consumer (B2C) model. It is also noteworthy to note that all of the datasets are in the scale of census tract.

Methodology

The main objective of the research is to identify key factors influencing CS trip production. The process involves integrating the above datasets, using the pickup coordinates in ArcGIS. First, the pickup locations are grouped into the corresponding census tracts, and then the other three datasets are matched at the census tract level. Notably, a business heavily utilizing CS in Atlanta prompted the exclusion of 7,636 trips from the original dataset of 24,785 to prevent overrepresentation and ensure data integrity. This exclusion aimed to maintain a balanced representation and avoid biases associated with specific senders. After addressing missing data, the final dataset consists of 185 census tracts and 79 attributes, including 33 built environment factors, 45 socio-demographic factors, and aggregated CS trip counts at the census tract level.

For data analysis, three different machine learning models are employed to build a trip production prediction model and identify significant factors. These models are Decision Tree, Random Forest, and Gradient Boosting, which are advanced and efficient for regression models (Ghasri et al. 2017; Li et al. 2021; Pourebrahim et al. 2019; Xu et al. 2005). Each model's performance is evaluated by R-square for predictive accuracy. The analysis also identifies the most important features of the models and their corresponding SHAP (Shapley additive explanations) values.

Decision tree regression is a tree-based modeling technique employed to make numerical predictions for the dependent variable (Rathore and Kumar 2016). Random Forest is a regression method that leverages multiple Decision Tree algorithms to classify or predict the value of a variable, effectively enhancing performance and accuracy (Breiman 2001; Guo et al. 2011; Rodriguez-Galiano et al. 2015, 2012). Lastly, Gradient Boosting is the third machine learning model to our dataset. Gradient Boosting and Random Forest are both ensemble models utilized in regression and classification tasks to combine the outputs from individual models. But their approach to constructing the individual trees differs. In Gradient Boosting, boosting is employed, wherein weak learners like decision stumps (decision trees with only one split) are sequentially combined, with each new tree aiming to correct the errors of its previous one.

For each method we use the SHAP values to find and interpret the most important factors from the model results. The SHAP values , which stands for Shapley Additive Explanations, are an explanation approach based on model additivity, where each prediction is explained by attributing the contribution of each feature in the dataset to the model's output (Lundberg and Lee 2017; Marcílio and Eler 2020). By decomposing the model's predictions and attributing the contributions of each feature to the final output, SHAP provides a comprehensive and intuitive explanation of how the model arrives at its decisions (Futagami et al. 2021). This approach help to better understand the relative importance of different features and gain valuable insights into the underlying relationships between the input variables and the model's output (Javadinasr et al. 2023).

RESULTS

Explanatory Analysis

The model fitting utilized a filter-based selection method, considering Pearson correlations and addressing collinearity. Eight key features were identified including both the built environment and the socio-demographic attributes, while the others were excluded due to insignificance or correlation with essential features to prevent overfitting. Figure 1 illustrates generally low to moderate inter-feature correlations, with the highest correlation at 55% between age_18to20_r and Income Below 15K. Notably, certain factors—Income Over 40K, Home Appliance Stores, Food Stores, and Shipping Stores—demonstrate strong correlations with the target, suggesting their potential significance in the models. The subsequent analysis focused on these key features to gain profound insights.

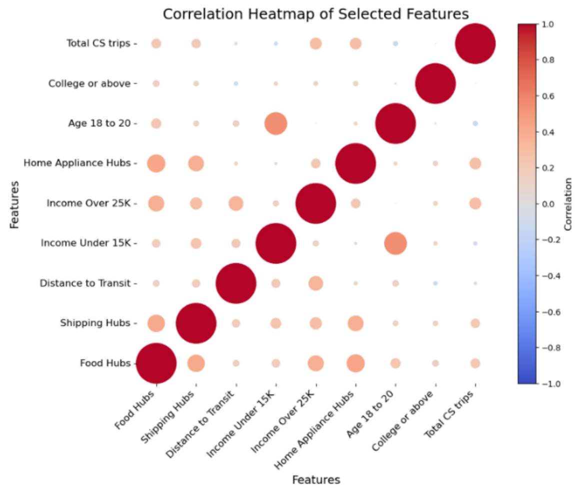

Figure 1. correlation between features and target variable

Based on the results, the effect of Home Appliance Stores on the CS trip production appears interesting and warrants further investigation, especially since the package size for this type of delivery differs from other businesses like pharmacy, food, and grocery. Analyzing the package size for Home Appliance Stores, Figure 2 reveals that the majority of delivered packages are medium size of roughly 20*20*16 in^3 in dimension and 46 lbs in weight (Shen and Lin 2020). In other words, CS is primarily used for delivery of medium-sized home appliances since most of the crowdshippers use their personal vehicles for delivery.

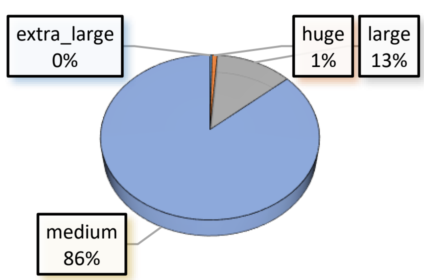

Figure 2. Package size composition for Home Appliance Stores in CS trips

Models Output

Following data preprocessing and feature correlation analysis, three machine learning models were employed to predict the total number of CS trips based on the identified features. Using the scikit-learn library and an 80-20 train-test split technique, the Decision Tree model yielded an R-square value of 53%, with crucial features being the number of Food Stores, Home Appliance Stores, and Shipping Stores. The Random Forest model, optimized through a Greedy algorithm, achieved an R-square value of 57%, with consistent significant features. The Gradient Boosting Regressor, fine-tuned through a greedy algorithm, demonstrated a notable improvement with an R-square value of 71%, maintaining consistency in crucial features like Food Stores, Home Appliance Stores, and the number of high-wage residents in census tracts. The use of a constant random state ensured a fair comparison among the models.

The comparison of feature importance across all models is illustrated in Figure 3. The results show that across all three models, the number of food stores consistently emerging as the most crucial factor in CS trips. Moreover, among the top five most important features, food stores, home appliance stores, and income over 40K are consistently on the list across all three models, Additionally, shipping stores, home appliance stores, and income over 40k are important factors in the Decision Tree model, while they also hold significance in the Gradient Boosting model with a lesser impact compared to food stores. On the other hand, the Random Forest model assigns greater importance to the food stores and highlights home appliance stores and income under 15k as relatively influential factors in CS trips.

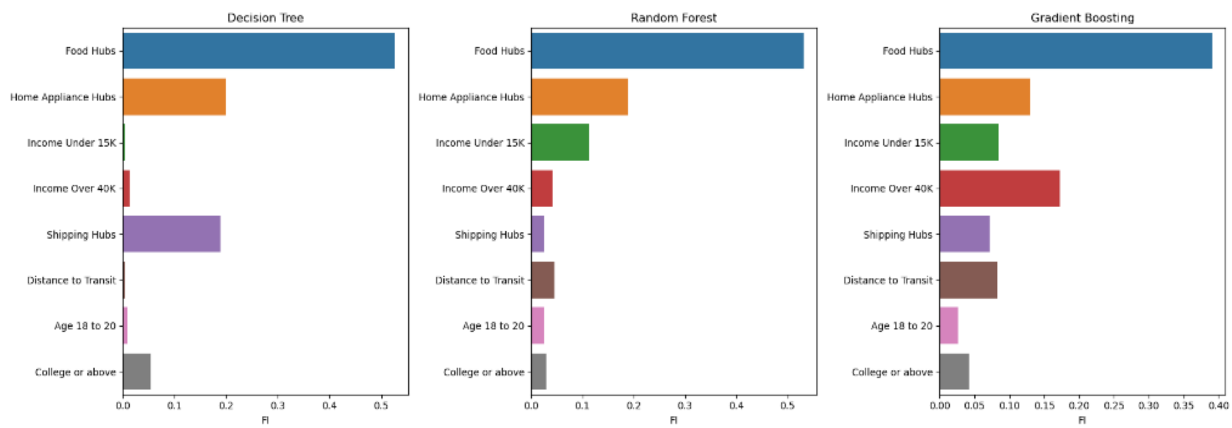

Figure 3. Feature importance for Decision Tree, Random Forest, Gradient Boosting Models

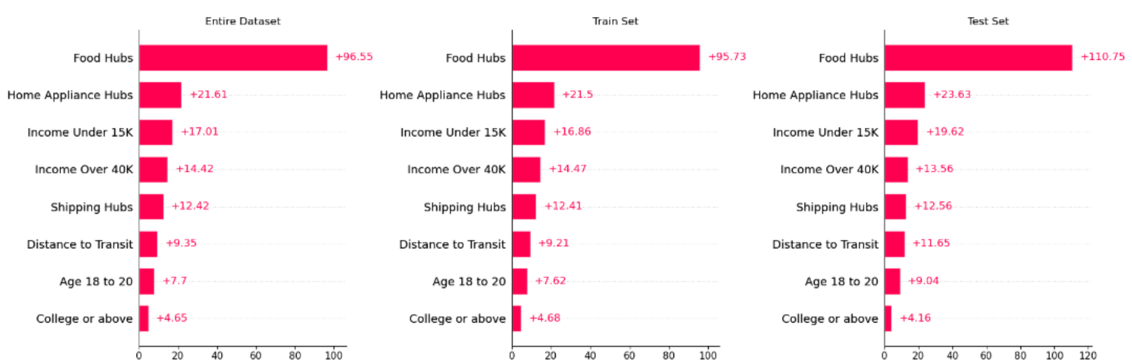

Figure 4. Mean Absolute SHAP values for train, test, and entire dataset of Gradient Boosting

In evaluating the Gradient Boosting model, a comparative analysis of mean absolute SHAP values was conducted for the training, test, and entire datasets, as depicted in Figure 4. The comparison revealed consistent, similar SHAP values across the three datasets, indicating stable importance of features and mitigating concerns of overfitting. SHAP values were further visualized in Figure 5, demonstrating the positive and negative impacts of features on CS trips. Notably, an increase in the number of Food Stores, Home Appliance Stores, individuals aged 18-20, highly educated individuals, distance to public transit, and low-wage individuals positively influenced CS trips. Conversely, an increase in the number of Shipping Stores and high-wage individuals led to a decrease, aligning with expectations and showcasing the model's interpretability. Despite exploring the correlation matrix and finding no meaningful correlation between low and high-wage individuals and highly educated individuals, the presence of another medium wage group might explain observed patterns.

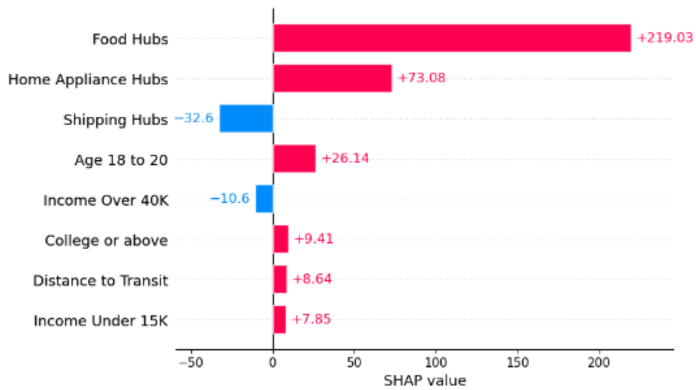

Figure 5. SHAP values for Gradient Boosting

Factors Affecting CS Production

The results of our Gradient Boosting model are depicted in Figure 5 through SHAP values, highlight the most significant variable as the number of Food Stores, which also exhibits a positive coefficient with the CS trips. This finding aligns with previous studies by Le and Ukkusuri (Le et al. 2019; Le and Ukkusuri 2019), stated that CS is particularly well-suited for specific goods categories, such as groceries and home-delivered food. These types of deliveries often necessitate same-day service, which may not be easily achievable through traditional shipping methods, making CS an attractive and affordable alternative for Food Stores seeking fast last-mile delivery solutions. Thus, CS is an affordable and rapid last-mile delivery option, especially favorable for Food Stores seeking timely and reliable deliveries.

Our results also highlight the number of Home Appliance Stores, such as Home Depot stores, as the second significant factor influencing CS trip production. Similar practices have been observed with Walmart using CS for retail purposes (Punel and Stathopoulos 2017). Interestingly, the Home Appliance Stores being delivered through CS are predominantly of medium size, as shown in Figure 2. This finding also supports the idea that CS is particularly well-suited for specific product categories, that include medium-sized Home Appliance Stores, due to its efficient and cost-effective delivery. In the Atlanta context, CS has emerged as the preferred choice for delivering certain goods that require fast and on-demand delivery. This preference can be attributed to the absence of delivery services from these stores, making CS an affordable and prompt solution for product delivery.

The next significant variable in the Gradient Boosting model is the number of Shipping Stores. Our analysis of SHAP values indicates that CS trips are more prevalent in census tracts with fewer Shipping Stores. This finding supports the notion that CS is more appealing in areas where shipping services, such as traditional Shipping Stores (e.g. FedEx), are limited. Accessibility to main delivery services plays a crucial role in the CS trip production level, and the negative correlation suggests that CS fills a demand gap in areas with fewer available shipping options.

The age group is another significant factor in CS trip production, as indicated in Figure 5. In areas where there are more people aged between 18-20, the number of CS trips tends to be higher. This finding is consistent with previous research by Punel and Stathopoulos (Punel and Stathopoulos 2017), which suggested that young people are more likely to use CS. The preference for CS among younger individuals could be attributed to their familiarity with technology, as well as their desire for more flexible and on-demand delivery services.

Income level is another crucial factor influencing CS trip production, as evident from the SHAP values. Areas with higher-income residents, earning more than 40,000 USD annually, are associated with a lower likelihood of using CS. On the other hand, census tracts with a higher proportion of low-income residents, earning less than 15,000 USD annually, positively affect the model, as indicated by their positive SHAP coefficients. This observation aligns with the affordability aspect of CS as mentioned by Hui and Lin (Shen and Lin 2020),that it is more prevalent in areas with a larger population of low-income individuals who may find CS to be a more cost-effective option than traditional delivery services.

Education level also emerges as the next significant feature influencing CS trip production. The results of the model in Figure 5 indicate that CS is more popular in areas with a higher number of residents holding college degrees or higher qualifications. This finding aligns with the work of Punel and Stathopoulos (Punel and Stathopoulos 2017), who observed that individuals with higher levels of education are more likely to be users of sharing systems, such as CS. The preference for CS among more educated individuals can be attributed to their familiarity and comfort with modern technologies and their inclination towards sustainable and innovative delivery options.

The Gradient Boosting model highlights accessibility to public transport as a significant factor based on SHAP values. Specifically, the Distance to Transit feature, measuring proximity to transit stops, positively impacts CS trip production. This indicates higher demand for CS in areas with limited public transport accessibility. Figure 2 supports this finding, revealing that over 70% of packages ordered by individuals are small to medium-sized, suitable for personal transportation using public transit. Hence, in regions with restricted access to public transport, CS becomes a convenient and cost-effective delivery alternative, explaining its prevalence in census tracts with less accessible public transport options.

CONCLUSION AND DISCUSSION

Discussion and Policy Implications

This study delves into CS trip production characteristics using data from Atlanta between 2015 and 2018. The findings reveal preferences for CS in delivering groceries and medium-sized home appliances. By combining trip data with socio-demographic and built environment features at the census tract level, we explored the factors influencing CS trips. Machine Learning techniques like Decision Tree, Random Forest, and Gradient Boosting highlighted the importance of factors like the number of food providers, home appliance sellers, and the socio-demographic makeup of census tracts in driving CS trip numbers, as indicated by SHAP values and feature importance analysis. Based on the findings derived from our Machine Learning models, we propose two policy recommendations aimed at enhancing the effectiveness of CS usage:

Improving CS Service in Disadvantaged Areas

Per the findings, areas with limited shipping service facilities (i.e., post offices) and poor transit accessibility (i.e., high distance to transit) generate a higher number of CS trips. This indicates that individuals residing in such areas, with restricted access to shipping services directly or via transit, are more inclined to use CS for their shipments. Additionally, the results indicate that CS is more prevalent in areas with a higher proportion of low-income groups, suggesting that disadvantaged regions with limited shipping options rely more on CS services.

From a policy perspective, this finding highlights the potential of CS as a promising and cost-effective delivery option in disadvantaged areas with limited access to traditional shipping services. Policymakers may consider incentivizing business opportunities for CS services in these areas to offer a reliable and affordable shipment alternative.

Partnership with Businesses

The findings highlight a significant correlation between CS production and the presence of food and home appliance stores. This suggests that businesses lacking their own delivery services in these industries rely on CS as a cost-effective alternative. To enhance cost-effectiveness, service providers can establish cooperative programs with these businesses, offering a low-cost delivery option. This collaboration benefits both CS service providers and businesses by increasing usage rates and expanding customer bases, particularly advantageous for small businesses without the resources for independent delivery services.

Furthermore, CS services present a unique opportunity for small businesses dealing in disposable products (Mittal et al. 2022). By offering a low-cost same-day delivery option, CS surpasses traditional delivery services (e.g., FedEx) and provides a competitive edge for these businesses. Through these cooperative initiatives, CS not only serves as a practical and affordable solution for businesses lacking their own delivery infrastructure but also fosters a mutually beneficial ecosystem that supports the growth of small businesses.

Limitations and Future Directions

This study focused on examining CS trip characteristics using Atlanta-specific data. While the findings offer valuable insights into CS trends, it's important to recognize their potential limited applicability to other cities due to variations in urban landscapes and socio-economic contexts. To enhance generalizability, future research should broaden the analysis to include multiple cities and regions, considering diverse geographical settings and socio-economic factors for a more comprehensive understanding of CS dynamics on a broader scale.

Furthermore, our analysis utilized aggregated socio-demographic data at the census tract level, potentially missing individual preferences. To address this limitation, conducting survey-based studies could validate and complement our findings, offering a more nuanced understanding of CS user profiles. Besides, from a planning perspective, it is essential to explore the specific shipping services from which CS users have transitioned. Understanding why users prefer CS over traditional shipping services allows for improvements that enhance the appeal and efficiency of CS solutions.

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Optimizing Paratransit Routing Considering Dwell Time Uncertainty

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ABSTRACT

This research aims to enhance paratransit services for vulnerable road users amid Medicaid privatization trends. Addressing challenges in determining dwell time (time spent at a stop without progressing), we present adaptive reinforcement learning for more accurate predictions. Unlike traditional methods, we model the interaction between key factors influencing dwell time uncertainty, creating a reliable service tool. This framework optimizes paratransit routing by accurately estimating service times, contributing to more efficient healthcare access in underserved areas. The framework may lessen dwell time uncertainty and in-vehicle travel times, which could enhance the general quality of paratransit services for the elderly and disabled.

BACKGROUND

The national shift from fee-for-service to Managed Care Organizations (MCOs) in Medicaid has grown significantly. Uber Health transports medical patients through MCO contracts, aiming to reduce costs. However, this transition may impact non-Medicaid recipients' access to essential destinations. Existing transit tools struggle to adapt without sufficient data on Medicaid privatization trends. In North Carolina, the move towards broker-based privatization prompts a crucial analysis of community attributes and interactions' impact on transit performance. Scheduling software must balance pick-up times for efficiency and user convenience. Delays can have serious consequences, especially for paratransit riders with critical medical appointments. This research addresses time window uncertainty in scheduling due to Medicaid transformation, focusing on small cities and rural areas. It introduces new scheduling principles based on localized attributes, optimizing transit service efficiency under the influence of Medicaid shifts. This research stands at the forefront of demand response transportation systems, leveraging unique patterns from Medicaid transformation to enhance service quality.

Routing for paratransit vehicles broadly falls under the category of vehicle routing problems (VRPs). VRPs have received considerable research interest since its introduction (Dantzig and Ramser 1959). It seeks optimal routes for vehicles to efficiently serve customers or locations. Variations like pickup dropoff with time window (PDPTW) have been explored, with variants of alternative solutions (Ehmke, Campbell, and Thomas 2018, Cattaruzza, Absi, and Feillet 2018). For more comprehensive review, recent surveys of the VRP literature are available (Braekers, Ramaekers, and Van 2016, Konstantakopoulos, Gayialis and Kechagias 2020).

There are two operation schemes available for vehicle routing: offline and online. In the offline setting, passengers are required to reserve a ride in advance, allowing sufficient time for vehicle routes to be planned by matching requests. Information about daily operations is shared with both passengers and drivers. On the other hand, the online setting enables real-time interaction among stakeholders. Passengers can request service whenever they need it, and operators can assign them to vehicles almost immediately.

This study focuses on improving dwell time models for paratransit services, acknowledging its substantial impact on on-time performance in paratransit and other transportation modes (Fernande et al. 2010, Soltan et al. 2015). Contrary to common perception, dwell time accounts for a substantial portion of overall trip time, ranging from 26% to 50% (Sadeghpour and Ö˘güt 2017). However, accurately predicting dwell time remains a significant challenge due to several uncontrollable factors such as traveler behavior and mobility needs. While traffic introduces uncertainty, detours can assist, but abandoning passengers isn't an option. Hence, the study suggests incorporating dwell time uncertainty into paratransit systems.

Past studies suggested diverse dwell time estimation methods. Some observed actual dwell times, utilizing statistical measures like mean or distributions, while others applied constant values universally. (Gupta, Chen, Miller, and Surya 2010, Cokyasar et al. 2023). Majority of studies have focused on applying different linear regression models (e.g., multiple, log-linear, quantile, etc.), considering attributes such as the type of vehicle used, and passenger characteristics (Glick and Figliozzi 2019, Klumpenhouwer and Wirasinghe 2018). However, these models often tend to inaccurately estimate dwell time, leading to significant underestimation or overestimation due to reliance on assumptions, such as, linear regression models assuming constant variance across all dependent variable values, which doesn't align with the variability in dwell time models. Multiple linear regression has been suggested for adjusting dwell time in paratransit services (Garnier, Trepanier, and Morency 2020).

While this approach provides a thorough analysis of independent variables, it overlooks potential interactions and assumes linearity in relationships. Other studies have explored incorporating variable or deterministic dwell time for scheduling transit systems (Wu, F 2012, Li, Rousseau and Gendreau 1995). However, these approaches have inherent limitations in accurately capturing dwell time uncertainties during scheduling.

To enhance paratransit and bus system efficiency, a dynamic dwell time mechanism adapting to real-time customer requests is vital. This improves routing and scheduling accuracy by continuously updating dwell time estimates based on service progress. The study introduces a novel methodology, sequentially updating dwell time prediction (DP) model parameters after each request is fulfilled.

Our focus is primarily on the advanced request scenario, where the problem is defined prior to the need for a solution. In this scenario, customers are required to request services well in advance, allowing for efficient routing of paratransit vehicles before their departure from the depot. Once the vehicles have been dispatched, no additional requests for service can be accommodated.

This study develops a novel approach that involves continuously updating the dwell time model by sequentially adjusting its parameters. To achieve this, we employ a reinforcement learning (RL) framework (Lin, Ghaddar, and Nathwan 2021, Garces et al. 2022). Treating the problem as a sequential decision-making process, the RL framework enables learning and adaptation based on observed data and environmental feedback. This captures the complex dynamics and dependencies inherent in the PDPTW problem, resulting in more accurate and effective predictions of dwell time. While scalability and interpretability of RL methods can be challenged (Rudin et al., 2022), it is still valuable for solving problems with complex sequential dynamics.

METHODOLOGY

We now provide a detailed description of the PDPTW problem for paratransit services, present its mathematical formulation, and subsequently introduce the reinforcement learning (RL) framework developed to address this problem.

Problem Description

Figure 1 illustrates the proposed paratransit routing problem, considering customer requests and a dwell time prediction (DP) model. The customer request comprises pickup and drop-off locations and is implemented as pairwise precedence constraints.

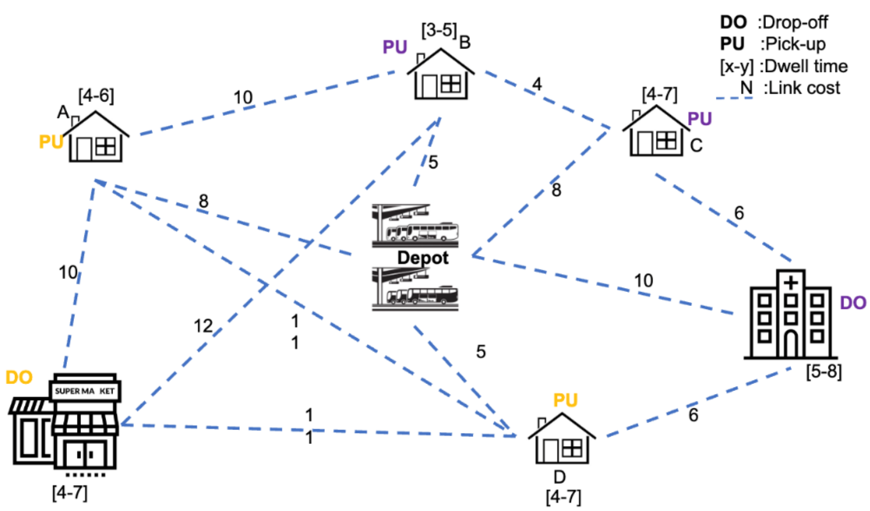


FIGURE 1: Paratransit route optimization to minimize travel time of fleet.

These constraints play a crucial role in paratransit operations, ensuring the correct sequence of activities such as picking up customers before dropping them off at their destinations. By incorporating these constraints, valid route construction is simplified. Each request must be fulfilled within a specified time window and this window is established when a customer requests a pickup and drop-off within a specific time period. The time window specifies the earliest and latest times for service to begin and end. For instance, a paratransit vehicle may be required to pick up a customer from their residence between 8:00 AM and 8:30 AM and drop them off at their destination by 9:00 AM. Time window constraints can make finding feasible routes more challenging but are crucial for ensuring timely service for customers with disabilities or limited mobility.

Each paratransit vehicle has a limited capacity (i.e., whether limited by the total weight of the passengers or the available space, or capacity, of the vehicle, or, in some applications, both weight and capacity limitations) are stationed at a depot and are available to serve the customers during the planning horizon.

To incorporate and update the parameters of the Dwell Time Prediction (DP) model as customer requests are fulfilled, we begin by representing the model's parameters (weights) as a probability distribution with a prior. This prior is learned from historical paratransit service data and captures the initial uncertainty surrounding the parameters. The variance within the prior distribution reflects the level of uncertainty associated with the model. After each request is fulfilled, we use the observed data (actual dwell time) to update the DP model's parameters, resulting in a reestimation of the probability distribution over the weights, which represents the posterior distribution. Our goal is to use the observed data such as observed dwell times and traffic uncertainty, to maximize the posterior distribution and reduce uncertainty in the model. The updated posterior distribution provides more accurate knowledge about the model's parameters, allowing us to make more accurate predictions of dwell time and improve overall system performance.

Mathematical representation

Mathematically, we can express the described problem as follows: The paratransit routing problem is formulated on a graph consisting of three types of vertices: customer pickup vertices denoted as V_p, customer drop-off vertices denoted as V_d, and depot vertices denoted as V_{dep}. Each vertex i is associated with an array X_i^t = (x_i , z_i, l_i , u_i, dp_i^t , r_i^t), where x_i and z_i represents the geographical coordinate of vertex i, l_i (lower bound), and u_i (upper bound), represent the corresponding time window, dp_i^t, is the predicted dwell time (time it takes the bus to complete the request once the bus has arrived at the vertex), and r_i^t is the remaining request at vertex i at step t. The variables d_{pi}, r_i, and X_i are characterized by the step t because we solve the problem in a sequential manner, and these three elements would change over time. All other elements in X_i^t are static. The time window at the depot is defined as starting from 0 up to the end of the planning horizon denoted as T ([0, T]). Additionally, the predicted dwell time and remaining request at this vertex are both set to zero.

At each step t, the set of vertex arrays X^t describes the local information at the vertices. The graph is complete, and the weight of each edge (travel time) is the Euclidean distance between the connected vertices. The nodes in the graph have access to a common set of global variables denoted as Gt $= \{\tau^t, \sigma^{2,t}, p^t\}$ where τ^t, $\partial^{2,t}$ and p^t indicate the time, variance of the parameter distribution of the DP model, and the number of bus(s) available at the start of step t, respectively. The values of τt and pt are initially set to 0 and the size of the fleet respectively. The initial value of $\partial^{2,t}$ is the prior variance of the distribution over the weights of the DP model. All the global variables could change over time.

A solution to the paratransit routing problem is represented by a sequence of vertices in the graph, interpreted as the routes taken by buses. The routes for different buses are separated by the depot. For example, if vertex 0 represents the depot, a vertex sequence of {0,2,5,0,4,3,0} corresponds to two routes: one that travels along 0 → 2 → 5 → 0 and another that travels along 0 → 4 → 3 → 0. This implies that two buses were used to complete the solution. To satisfy the precedence constraint between pick-up and drop-off requests, vertices 2 and 4 are pickup requests, while vertices 5 and 3 are drop-off requests.

Reinforcement Learning Representation

Looking at the problem of PDPTW for paratransit services from a reinforcement learning perspective, we assume that an agent is responsible for generating a solution to the problem by taking a sequence of actions. At each step, the agent observes the current state of the system and makes an action based on the available information. This action then leads to a change in the system state, and the process repeats until a termination condition is met. The goal is to guide the agent to improve its performance over time.

The state of the system in this context is described by the information contained in X^t and G^t, which pertains to the graph. An action involves adding a vertex to the end of the current sequence, which is denoted by y^t. The vertex sequence formed up to step t is denoted by Y^t. The termination condition is that all customer requests are satisfied, which occurs at step t_m. At each step t, we estimate the probability of adding each vertex i to the sequence, given G^t, X^t, and travel history Y^t, as Pr $(y^{t+1} = i \mid X^t, G^t, Y^t)$. We then find the next vertex to visit, yt+1, based on this probability distribution. Finally, we update the system states using transition functions based on y^{t+1}:

$$\tau^{t+1} = \begin{cases} \tau^t + DT_{y^t} + w(y^t, y^{t+1}) & if\ y^t \in V_{p,d} \\ w(y^t, y^{t+1}) & if\ y^t \in V_{dep} \end{cases} \tag{1}$$

where $w(y^t, y^{t+1})$ is the travel time from vertex y^t to vertex y^{t+1}, DT_{y^t} is the observed (actual) dwell time to pick-up or drop-off customers at vertex y^t (representing the service time at the customer vertex). Next, the variance of the distribution over the weights of the DP model is updated as (Murphy 2007):

$$\partial^{2,t+1} = \begin{cases} \frac{\partial^{2,t}\partial'^{2,t}}{n\partial'^{2,t}+\partial^{2,t}} & \text{if}\ y^t \in V_{p,d} \\ \delta'^{2,t} & otherwise \end{cases} \tag{2}$$

Where $\partial'^{2,t}$ is the prior variance, $\partial^{2,t}$ is the new sample variance, and $\partial^{2,t+1}$ is the posterior variance of the distribution over the weights of the DP model and n is the sample size (new information). Finally, the number of buses available p^t, and the remaining request r_i^t at each vertex are updated as follows:

$$p^{t+1} = \begin{cases} p^t - 1 & if \quad y^t \in V_{dep} \\ p^t & otherwise \end{cases} \tag{3}$$

$$r_i^{t+1} = \begin{cases} 0 & if \quad y^t = i \\ r_{i,}^t & otherwise \end{cases} \tag{4}$$

We define the reward function for a sequence of vertices, denoted by $Y^{t_m} = \{y^0, y^1, \ldots, y^{t_m}\}$, such that a high reward value indicates a high-quality solution. To achieve the objective of the problem, which is to minimize the total travel time of the fleet, the variance of the distribution over the weights of the DP model, and the number of vehicles used, we set the first term of equation 5 to be the negative total travel time of the fleet, which prioritizes lower travel time solutions. The second term accounts for the variance of the distribution over the weight of the DP model, making the agent select sequences that minimize the uncertainty of the DP model parameters.

$$r(Y^{tm}) = \alpha_1 \sum_{t=1}^{t_m} w(y^{t-1}, y^t) + \alpha_2 \sigma^{2,tm} \tag{5}$$

where $w\ (y^{t-1}, y^t)$ is the travel time on edge (y^{t-1}, y^t) along trajectory Y^{tm}, α^1 and α^2 are negative constants. All additional constraints of the problem, such as the pickup and drop-off precedence constraint, are defined as follows: If the paratransit vehicle is at vertex i at step t and there exists a vertex j (where j is not equal to i) that satisfies any of the specified conditions, we set the transition probability p_i^t to be 0 for moving to that particular vertex.

- Vertex j $\in v_p$ represents an unsatisfied pick-up request and the remaining capacity of the bus is zero.
- The earliest arrival time at vertex j violates the time window constraint (i.e., $\tau^t + w\ (y^{t-1}, y^t)\ >\ u_j$)
- Let pre(j) denote the set of nodes that must be visited before node j and Y^{t_i} denote the set of nodes that have already been visited by the agent up to current node i. The node j is infeasible if $pre(j) \notin Y^{t_i}$. This masking scheme enforces the pickup and drop-off precedence in the paratransit routing problem. Note that all pickup nodes ($i\ \notin\ V_p$) have no precedence nodes (empty set), and each drop-off node ($i\ \notin V_d$) has exactly one pickup node as precedence.
- We mask all the vertices except the depot if the paratransit vehicle is currently at the depot and there are no remaining customer request vertices.

Reinforcement learning encompasses diverse algorithms, each with its unique approach to solving tasks. Value Iteration and Q-Learning focus on estimating optimal state or action values, while Policy Iteration integrates both policy evaluation and improvement for convergence. Methods like Deep Q Networks leverage neural networks for complex state spaces, and Actor-Critic that combine value and policy-based strategies have bene proposed. In this article, we provide the numerical example for solving such problems and the usefulness of incorporating dwell-time estimates and leave the comparisons of RL algorithm performance as part of next steps.

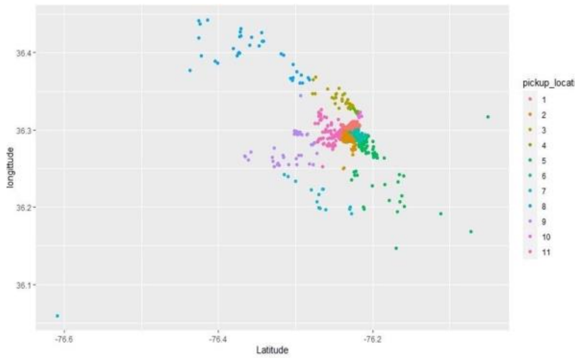
NUMERICAL EXAMPLE

In this section, we first provide an exploratory analysis of real-world dwell time distributions, followed by a numerical example using toy data to illustrate and discuss our developed sequential update of the dwell time model. Subsequently, we provide an example that discusses routing scenarios, incorporating relevant route considerations as described in the methodology.

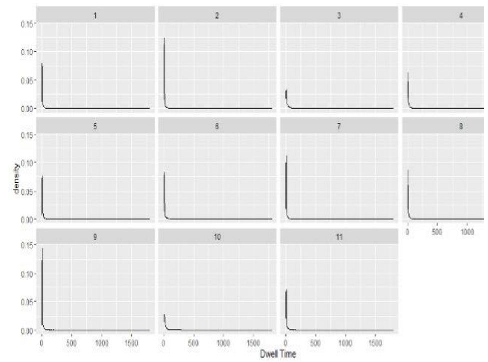
Exploratory analysis of dwell time distribution

Firstly, we performed a cluster analysis on the pick-up longitude and latitude coordinates for sample data from Elizabeth City. Using K-means clustering, we identified eleven distinct clusters. The obtained results in Figure 2a showed a significant clustering performance with an F value of 164.5 and Pr (>F) < 2e-16, indicating statistical significance in the clustering outcome. For each cluster, we constructed its respective dwell time density function (Figure 2b), which characterizes the distribution of dwell times within that specific group.

We noticed distinct paratransit activity patterns across different regions. Some clusters showed denser short dwell times, indicating efficient drop-off and pick-up processes. Others had longer dwell times, possibly signaling locations with higher demand or operational complexities. This analysis provides insights into dwell time distribution, allowing for the identification of trends and correlations to enhance future dwell time predictions.



(a) Elizabeth City Scatter plot of pick-up coordinates clusters



(b) Dwell time density function by cluster

FIGURE 2: Cluster analysis of dwell time data

Sequential Updates for the Dwell Time Model

We first illustrate the sequential update process for the dwell time model using Bayesian inference. Specifically, we consider a dwell time model with two weights: Weight 1 and Weight 2. The goal is to iteratively update the mean and variance of these weights based on observed dwell time as each request is served. To demonstrate the sequential update, we perform Bayesian inference for the mean and variance of the weights using the dwell time data in the given scenario. Assuming a normal distribution prior for the weights, we update them sequentially after processing each request. Table 1 shows assumed values for the computation of updated weights. Moving on to Request 2 at Stop C, the observed dwell time for this request is 5 minutes. We calculate the likelihood (L2), resulting in a value of 0.3. Using the updated mean (μ) and variance (σ2) from the previous step as the prior distribution, we compute the posterior distribution for Request 2. This posterior distribution (P2) represents the refined belief about the weights after considering the new observation.

TABLE 1: Assumed values for the computation of updated weights.

Description	Assumed Values
Prior Mean (μ_{w1})	3
Prior Variance (σ_{w1}^2)	1.5
Prior Mean (μ_{w2})	2
Prior Variance (σ_{w2}^2)	2
Likelihood (Req.1)	0.2
Likelihood (Req.2)	0.3

Similarly, we update the mean and variance of each weight using the posterior distribution P2. These updated values represent the improved estimates of the weights after incorporating the observed dwell time for Request 2. The sequential update process continues for each subsequent request (Table 2), allowing the dwell time model to adapt and refine its parameters based on the observed data. This iterative Bayesian model update ensures that the dwell time predictions become more accurate and reliable as more requests are served.

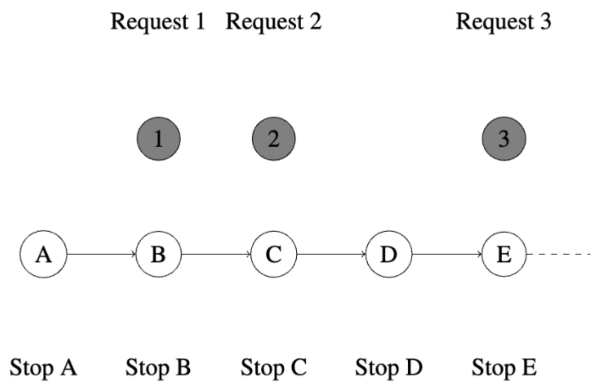


FIGURE 3: Stop sequence and requests.

TABLE 2: Sequential update process for DT model as requests are served.

Request	Stops	Observed. DT	μ_{w1}	σ_{w1}^2	μ_{w2}	σ_{w2}^2	Pred. DT
-	A	-	3	1.5	2	2	[5, 6, 7]
1	B	4	3.178	0.171	2	2	[6.34, 7.17]
2	C	5	3.625	0.2813	2.5	1.5	[8.625]
-	D	-	3.625	0.2813	2.5	1.5	[8.625]
3	E	7	4.1563	0.2109	2.9688	1.1719	[]
-	A	-	4.1563	0.2109	2.9688	1.1719	[]

Optimal customer service sequence

Figure 6 presents a simple numerical example for a typical paratransit service serving customers. The options are organized based on the assignment of customers to two available vehicles, referred to as Vehicle 1 and Vehicle 2. Each routing option is denoted by a distinct combination of customers served by the respective vehicles, and their corresponding total travel times are provided for evaluation. A critical aspect of this paratransit service lies in the constraint of feasible routing options, which is determined by the pickup and drop-off time windows. These time windows play an important role in ensuring that the service adheres strictly to predefined time constraints. Table 4 provides further details about the characteristics of each customer request.

Each row represents a different customer, identified by their unique identifier (Customer a, b, c, d, and e). The table includes information about the pickup location, drop-off location, pickup time window, drop-off time window, mobility need, and time of day for each customer's trip. Looking at Figure 4, three main options satisfy the PU/DO constraints time window of the customers. In Table 4, we present the various routing options for serving customers in our paratransit service, along with their corresponding total travel times. In option 1, Vehicle 1 serves 4 customers a, b, and c, in that order with a total travel time of 40 minutes, while Vehicle 2 serves 5 customers d and e, with a travel time of 30 minutes, leading to a combined total travel time of 70 minutes. Similarly, option 2 involves Vehicle 1 serving customers b, a, and c, resulting in a travel time of 47 minutes, and Vehicle 2 serving customers d and e, with a travel time of 30 minutes.

TABLE 3: Customer Requests and Travel Times

R	PU Loc.	DO Loc.	PU TW	DO TW	Mobility Need	Time of Day
a	A1	DA	8:00 AM -8:30 AM	9:00 AM -9:30 AM	2 (cane)	1 (afternoon)
b	A2	DA	8:15 AM -8:45 AM	9:15 AM -9:45 AM	1 (no support)	1 (afternoon)
c	A3	DA	8:30 AM -9:00 AM	9:30 AM -10:00 AM	3 (wheelchair)	1 (afternoon)
d	B1	DB	8:45 AM -9:15 AM	9:45 AM -10:15 AM	2 (cane)	2 (morning)
e	B2	DB	9:00 AM -9:30 AM	10:00 AM -10:30 AM	3 (wheelchair)	2 (morning)

TABLE 4: Routing Options and Total Travel Time

Routing Option	Vehicle 1 Customers	Vehicle 2 Customers	Total Travel Time (min)
Option 1	a, b, c	d, e	70
Option 2	b, a, c	d, e	77
Option 3	a, b, c, d, e,	-	65

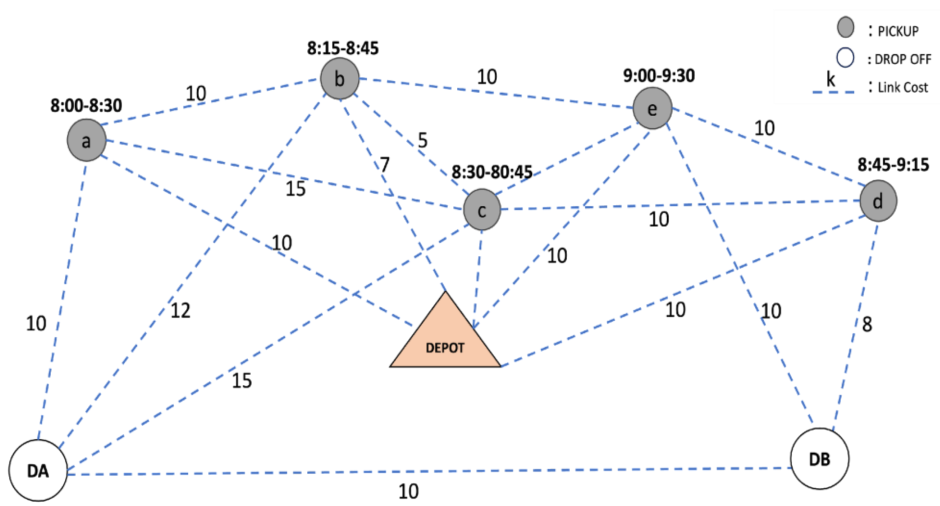


FIGURE 4: Numerical example for paratransit

This results in a combined total travel time of 77 minutes. The best routing option estimated as option 3. In this configuration, one vehicle serves all the customers efficiently in this order a, b, c, d, and e, leading to a total travel time of 65 minutes. This arrangement achieves a notably reduced total travel time. Compared to options 1 and 2, option 3 reduces travel time by 7.14% and 15.58% respectively. By choosing the most efficient routing, the service providers can ensure timely and satisfactory transportation for all customers while optimizing resource utilization.

CONCLUSION

In this study, we introduced a sequential update process for a paratransit dwell time model, addressing the dynamic and uncertain nature of the problem. We employed data-driven reinforcement learning framework to minimize delays in on-demand requests, incorporating Bayesian inference for parameter refinement after each served request. Our paratransit routing anticipates dwell time considering the diverse context of serving individuals with disabilities and the elderly.

Using a numerical example, we demonstrated the sequential update process for a dwell time model with mean and variance as weights. We calculated the likelihood of each observation, updated the posterior distribution, and obtained the revised mean and variance of the weights. This process enables the model to adapt and enhance predictions over time, becoming more accurate and reliable in estimating future dwell times. The study emphasizes new framework that potentially optimizes travel time and reduces uncertainty in dwell time predictions. The sequential update process facilitates learning from observed data, leading to improved routing decisions and enhanced service quality.

The proposed framework significantly contributes to optimizing paratransit routing by providing accurate estimates for a sequence of requests, a substantial portion of paratransit service time. By concurrently reducing in-vehicle travel time and uncertainty in dwell time predictions, it has the potential to enhance overall paratransit service quality, improving transportation experiences for individuals with disabilities and the elderly. Future research can explore more advanced dwell time models, examine the impact of different prior distributions, and consider factors like passenger characteristics or traffic conditions to further improve accuracy and robustness in dwell time predictions.

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Barriers to Community Connectivity: An Assessment of Reconnecting Communities Pilot Program

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ABSTRACT

Historically, transportation planning emphasized rapid, often more expensive modes like driving, frequently sidelining community preservation and connectivity. Such trends predominantly affected mixed-use urban locales, advancing vehicle-centric designs over the accessibility, quality of life, and economic interests of residents. However, a recent pivot toward transportation equity, as evidenced by the Bipartisan Infrastructure Law (BIL), is notable. The BIL champions, the Reconnecting Communities Program (RCP), an initiative committed to repairing historically induced community separations and promoting accessible, cohesive, and flourishing neighborhoods. This research evaluates the concept of transportation burdening facilities as defined in various studies and synthesizes the existing literature on the methods for assessing barrier effects. Employing data analytics, the study scrutinizes the 2022 RCP awarded applications to discern common patterns in the outcomes of transportation infrastructure that either segregate or impose burdens on communities. This analysis aims to categorize these patterns, which could highlight community severance by pinpointing and addressing divisions caused by previous transportation decisions. Our findings aim to empower decision-makers with actionable knowledge to understand, address, and potentially eliminate such community disjunctions, fostering more integrated and holistic urban planning.

INTRODUCTION

Transportation networks play a vital role in connecting societies, boosting economic growth, reducing poverty, improving educational opportunities, and supporting sustainable development. Nonetheless, historical imbalances in the distribution and quality of these networks have led to inconsistent levels of connectivity, mobility, and economic and social opportunities (Kaiser and Barstow 2022). While transport infrastructure is instrumental in shaping urban economies, environments, and societal interactions by providing access to diverse destinations, it can concurrently create hindrances, particularly for pedestrians and cyclists (Xueliang 2013). These obstacles may cause detours, reduced social contact, limited job, and service accessibility, and diminish the attractiveness of active modes of transportation (van Eldijk, Gil, and Marcus 2022).

While many studies have focused on the beneficial aspects of transportation infrastructure, there remains a notable gap in literature exploring its adverse effects on communities, including the potential for causing disconnection and fragmentation (Gbban et al. 2023; Lara and Rodrigues da Silva 2019). For instance, the construction of the Southeast Expressway and

Massachusetts Turnpike in the mid-1900s severely impacted Boston's Chinatown. This project demolished many of the neighborhood's homes and businesses, displacing hundreds of Chinese families and destroying much of the community's historic and economic fabric. As a result, the remaining residents face increased isolation, lack of access to essential services, and exposure to high levels of pollution and traffic congestion. Chinatown now being the most polluted neighborhood in Massachusetts and suffers from low income and limited economic opportunities (Andrew Emanuele ,Charlene Wang,Jordan Wainer Katz 2023).

To underscore the significance of this research, the Biden-Harris Administration's Justice 40 Initiative focuses on addressing the historical issue of insufficient investment in marginalized communities. Additionally, the United States has invested substantial funds in improving its highway infrastructure to promote national socio-economic development. The Reconnecting Communities program is specifically designed to bridge communities previously isolated by transportation infrastructure, offering funding for planning, capital construction, and technical assistance to improve connectivity by modifying or replacing relevant transportation facilities (U.S. Department of Transportation 2022). For the successful execution of the Justice 40 Initiative and to mitigate the social effects of transportation infrastructure, it is essential for policymakers to possess adequate knowledge to pinpoint infrastructure that poses a barrier for communities. This knowledge is crucial in addressing the requirements of all communities and guaranteeing fair outcomes in transportation infrastructure (Jones and Armanios 2020; Levitt 2007).

In recent times, there has been a notable increase in research focusing on burdensome transportation facilities. Efforts are being made to develop equitable transportation systems, yet there is a distinct gap in the availability of tools for identifying and quantifying the impact of transportation barriers on communities. The complexity of this issue is amplified by its interdisciplinary nature, encompassing fields like public health, economics, geography, and urban studies, each bringing unique concepts and methodologies (Anciaes, Jones, and Mindell 2016; van Eldijk et al. 2022).

To effectively pinpoint a barrier transportation facility, it is crucial to first gain a comprehensive understanding of the definition and its effects on a community. This article underscores the importance of offering an overview of barrier transportation facilities and sheds light on the relevant outcomes that result from these barriers within communities. We suggest an approach to identifying transportation barriers by examining the outcomes and consequences of existing transportation facilities that are identified as a barrier by governors and local communities. To implement this, we evaluate the 2022 awarded RCN applications in terms of the types of challenges they present and the severance they pose for the people. Section 2 is devoted to clarifying the terminology associated with barrier effects and delineating methods for the assessment of barrier effects. Section 3 highlights the main factors derived from the transport barriers evident in the FY2022 RCN applications. The article culminates in a discussion of the analytical results, followed by recommendations for the identification of barriers within transportation infrastructure. This provides crucial insights for both policymakers and practitioners to better assess the transportation barriers infrastructure.

LITERATURE REVIEW

2.1. Scope and Terminology

While transport infrastructures such as highways and railways are essential for effective urban, regional, and national connectivity, they simultaneously create barriers to local mobility systems. These barriers, through a complex set of cause and effect, can lead to various negative effects (Eldijk 2019).

According to the RCP program, the barrier refers to hindrances in community connectivity, encompassing obstacles related to mobility, access, or economic development. These impediments may arise from factors such as high speeds, grade separations, or other design elements. Alternatively, a burdening facility is defined as a surface transportation facility that contributes to air pollution, noise, stormwater, heat, or other challenges for a disadvantaged or underserved community (U.S. Department of Transportation 2022).

In academic discussions, the word 'severance' is commonly used to denote the divisive effects of traffic and infrastructure. The term is often associated with specific characteristics, such as separation from society, physical severance, social severance, secondary severance, or psychological severance (van Eldijk et al. 2022).

Although the term 'severance' is widely used in relation to transportation infrastructure, there's still no clear consensus on its precise definition. Typically, it suggests that a community already existed before a barrier was introduced. The term is also applied to describe the relocation of residents and businesses resulting from an infrastructure project, even when there isn't an obvious barrier involved (Handy 2003). Since the use of 'severance' varies across different sources, we use the 'barrier effect' as a term to represent the emerging consequences of transportation barriers.

2.2. Barrier effects

Transport infrastructure becomes a barrier only when it obstructs someone's path to their destination (van Eldijk and Lundberg 2023). To comprehend barrier effects, it's important to recognize that they don't emerge as a self-contained externality like noise or pollution. Barrier effects can occur: 1) Changes in crossability, resulting from the construction of new infrastructure or alterations in design or travel flow on existing routes; 2) Changes in the need to cross, caused by the establishment of new destinations, removal or alteration in the appeal of existing ones; 3) Changes in the capacity to cross, owing to demographic shifts, such as an increasing number of elderly or children (Eldijk 2019).

Transport infrastructure can lead to three kinds of barrier effects: a) direct, b) indirect, and c) catalytic/wider. Direct barrier effects represent a tolerable level of the barrier, requiring extra effort to overcome but not necessarily prompting a behavior change. An example is a road-rail level crossing causing some delay; people might accept this delay and stick to their usual travel paths rather than choosing a different route or mode. Indirect barrier effects, on the other hand, lead to changes in behavior. For instance, if congestion at a road-rail level crossing exceeds a bearable level, individuals might alter their usual travel routes or modes. Wider barrier effects have broader implications, extending beyond the behaviors directly related to the barrier. Changes in travel routes or destinations, for example, might encourage urban development away from a crossing or diminish economic activities near it (van Eldijk et al. 2022; Gbban et al. 2023).

Given its complex nature, it's important to understand that barrier effects shouldn't be assessed in isolation as a separate outcome. Instead, they require input from various stakeholders and areas of expertise. Therefore, it's crucial to distinguish between the barrier effects and what causes them, to grasp how different determinants interact, and to clarify the different layers of barrier effects (van Eldijk et al. 2022).

2.3. The process of assessment of barrier effects

Barrier effects are considered a significant concern in transport policy, as the transportation system is largely responsible for creating divisions in urban neighborhoods. This includes linear infrastructures like roads and railways, as well as substantial facilities such as airports, railway stations, and car parking areas (Anciaes, Boniface, et al. 2016).

The barrier effects concept in urban planning, described by scholars covers various effects that infrastructure has on social dynamics (Bradbury, Tomilnson, and Millington 2007; Clark 1991). Primary barrier effects, like increased travel time and effort, result in limited access to key facilities such as schools, healthcare, and leisure activities, and impact the effectiveness of services such as public transport and emergency response (Cline 1963; Eldijk 2019). Secondary effects are seen as changes in how people move around, including how often they travel, where they go, and their chosen modes of transportation. Tertiary effects have wider societal implications, such as decreased social interactions within neighborhoods, affecting how communities connect and their overall cohesion (Eldijk 2019).

Research into how to evaluate barrier effects is quite limited. In one study on the social impacts of traffic barriers, it was found through interviews with local authority officers in England that many of them had difficulty explaining the practical assessment of barrier effects, mainly because most practitioners were not well-informed about the process (James, Millington, and Tomlinson 2005).

The literature discusses various methods for measuring urban planning barrier effects. This model covers five key factors: people's needs, land use, transport features, people’s abilities, and crossing facilities and routes. The first three - people's needs, land use, and transport features - positively correlate with the barrier effect, meaning an increase in these factors leads to a greater barrier effect. In contrast, the last two - people’s abilities and crossing facilities and routes - have an inverse relationship with the barrier effect, indicating that their improvement reduces the barrier effect (van Eldijk et al. 2022)

Another study developed indicators for "population-interaction potential," specifically for measuring the decrease in potential for social interactions between neighborhoods separated by highways, a unique approach to evaluate the decline in social contact potential (Anciaes 2013). Along with other researchers, another study stresses that travel behavior is largely influenced by individuals' subjective perceptions of their physical environment. Therefore, they advocate for the integration of qualitative methods, like surveys and interviews, with quantitative approaches. Interviews are particularly crucial, as they can uncover responses to barriers, such as avoiding road crossings, that are not observable through other means (Russell and Hine 1996).

Finally, a study introduced a stated preference technique for valuing barriers. This method involves presenting people with various road designs and gauging their willingness to cross these designs to access a facility, such as a more affordable store (Anciaes, Jones, et al. 2016).

In summary, effective assessment of barrier effects requires considering infrastructure and traffic, the built environment, and people, with indicators for catchment areas, facility offerings, and social contact potential (Eldijk 2019).

To enhance our understanding of barrier effects, we propose examining the outcomes of transportation facilities that are recognized as barriers by both the public and stakeholder agencies. Therefore, we are focusing on the awarded Reconnect Communities Program (RCP FY 2022) application to evaluate the impact of these burdening facilities. By doing so, we aim to identify the pattern of outcomes that emerge from these obstacles.

METHOD

Given the complexity of the barrier effect, our approach focuses on pinpointing the key factors stemming from a transport barrier. This is aimed at guiding stakeholders and decision-makers in recognizing these barriers, while simultaneously providing scientists with insights to develop streamlined identification tools. This involves examining the outcomes of projects perceived as barriers from both public and governmental perspectives. To this end, we suggest analyzing the awarded projects in the RCP FY 2022 to identify common patterns and outcomes of these barriers.

The Reconnecting Communities Program (RCP) aims to fund transportation projects that focus on the needs of communities. Aligned with the Biden-Harris Administration's goals, the RCN Program addresses key issues like equity, sustainability, and economic strength in transportation. It seeks to correct the negative impacts of past transportation infrastructure, such as community displacement and environmental damage. The program offers two types of funding: Community Planning Grants and Capital Construction Grants. In early 2023, the program allocated $185 million in grants across 45 communities, including 6 Capital Construction Grants and 39 Planning Grants (U.S. Department of Transportation 2022).

Figure 1 presents the key factors as an outcome of the transport barrier. The chart organizes various outcomes associated with the barrier effect under five main categories.

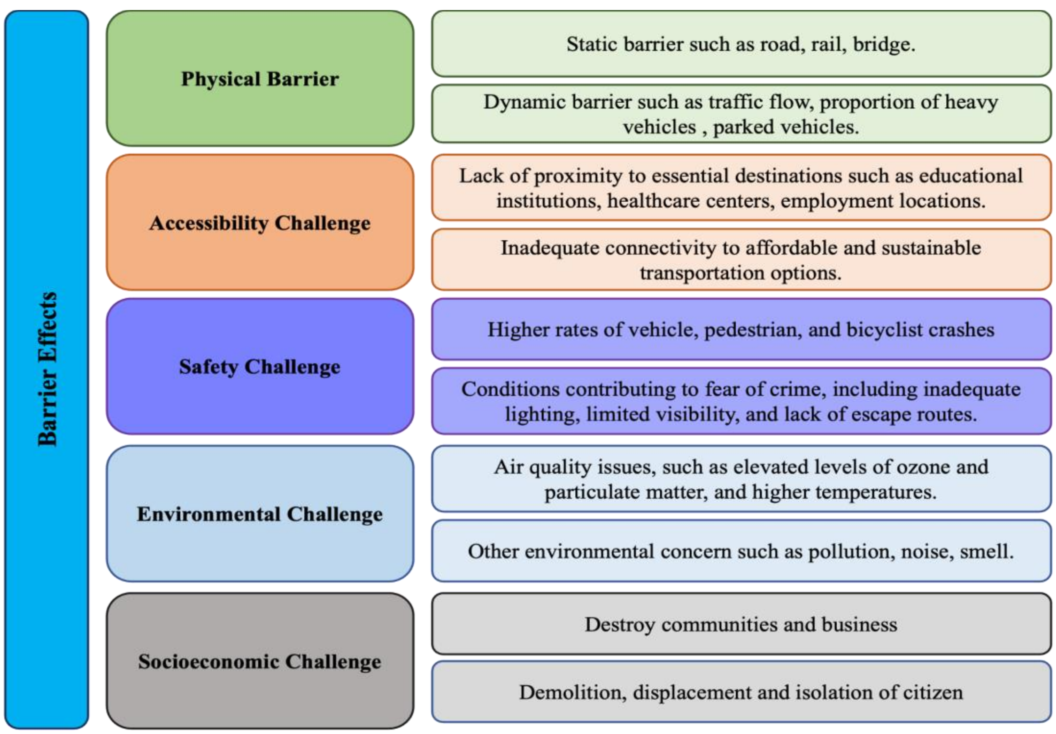

Figure 1. Key outcomes associated with the barrier effect.

Physical Barrier

Static barriers consist of permanent structures like roads, railways, and bridges that hinder movement because they provide a limited number of crossing facilities, especially for pedestrians and bicyclists (Anciaes, Jones, et al. 2016; van Eldijk et al. 2022; U.S. Department of Transportation 2022).

Transportation structures and road traffic can act as physical obstructions, even when crossing provisions are available. Inadequate or neglected facilities can lead to 'secondary severance,' whereby certain individuals find them inaccessible or view them as unsafe or disagreeable (Bradbury et al. 2007). Crossings with steps are not accessible for those with limited mobility, and underpasses are often seen as daunting, particularly during the night (Eldijk 2019).

In contrast, dynamic barriers are those that are subject to change over time or are temporary in nature. Examples include fluctuating traffic flow, a significant presence of heavy vehicles, or parked vehicles, all of which can act as temporary impediments to movement. For example, traffic congestion caused by the slow movement of trucks and heavy vehicles near a cargo rail, though the rail itself is not a barrier, can become a significant barrier for residents.

Accessibility Challenge

Accessibility was described as the potential for interaction (Hansen 1959). High accessibility is characterized by the ease of obtaining what one needs, having destinations nearby, and a variety of choices. Conversely, poor accessibility is marked by the difficulty in fulfilling needs, with destinations being distant or lacking available transportation modes (Pyrialakou, Gkritza, and Fricker 2016).

The lack of proximity to essential destinations underscores a challenge in accessing vital services and facilities such as educational institutions, healthcare centers, and jobs, often a consequence of transportation barriers. Additionally, inadequate access to affordable and sustainable transportation options presents another facet of this accessibility challenge. This situation illustrates how transport barriers can impact the availability and choice of transportation modes, creating further barriers for communities.

Safety Challenge

Higher incidents of accidents involving vehicles, pedestrians, and bicyclists are often observed in areas with barrier effects, primarily due to limited crossing accessibility. Additionally, factors such as poor lighting, restricted visibility, and a lack of clear escape routes contribute to a heightened fear of crime, further exacerbating safety issues by creating an environment that feels insecure (Anciaes and Jones 2018). For example, the underpasses along I-244 in downtown Tulsa, Oklahoma, the sole connections through the highway embankment, present a physical and visual barrier, especially for non-vehicular travelers like pedestrians and bicyclists. These underpasses, mostly dimly lit and visually restrictive, not only limit access and mobility but also create an environment perceived as unsafe (Oklahoma Department of Transportation 2022).

Environmental Challenge

Air quality issues, including high levels of ozone and particulate matter coupled with rising temperatures, pose serious risks to both human health and the environment. For example, the Gulfton area in Houston is adversely affected by significantly higher heat levels due to its highway. The 2020 Houston Heat Watch campaign pinpointed Gulfton as Harris County's hottest neighborhood, with temperatures reaching 17 degrees more than the coolest area. The 'Greener Gulfton' report indicates that this is due to the extensive concrete surfaces and lack of greenery characteristic of its automobile-focused transportation infrastructure (City of Houston 2022). Complementing these concerns are additional environmental challenges such as pollution, excessive noise, and offensive odors, all of which can deteriorate living conditions and further harm the ecological balance (van Eldijk et al. 2022; Hamersma et al. 2014).

Socioeconomic Challenge

Barriers have the potential to devastate communities and businesses, leading to their decline or failure, often as a result of isolation or inaccessibility. Furthermore, they can bring about the demolition of properties, displacement of residents, and the social isolation of individuals, severing their connection with the wider community and disrupting the social fabric(van Eldijk and Lundberg 2023).

In Baltimore, the construction of US 40, also known as the Franklin-Mulberry Expressway, led to significant socioeconomic challenges, particularly in the predominantly Black communities of West Baltimore. Originally intended to enhance connectivity for commuters from the western suburbs to the Baltimore Central Business District, this roadway instead severely impacted the local communities. The highway, often referred to as “The Highway to Nowhere,” caused the demolition of 971 homes, the displacement of over 1,500 people, and the loss of 62 businesses, leaving these areas struggling with blight and disinvestment.

The expressway not only physically divided large sections of West Baltimore but also became a symbolic barrier to progress, severing the once-thriving communities and leading to a prolonged period of economic and social decline. The impact of this infrastructure on these communities is a stark example of how such projects can have long-lasting and profound effects on the socioeconomic fabric of urban areas (Baltimore City Department of Transportation 2022).

DISCUSSION

The proposed categories are derived from key outcomes and patterns identified in the projects awarded under the RCP program. It should be stated not all barrier transport infrastructures will display every outcome we've discussed. The impact of each barrier effects category varies based on the type of transportation infrastructure and the community it affects. However, it is crucial for various stakeholders and decision-makers to consider these categories when identifying transportation barriers. The collaborative approach, where each stakeholder contributes, is akin to assembling a puzzle. By bringing their unique 'pieces' of information to the table, stakeholders can more effectively pinpoint the transportation barriers within their jurisdiction. Given that the intensity of each category's impact varies, input from the community, as a key stakeholder, is invaluable. Their perspectives and experiences are crucial in filling the gaps of this puzzle, providing a comprehensive understanding of the transportation barriers and their impact on communities.

CONCLUSION

Transportation networks are essential in linking societies, fostering economic growth, enhancing educational access, and promoting sustainable development. Yet, they can also have a profound negative impact, often disrupting rather than connecting communities and limiting opportunities. Highway expansions can lead to demolition, displacement, and isolation of citizens, destroying prosperous communities and businesses, and making it challenging for communities to establish stable livelihoods. Recently, there has been a growing focus on the barrier effects of transportation infrastructure. By identifying, eliminating, or redesigning these barriers, we can improve community access to jobs, healthcare, education, and daily necessities. This study evaluates existing definitions of transportation barriers and methods to assess their impact. We also review awarded RCP applications to determine common outcome patterns resulting from barriers. Our findings indicate that barrier effects encompass physical barriers, accessibility challenges, safety concerns, environmental impacts, and socioeconomic challenges. These insights are vital for policymakers and practitioners in better evaluating and addressing these barriers.

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Development of a Causal Model for Improving Rural Seniors' Accessibility to Resources: Data-Based Evidence

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ABSTRACT

Seniors residing in rural areas often encounter limited accessibility to opportunities, resources, and services. This paper introduces a model proposing that both aging and rural residency are factors contributing to the restricted accessibility faced by rural seniors. Leveraging data from the 2017 National Household Travel Survey, the study examined three hypotheses pertaining to this causal model. Multiple causal pathways emerge in the data analysis, with mobility identified as a mediator in one of them. The study further identified specific challenges faced by rural seniors, such as the reduced accessibility in reaching medical services and assisting others. These challenges stem primarily from aging and geographic obstacles that not only diminish their willingness to travel but also restrict the group from choosing transportation modes with higher mobility. Insights gained from this study serve as a foundation for devising effective methods to enhance transportation accessibility for seniors in rural areas.

INTRODUCTION

People have unequal accessibility to spatially distributed opportunities, resources, and services that they intend to reach. Seniors in rural areas are a group with more restricted accessibility for multiple reasons. To promote equitable accessibility for this group, it is important to identify the root causes for their reduced accessibility. Compared to younger adults (aged 16 to 64) in rural areas, rural seniors have inherently different needs to access spatially distributed destinations. For example, a local clinic may no longer meet their special need for medical services. Due to the lower population density in rural areas, the cost for rural seniors to access certain destinations is more expensive than their counterparts in urban areas. That is, aging and rural residency are part of the reasons for the reduced accessibility of rural seniors. Aging and rural residency influence people's accessibility through other causal pathways too. For example, some rural seniors cease driving once it becomes impractical. Their heavy reliance on automobiles and the increased restriction for them to choose this transportation mode also reduce rural seniors' accessibility. That is, mobility is part of a causal pathway, and it is a mediator of the causal relationship to be studied in this paper. Ignoring this causal pathway may underestimate the impact of aging and rural residency to the accessibility of rural seniors.

The study of this paper aims to determine how aging and rural residency negatively impact rural seniors' accessibility via multiple causal pathways and verify if mobility is a mediator. The National Household Travel Survey (NHTS) dataset (NHTS 2017) was used by this study, which is the only source of national data to study personal travel behavior. However, related work indicates that the selection of metrics for accessibility and mobility is affected by the study context and data availability. Therefore, discussions in this paper are driven by the following two questions. What metrics of accessibility and mobility can be derived from the NHTS dataset? What evidence can be found in this dataset to verify the assumed causal relationship?

The remainder of the paper is organized as follows. The literature is reviewed to identify the foundation for this study and the gaps to be filled. Then, the research methodology is introduced, which is followed by the result discussion. In the end, the paper summarizes the major findings and recommendations for future work.

THE LITERATURE

The literature relevant to this study includes research focused on developing indicators or measures for mobility and accessibility, determining their relationship with topological features, and examining the challenges faced by rural seniors.

Accessibility and Mobility. Accessibility is usually defined as the ability to reach the intended destinations (Litman 2003). According to Geurs and van Wee (2004), the four components contributing to accessibility encompass transportation, land use, individual factors, and time cost. Nonetheless, incorporating all these components as direct indicators of accessibility is challenging (Pyrialakou et al. 2016). Boisjoly and El-Geneidy (2017) reviewed various travel accessibility indicators such as the count of accesses to specific purposes within a defined time frame, which are influenced by factors like land use, opportunity distribution, and mobility. They also introduced two location-based measures of accessibility, namely the gravity-based measure and the cumulative opportunity measure. These measures have reached a level of maturity, extensively discussed in numerous research papers (El-Geneidy and Levinson 2006; Scott and Horner 2008; Casas 2007).

Mobility is defined as the movement of people and goods (Litman 2003). This concept underscores the act of movement rather than a mere means to a destination. Mobility was assessed using travel surveys to quantify person miles, ton-miles, and travel speeds. Furthermore, traffic data were utilized to gauge the average speeds of both automobiles and transit vehicles (Litman 2003). Mobility cannot be measured by a definitive or singular metric (Pyrialakou et al. 2016). Therefore, multiple indicators were developed, including travel mode distribution, travel frequency, and vehicle ownership (Pucher and Renne 2005; Jansuwan et al. 2013). To assess transportation disadvantages related to mobility, Kamruzzaman and Hine (2011) developed a comprehensive indicator called “participant index” (PI). It combines various elements, including the number of destinations visited, travel distance, space, travel frequency, types of activities, and duration. The mobility of individuals who do not drive can be enhanced by improved public transit infrastructure, reduced time required to reach transit stations, and increased proximity to their intended destinations (Case 2011).

Transportation network topological features play a significant role in determining the efficiency in low-volume roads, especially in rural area, from a micro perspective. Connectivity and node accessibility measures, which are integrated in the accessibility concept, are introduced to evaluate topological accessibility (Garrison 1960). Labi et al. (2019) presented three models of connectivity, accessibility, and mobility (CAM) relationship. The overall impact of CAM was considered in their proposed basic classification of measures. Sarlas et al. (2020) proposed betweenness-accessibility, a centrality measure allowing to quantify accessibility from a network-based view. Thus, measures can be dedicated to spatial- and social-equity analysis, vulnerability analysis, and cost-benefit analysis.

Disadvantage of Seniors in Rural Areas. Martens (2015) introduced a framework for assessing accessibility offered by a transport-land use system and the potential mobility facilitated by the transport system. This study indicated that the improved accessibility is partially attributed to the enhanced mobility. Actually, mobility data were employed to assess accessibility (Mittal et al. 2023). However, the popularly used gravity-based measurements do not adequately account for the influence of mobility on accessibility. Both mobility and proximity play pivotal roles in enhancing accessibility, but they often exist in a trade-off relationship (Grengs et al. 2010). In areas where the origin and the destination are close (high proximity), travel speeds typically tend to be slower (low mobility). Therefore, accessibility measures should take into account the combined influence of location- and mobility-related factors.

Rural seniors are often perceived as a disadvantaged group, and their demographic characteristics are considered as reasons. For example, "young elderly" (aged 65-75) and the "old elderly" (aged 75+) have different travel patterns and expectations on accessibility (Alsnih and Hensher 2003). When aiming to enhance the accessibility of seniors, it is imperative to consider their mental and physical needs. Accessibility varies significantly among different groups of travelers, such as individuals with mobility impairments attributed to aging and those reliant on public transit (Márquez et al. 2019). In the United States, automobiles are the predominant travel mode in rural areas (Pucher and Renne 2005), and seniors particularly rely on automobiles for travel (Kim 2011). Rural seniors' mobility for daily travel needs is restricted when it comes to public transit and walking (Ravensbergen et al. 2021). Rural areas are typically less developed than urban areas from the view of accessibility to opportunities, resources, and services (Vitale Brovarone and Cotella 2020).

METHODOLOGY

Hypotheses About the Causal Relationship. This paper posits a causal relationship wherein the attributes of rural seniors are factors (i.e., independent variables) causing reduced accessibility (i.e., the dependent variable). While the interested relationship has multiple causal pathways, this paper examines two, as shown in Figure 1. The first causal pathway goes directly from the group's attributes to its accessibility. In the second pathway, the attributes impact accessibility via mobility, a mediator variable. Three hypotheses delineated in Figure 1 are underlying this causal relationship:

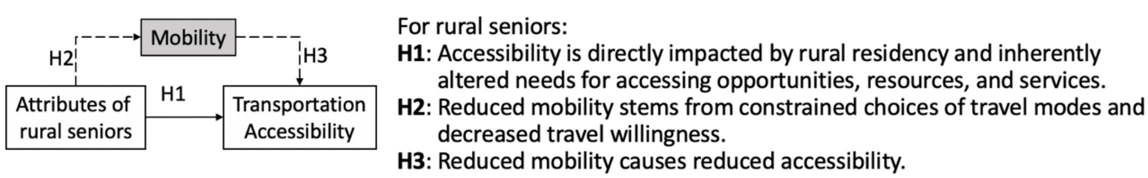

Figure 1. The proposed causal model of accessibility for rural seniors.

The NHTS Dataset. This study examined the hypothesized causal relationship in Figure 1 by extracting evidences from the 2017 National Household Travel Survey (NHTS 2017). This dataset contains a completed survey from 129,696 households and 923,572 person trips. We defined the scope of data analysis by concentrating on four primary travel modes (automobiles, bicycles, walking, and public transit), six key travel purposes (home, work, medical service, shopping, recreational activities, and transporting someone), and local travel with distance being within 75 miles.

Attributes and Measures. Attributes or measures are defined for examining the influences among variables in the causal model. Age and residency area are selected as the demographic attributes for characterizing travelers. We efine adults 16~64 years old as Yadults and those aged 65 or older as senior. Comparing rural seniors to rural Yadults facilitates the measurement of aging-induced changes, while comparing them to urban seniors allows for the measurement of location-induced changes. This study chose travel distance and travel time to intended destinations as measures of accessibility. Because both are random variables, their 75th percentiles conditioned on a specific travel purpose are used as indicators of the ease to reach an intended destination. This study chose four indicators as the basis for evaluating mobility, including the distribution of trips by travel modes, travel frequency, travel speed, and time to access public transit stations. Notably, travel frequency, often expressed as the number of trips per person per day, is the principal indicator for measuring mobility in numerous prior studies (Pucher and Renne 2005; Szeto et al. 2017). Although factors like congestion and travel miles per person also hold significance for assessment (Litman 2003), this study selected travel speed and time to access public transit considering the data coverage of NHTS.

DATA ANALYSES

The Direct Impact of Rural Residency on Accessibility. Hypothesis H1 asserts that the increased travel distance for rural seniors to reach their intended destinations, in contrast to their urban counterparts, is a contributing factor to their reduced accessibility. To verify this hypothesis, this study compared rural seniors to urban seniors on their cumulative distribution functions (CDFs) of travel distance, $\boldsymbol{F_{D,RSr}(x)}$ and $\boldsymbol{F_{D,USr}(x)}$, for each specific travel purpose. These two groups were also compared in terms of their travel time CDFs, $\boldsymbol{F_{T,RSr}(x)}$ and $\boldsymbol{F_{T,USr}(x)}$. Statistics of travel time and travel distance are further summarized in Table 1.

Table 1. Statistics of travel distance and travel time by groups and travel purposes.

	$D_{0.5}$ (mile)			$D_{0.75}$ (mile)			$T_{0.5}$ (min)			$T_{0.75}$ (min)		
Purpose	RSr	RYa	USr	RSr	RYa	USr	RSr	RYa	USr	RSr	RYa	USr
Home	7.2	8.2	2.7	14.1	16.0	6.2	15.0	16.0	15.0	30.0	30.0	25.0
Work	7.7	9.4	4.4	16.0	19.4	10.3	15.0	18.0	15.0	30.0	30.0	30.0
Medical	13.3	12.1	5.0	22.9	20.4	11.2	30.0	23.0	20.0	45.0	32.0	30.0
Shopping	4.3	4.1	2.3	10.6	10.4	4.8	12.0	10.0	10.0	20.0	20.0	17.0
Recreational	4.7	5.7	3.1	11.2	13.8	7.9	15.0	15.0	15.0	17.0	30.0	25.0
Transport someone	7.0	6.0	3.6	14.9	11.3	7.9	15.0	15.0	15.0	30.0	20.0	21.0

Note:
RSr: Rural seniors; RYa: Rural Yadults: USr: Urban seniors
$D_{0.5}$ (mile): 50th percentile of travel distance; $D_{0.75}$ (mile): 75th percentile of travel distance
$T_{0.5}$ (min): 50th percentile of travel time; $T_{0.75}$ (min): 75th percentile of travel time

Within a specific travel distance, $F_{D,RSr}(x) < F_{D,USr}(x)$ for all the travel purposes of study. That is, rural seniors can access fewer intended destinations than their urban counterparts within the same travel distance. For example, within 15 miles rural seniors reach 52.8% of their destinations for medical services, whereas this percentage for urban seniors is 82.9%. Similarly, given a specified travel time limit, $F_{T,RSr}(x) < F_{T,USr}(x)$ for the purposes of going home, accessing medical services, shopping, and transporting someone. That is, rural seniors experience drawbacks while accessing intended destinations than their counterparts in urban areas within the same travel time. For example, rural seniors reach 69.0% of their shopping destinations within 20 minutes, whereas urban seniors can reach 76.1%. Differences in their travel distance and travel time distributions are verified by the Kolmogorov-Smirnov (KS) test (p-value = 0).

Hypothesis H1 also states that aging is a factor that alters the intended destinations of rural seniors, which in turn changes their accessibility. To determine the direct impact of aging on accessibility, rural seniors were compared to rural Yadults with respect to their travel distance and travel time. For work commute, home returning, and recreational activities, $F_{D,RSr}(x) > F_{D,RYa}\,(x)$ at any given travel distance, and $F_{T,RSr}(x) > F_{T,RYa}(x)$ at any given travel duration. Those distinctions were verified by the KS test (p-value=0). For example, the observations pertaining to the purpose of work commute indicate that rural seniors intend to take job opportunities that are spatially and temporally closer to their homes than Yadults in rural areas.

Rural seniors are supposed to travel for a longer distance to access medical services, as compared to rural Yadults. For example, the 75th percentile travel distance to medical services is 22.9 miles for rural seniors and 20.4 miles for rural Yadults, as shown in Table 1. The difference in their travel distance CDFs was further verified by the KS test (p-value = 0.22), suggesting that these two groups have a moderate level of difference in travel distance to medical services. We conjectured that rural seniors may require special medical services more likely at farther destinations (e.g., in urban areas with well-developed medical services), but not for Yadults. Furthermore, in contrast with Yadults, rural seniors also have to travel for a longer time to access intended medical services. For example, Table 1 shows that 75% of rural seniors' trips to medical services are within 45.0 minutes, but it is 32.0 minutes for rural Yadults. The results indicate a restraint on accessing medical services for seniors than Yadults in rural areas both from the travel time and travel distance aspects.

For transporting someone, the disparity in travel distance CDFs between seniors and Yadults in rural areas is statistically significant (p-value of KS test is 0). Table 1 further shows the 75th percentile travel distance for rural seniors is 14.9 miles, whereas it is 11.3 miles for rural Yadults. Meanwhile, the difference in travel time between these two groups is also evident. The longer travel distance and travel time for rural seniors to transport someone to intended destinations is probably associated with the fact that rural seniors are more available than rural Yadults in providing transportation to others whose intended destinations are farther from their homes.

In summary, rural seniors encounter restricted accessibility for accessing medical services and assisting others. Nevertheless, it is noteworthy that they do not face equivalent limitations in activities such as returning home, work commute, shopping, or recreational pursuits. This distinction can be attributed to the special needs and willingness of this group to access some services or resources.

The Impact of Aging and Rural Residency to Mobility. The hypothesis H2 asserts that the reduced mobility among rural seniors stems from more restricted choices of their preferred transportation modes. In verifying this hypothesis, the study first analyzed the distribution of trips by transportation modes and traveler groups, as shown in Table 2. The marginal distribution of trips by transportation modes shows that automobiles are the most preferred mode, fulfilling 89.01% of trips. The frequency distribution of trips by transportation modes varies among the three groups according to the chi-squared contingency test(p-value=0). Rural seniors heavily rely on automobiles, which are used for 93.9% of their trips (=10.45%/11.13%). Walking is the secondary transportation mode for rural seniors, which fulfills 5.1% (=0.57%/11.13%) of their trips. Other modes count for an almost negligible amount. Although automobiles are still the primary transportation mode for urban seniors, the percentage of trips via automobiles is 84.3% (=38.32%/45.48%), 10.2% less compared to rural seniors. Besides automobiles, walking and transit are also their choices, which count for 11.3% (5.14%/45.48%) and 3.4% (=1.53%/45.48%) of their trips, respectively. What's more, the frequency of the trips among the transportation modes is similar between rural Yadults and rural seniors except that the former has a slightly lower proportion (92.8%) of trips using automobiles and a sensibly higher proportion (0.7%) of trips by transit. The heavy reliance on automobiles exposes rural seniors to the risk of compromised mobility when driving becomes unsuitable for them and fewer people can provide transportation to them.

Table 2. Distribution of trips by transportation modes and groups.

	Automobile	Walking	Transit	Bicycle	Others	Total
Rural Seniors	10.45%	0.57%	0.04%	0.01%	0.06%	11.13%
Rural Yadults	40.25%	2.24%	0.32%	0.14%	0.45%	43.39%
Urban Seniors	38.32%	5.14%	1.53%	0.24%	0.25%	45.48%
Total	89.01%	7.95%	1.90%	0.39%	0.75%	100.00%

The study further calculated the measures of mobility, including travel frequency, travel speed, and time to public transit, for the three groups of travelers, which are summarized in Table 3. From the table, one can find that rural seniors have an average of 2.98 trips per person per day, the lowest among the three groups. The low travel frequency of rural seniors indicates a lower level of willingness they possess for travel. The travel speed of rural seniors is higher than urban seniors, which is attributed to the fact rural seniors are usually farther from their intended destinations than their counterparts in urban areas (Pucher and Renne 2005), which necessitates high-speed travel. However, the travel speed of rural seniors is lower than rural Yadults, evident that aging negatively influences rural travelers' mobility. The faster travel speed of in rural areas is faster than people in urban areas should not lead to the conclusion that mobility is higher in rural areas. Recognizing the constrained transportation choices and the restricted availability of public transit services for residents in rural areas is essential. This circumstance consequently amplifies the predominant reliance on automobiles in rural areas. Surprisingly, rural seniors require less time to reach transit stations, with an average of 7.29 minutes, in contrast to the other groups. It may seem contradictory to our initial hypothesis. However, rural seniors demonstrate a reduced preference for public transit (see Table 2). This shorter average time to the public transit pertains to only a small portion of trips.

Table 3. Measures of travel mobility.

	Frequency (per person per day)	Travel speed (mph)			Avg. time to public transit (min)
		Automobile	Public transit	Non-motor	
Rural Seniors	2.98	27.6	19.2	5.7	7.29
Urban Seniors	3.24	20.0	11.6	3.8	7.85
Rural Yadults	3.31	30.8	21.7	6.2	10.89

In summary, aging and rural residency have been factors contributing to the reduced mobility among rural seniors. Aging is the main reason for the decreased travel frequency, and the lower density of opportunities, resources, and services in rural areas leads to their reliance on automobiles. Although automobiles meet their need for fast-speed travel, the heavy reliance on this mode without alternatives will cause a mobility crisis for this group if this preferred travel mode becomes infeasible.

The Impact of Mobility on Accessibility. Hypothesis 3 assumes that a higher level of travel mobility effectively increases accessibility, which is well discussed in the literature. This study attempted to verify this relationship using the NHTS dataset. Table 4 presents the 75th percentiles of travel distances, travel times, and travel speeds for the four travel modes associated with different travel purposes. Statistics in the table indicate long-distance trips rely on automobiles and public transit and, walking and riding bicycles are chosen for trips within short distances. The variation of trip distance CDF across those travel modes is further verified by the KS test (p-value=0).

Table 4. Statistics of travel distance, travel time, and travel speed by transportation modes and travel purposes

	$D_{0.75}$ (mile)				$T_{0.75}$ (min)				$S_{0.75}$ (mph)			
Purpose	Walk	Bicycle	Auto	Transit	Walk	Bicycle	Auto	Transit	Walk	Bicycle	Auto	Transit
Home	1.0	2.6	10.6	10.6	26.0	30.0	25.0	60.0	3.3	7.8	31.3	14.0
Work	0.6	3.2	15.6	14.0	15.0	30.0	30.0	60.0	3.4	8.7	35.9	15.9
Medical	0.6	2.2	13.5	7.8	15.0	25.0	30.0	60.0	2.8	6.5	31.9	12.6
Shopping	0.5	1.5	6.7	7.2	15.0	25.0	18.0	50.0	3.2	6.0	27.7	12.4
Recreational	0.8	2.5	11.5	9.9	19.0	30.0	27.0	46.0	2.0	9.4	32.8	15.5
Transport someone	0.6	1.2	8.4	9.0	15.0	15.0	20.0	45.0	3.2	7.5	30.4	19.7

Note:
$D_{0.75}$:75th percentile of travel distance; $T_{0.75}$:75th percentile of travel time; $S_{0.75}$:75th percentile of travel speed

While automobiles and transit are both options for long-distance trips, the former offers a higher level of mobility than the latter. The 75th percentile speed of automobiles is at least twice of the transit for all purposes except for transporting someone, and the 75th percentile travel time of automobiles is 41%~64% less than the transit. Automobiles move travelers to farther destinations of work, medical services, and recreational facilities than the public transit does, which is probably attributed to the higher level of mobility with automobiles. Notably, the 75th percentile travel distance to medical services via automobiles is 13.5, but it is 7.8 for the transit. Yet, for the purposes of shopping and transporting someone, the transit moves people to their slightly farther (0.5~0.6mi) destinations than automobiles. Table 2 shows that trips via automobiles are 89.01% whereas those via public transit are 1.9%. The distinctly different proportions of trips by those two transportation modes are probably a result of the public transit's lower level of mobility than automobiles.

While walking and riding bicycles are both short-distance transportation modes, the latter offers a higher level of mobility than the former. The 75th percentile speed of riding bicycles is 88%~370% faster than walking. Consequently, bicycles move travelers to destinations 100%~433% farther than walking. However, Table 2 shows only 0.39% of trips use bicycles, significantly lower than walking (7.95%).

To sum up, automobiles offer the highest level of mobility among the four transportation modes, making it the dominating mode of transportation in the United States for all travel purposes. Transit, as an alternative to automobiles for long-term travel, offers a lower level of mobility and thus transports travelers to closer destinations for certain travel purposes like accessing medical services. Riding bicycles provides a higher level of mobility than walking for short-distance travels, bringing travelers to farther destinations at a faster speed than walking can reach. However, the proportion of trips by riding bicycles is significantly lower than walking, indicating certain constraints such as biking infrastructure prevent travelers from switching from walking to riding bicycles. The observations underscore the fact that the higher level of service road system and the mass rapid transit system can improve mobility and, in turn, accessibility.

The Impact of Aging and Rural Residency to Accessibility via Mobility. The hypotheses H2 and H3 together indicate that mobility is a mediator on a causal pathway illustrated in Figure 1. That is, aging and rural residency of travelers raise mobility issues, which in turn limit rural seniors' accessibility to certain desired opportunities, resources, and services. This study further verified the mediator role of mobility by examining the travel distance and travel time of the three traveler groups under selected combinations of travel purposes and transportation modes. Table 5 summarizes the 75th percentiles of travel distance and travel time.

Table 5. Statistics of travel distance and travel time, by combinations of transportation modes and travel purposes among rural seniors (RSr), rural Yadults (RYa), and urban seniors (USr).

	Shopping						Medical Service						Transport Someone			
	Walk		Auto		Transit		Walk		Auto		Transit		Auto		Transit	
	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$	$D_{0.75}$	$T_{0.75}$
RSr	0.34	10.0	10.8	20.0	17.2	40.0	0.4	15.0	22.2	45.0	22.2	55.0	14.9	30.0	19.0	50.0
RYa	0.58	20.0	10.5	20.0	14.0	27.0	5.1	25.0	20.6	34.0	15.0	26.0	11.6	20.0	4.3	15.0
USr	0.44	15.0	5.2	16.0	4.7	48.0	0.7	20.0	11.9	30.0	10.3	50.0	8.1	22.0	16.5	45.0

Note:
$D_{0.75}$:75th percentile of travel distance (mile) ; $T_{0.75}$:75th percentile of travel time (min)

This study found that rural seniors need to access a larger percentage of medical services that are at farther distances and require a longer time to reach than rural Yadults and urban seniors. Table 5 shows that their 75th percentile travel distance to medical services using automobiles is 22.2 miles and the 75th percentile travel time is 45 minutes. These statistics are 20.6 miles and 34 minutes for rural Yadults and 11.9 miles and 30 minutes for urban seniors. The comparison indicates that automobiles, as a dominating transportation mode, offer a lower level of mobility for rural seniors in accessing medical services than for other groups. Rural seniors also undertake longer travel distance ($D_{0.75} = 22.2$) and time ($T_{0.75} = 55.0$) to access medical services if taking transit, due to its limited mobility for this group. Simultaneously, walking is also a transportation mode with a reduced level of mobility for rural seniors than their counterparts. The 75th percentile of travel distance is 0.4 miles and the 75th percentile of travel time is 15 minutes for rural seniors, whereas those statistics are 5.1 miles and 25 minutes for rural Yadults; and 0.7 miles and 20 minutes for urban seniors. Improving the mobility level of automobiles and transit for rural seniors would provide them with more equitable accessibility to medical services as compared to others.

The final focus of understanding mobility as a mediator centers on the purpose of transporting others. As found from the study of H1, rural seniors have a higher percentage of trips that spend longer time and travel for a longer distance to reach the destinations for assisting someone than rural Yadults. This difference is particularly distinct in using the transit. Table 5 shows the 75th percentile of travel distance is 19.0 miles and the 75th percentile of travel time is 50.0 minutes for rural seniors, and those statistics are 4.3 miles and 15 minutes for rural Yadults. Rural Yadults demonstrate different behavior than seniors in choosing transportation modes for transporting others, indicating the mobility levels of automobiles and transit are different among these groups. Meanwhile, the significant distinction between rural seniors and urban seniors is from the utilization of automobiles. As shown in Table 5, the 75th percentile of travel distance is 14.9 miles, and the 75th percentile of travel time is 30.0 minutes for rural seniors, but 8.1 miles and 22.0 minutes for urban seniors. This disparity of accessibility is attributed to fewer travel mode alternatives to automobiles. Specifically, poor public transit facilities and low-density distribution of opportunities, resources, and services in rural areas lead to the heavy reliance on automobiles.

In summary, mobility is a mediator through which aging can lower rural seniors' accessibility. Automobiles, as the dominating transportation mode for long-distance travel, offer a lower level of mobility to rural seniors than rural Yadults, especially in accessing medical services and transporting others. Walking is the major mode for short-distance movement, but it prevents rural seniors from accessing destinations that are a little farther and accessible by rural Yadults or urban seniors. Rural seniors have limited choices of transportation modes, for both long-distance and short-distance travel, making it more difficult to reach intended farther destinations.

CONCLUSION

This study presented a causal model delineating both the direct and indirect effects of aging and rural residency on travelers' accessibility to opportunities, resources, and services. In this model, mobility serves as a mediator through which the demographic attributes of rural seniors indirectly influence their accessibility. Descriptive statistics of the trip data in 2017 National Household Travel Survey support our hypotheses, confirming the presence of the proposed causal relationships.

An immediate step following this study is to estimate the coefficients that quantify the strengths and directions of the causal relationships. Given such a model, the effectiveness of improving equitable accessibility for rural seniors by enhancing their mobility can be estimated. Additionally, the causal model can be further improved by integrating additional causal relationships. Beyond aging and rural residency, various additional factors, such as land use, traffic congestion, opportunity density, and infrastructure density, impact travel mobility and accessibility. It is worth noting that using distance to evaluate accessibility has limitations due to the effect of distance decay, which represents the level of reluctance to travel long distances among regions. Future studies could explore modified indicators for accessibility and refine the construction of a comprehensive causal model to address these considerations.

ACKNOWLEDGEMENT

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Investigating Transportation Equity in Maryland: An AI-Based Approach

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ABSTRACT

Unequal mobility and accessibility have been a key constraint in accessing jobs, education and healthcare, and other opportunities across the nation. This is aggravated by differences in income, transport infrastructure, transit, and indeed all modes, vehicle availability, class of workers, and other variables which individually or collectively contribute to the commute inequity. Evaluating these can be challenging because there are types of equity and impacts to consider including horizontal and vertical commute equities and various ways to measure them. Horizontal equity assumes that people with similar needs and abilities should be treated equally; vertical equity assumes that disadvantaged groups should receive a greater share of resources. The present research process involves examining and measuring commute equity as a dependent variable, which is determined by a function of independent variables such as vehicle availability, worker participation rates, travel time/time arriving, class/type of worker, mode choices, and other crucial components. Different variations of the regression model will be employed to analyze the relationship between the independent variables and commute equity. These regression models will serve as tools to quantify the impact of each independent variable on commute equity and gain insights into the factors contributing to transportation inequities. The accuracy of each regression model will be thoroughly examined to assess their predictive performance in estimating commute equity. The results obtained from each model will be described and analyzed in detail to provide a comprehensive understanding of the relationships between the independent variables and commute equity outcomes. Based on the derived results, the research project will formulate informed recommendations aimed at guiding policymakers in improving inclusivity and accessibility within transportation systems. These recommendations will take into account the identified influential variables and their impacts on transportation equity, providing practical strategies to address inequality and enhance equity within the studied neighborhoods and beyond.

BACKGROUND

For many years, urban, regional, and state transportation plans and investments in various global cities have fallen short in adequately meeting the mobility needs of low-income communities of color. This failure has played a role in perpetuating uneven land-use patterns and has resulted in disproportionate health and economic consequences. The absence of comprehensive planning, effective policies, and equitable decision-making structures has hindered the just distribution of mobility benefits to these communities. This trend has given rise to car-centric development dominating metropolitan regions in North America and many other parts of the world, leading to notable social equity implications in transport policies. The expansion of highway networks and the dispersal of work, residential, and leisure activities have culminated in a transportation system heavily reliant on cars, making car ownership a necessity for many households. In this context, forced car ownership (owning a car despite limited economic resources) has emerged as a growing socio-economic issue, placing financial strain on low-income household (Curl et al., 2018; Mattioli, 2017; Abduljabbar, 2019). In the United States, the benefits of transportation advancements and investments are not uniformly distributed among all communities (Roberts, Bullard, & Johnson, 1997). Despite significant efforts and substantial social and economic progress over the decades, commute equity remains a noteworthy area of research concern. Commute equity, defined as the fair distribution of impacts (both benefits and costs), involves providing mobility benefits that are affordable, accessible, and sustainable. Transportation planning decisions can have wide-ranging and diverse equity impacts (Littman, 2022). With fewer than 9 in 100 people lacking access to a car in the U.S. and 32.7 percent of Americans relying on a single vehicle, there is a pressing need for equity considerations in transportation (LuumLght, 2021). Commute equity, as a guiding principle, seeks ways to make commute benefits flexible, accessible, and affordable to employees with diverse commute experiences. This acknowledgment comes with an understanding that commutes are highly individualized, and access or cost is not uniformly distributed equal (Luumlight, 2021). Commute equity is categorized into two main principles: Horizontal equity: Assumes that individuals with similar needs and abilities should be treated similarly. (a) Fair share of resources allocation: Implies that public resource allocation should align with the principle of individuals generally "getting what they pay for and paying for what they get." (b) External costs: Recognizes that costs imposed by travel activities, such as delay, risk, and pollution, should be minimized or compensated for to ensure fairness. Vertical equity: Assumes that disadvantaged individuals should receive favorable treatment. (a) Inclusivity: Considers how transportation systems serve people with disabilities, youths, seniors, and others with special mobility needs, justifying multimodal planning and universal design requirements. (b) Affordability: Examines how transportation systems impact lower-income individuals, advocating for policies that favor lower-income individuals and improve affordable modes while subsidizing low-income travelers. (c) Social justice: Considers how transportation systems serve disadvantaged and underserved groups, addressing structural injustices such as racism and sexism (Littman, 2022).

Transportation equity evaluation is challenging because there are many possible perspectives and impacts to consider. Because of this complexity, the best way to incorporate equity into planning is usually to define a set of measurable objectives. A planning process can evaluate specific policies and planning decisions based on whether they support or contradict the objectives. Horizontal Equity objectives comprises: Everybody contributing to and receiving comparable shares of public resources; transport planning that serves nondrivers as well as drivers; Involving affected people in the transport planning process; Minimizing external costs; Favoring resource efficient modes that impose less congestion, risk and pollution on other people and compensating for external costs; Vertical Equity objectives includes accommodate people with disabilities and other special needs; creating basic access (ensure that everybody can reach essential services and activities); Favoring affordable modes; Providing discounts and exemptions for lower-income users; Providing affordable housing in high accessibility neighborhoods; Protecting and supporting disadvantaged groups (women, youths, minorities, low-income, etc.); affirmative action policies and programs and correction for past injustices.

To measure inequality for the purposes of assessment of both horizontal and vertical inequity, key studies and theories need to be examined including:

Accessibility and Disparities*:* (Levinson & Krizek, 2008) explore the concept of accessibility and its impact on commuting patterns, highlighting how variations in accessibility can lead to disparities in commuting options. (O'Sullivan, D., & Williams, 2000) delve into integrated land use-transport modeling and its role in addressing accessibility and transportation disparities in urban planning. (Guo & Wilson, 2011) emphasize the importance of accessibility-based transportation planning, particularly in a post-peak oil context. (Hess, 2007) focuses on modeling choices of home and work locations and their effects on accessibility and commuting disparities. (Curtis & Scheurer, 2010)discuss tools and methodologies for planning sustainable accessibility, which can mitigate transportation disparities. Studies such as (Yu & Stuart, 2017) have evaluated the spatial distributions of NOx exposure in Hillsborough County, Florida, using measures like the standard deviation and range. Similarly, (Delmelle & Casas, 2012) applied the standard deviation to quantify the inequality of public transit need/provision gap among spatial districts in Cali, Colombia. Various methods, including analysis of variance (ANOVA), correlation analysis, and regression modeling, are widely used to assess vertical transportation equity.

Income and Transportation: In "Evaluating Transportation Equity" by (Litman, 2019), a comprehensive analysis of transportation equity is presented, encompassing various dimensions, including income-related disparities, and providing a foundation for assessing and addressing these issues in transportation policy. In "Travel model improvements and equity implications of pricing" by (Golob & Beckmann, 2004), the study delves into travel models and pricing policies, examining how these factors intersect with income-related considerations and their implications for equity. (Pendyala & Bhat, 2004) employ modeling techniques in "Modeling transportation network effects and land-use patterns," elucidating the complex relationship between transportation network effects, land-use patterns, and income-related disparities. Meanwhile, "Spatial variations in commuting" by (Murray & Wu, 2003) investigates spatial variations in commuting patterns within a metropolitan area, with a particular focus on how income disparities contribute to these variations, offering valuable insights into the geographical dimensions of income and transportation dynamics. Together, these references underscore the multifaceted nature of income and transportation disparities, providing critical knowledge for policymakers and researchers seeking to address equity issues in transportation systems.

Infrastructure Quality: "Underestimating costs in public works projects" by (Flyvbjerg, Holm, & Buhl, 2002)addresses the often-underestimated costs in infrastructure projects, highlighting the importance of accurate cost estimation for maintaining quality and effective planning. "Cost-Benefit Analysis and Infrastructure" by (Gomez-Ibanez, 2013)emphasizes the significance of cost-benefit analysis in evaluating infrastructure projects, particularly how it can help assess the quality of infrastructure investments. "Urban Mobility Report" by (Schrank, Eisele, & Lomax, 2019) offers an annual assessment of urban mobility, analyzing infrastructure quality's impact on traffic congestion and overall urban transportation. "Quality of public transport service" by (Holl & Raitviir, 2006) takes a consumer-oriented approach, examining the factors influencing the quality of public transport services and their implications for passenger satisfaction. Together, these references underscore the multidimensional nature of infrastructure quality in transportation, encompassing economic, environmental, and service-related dimensions.

***Demographic Factors*:** Correlation or causality between the built environment and travel behavior" by (Handy, Cao, & Mokhtarian, 2006) explores the interplay between demographic factors, the built environment, and travel behavior, questioning the causality and correlation between these elements. "Income's effect on car and vehicle ownership, worldwide" by (Dargay & Gately, 1997) offers a global perspective on how income levels impact car ownership, highlighting the role of income in shaping vehicle ownership patterns. (Scheiner, 2010) critically examines the influence of the built environment on car ownership and use, with consideration of the impact of demographic factors. Lastly, "Examining the impacts of residential self-selection on travel behavior" by (Cao, Mokhtarian, & Handy, 2007)investigates the phenomenon of residential self-selection and its effects on travel behavior, emphasizing how demographic factors play a pivotal role in shaping residential and travel choices. Together, these references underscore the importance of considering demographic factors in understanding travel behavior and their complex interaction with the built environment and other variables. Despite the valuable insights provided by existing research, several gaps and limitations in the literature necessitate further investigation:

Lack of Comprehensive Models: Many existing studies focus on specific aspects of transportation equity but lack comprehensive models that consider multiple variables simultaneously. This gap inhibits a holistic understanding of the complex factors contributing to transportation disparities.

Spatial Variation: While some research has explored transportation equity at the city or regional level, there is a need for more localized analyses that account for spatial variations in equity, as transportation disparities can vary significantly within a single urban area.

***Machine Learning Applications*:** While machine learning techniques have been applied in various fields, their application to transportation equity, as mentioned in (Wang & Mokhtarian, 2018), remains relatively unexplored. The novel aspect lies in how machine learning can be leveraged to predict and address both horizontal and vertical equity measures, thereby offering new insights into the problem.

By addressing these gaps and building upon the existing body of knowledge, this research project endeavors to contribute to a more comprehensive understanding of transportation equity and provide practical strategies for policymakers to create more inclusive and accessible transportation systems.

METHODOLOGY

The research process involves examining and measuring commute equity as a dependent variable, which is determined by a function of independent variables such as vehicle availability, worker participation rates, travel time/time arriving, class/type of worker, crucial components, and mode choices. Different variations of the regression model will be employed to analyze the relationship between the independent variables and commute equity. These regression models will serve as tools to quantify the impact of each independent variable on commute equity and gain insights into the factors contributing to transportation inequities. The accuracy of each regression model will be thoroughly examined to assess their predictive performance in estimating commute equity. The results obtained from each model will be described and analyzed in detail to provide a comprehensive understanding of the relationships between the independent variables and commute equity outcomes.

Machine learning finds extensive application across diverse global sectors, encompassing healthcare, transportation, advertising, economics, and image recognition. Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed (Mozaffarian, 2015). Furthermore, machine learning at its most basic level is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world (Das, Dey, Pal, & Roy, 2015). There are two major categories of problems often solved by machine learning i.e., regression and classification. The regression algorithms are used for numeric data and classification problems include binary and multi- category problems (Abduljabbar, 2019). Machine learning algorithms are further divided into two categories including supervised learning and unsupervised learning algorithms (Strecht, Cruz, Soares, Mendes-Moreira, & Abreu, 2015). The supervised learning algorithm is performed by using prior knowledge in output values whereas the unsupervised learning algorithm does not have predefined labels; hence, its goal is to infer the natural structures within the dataset (Sathya & Abraham, 2013). In this study, the supervised machine learning algorithm, namely logistic regression is used, to measure transit equity.

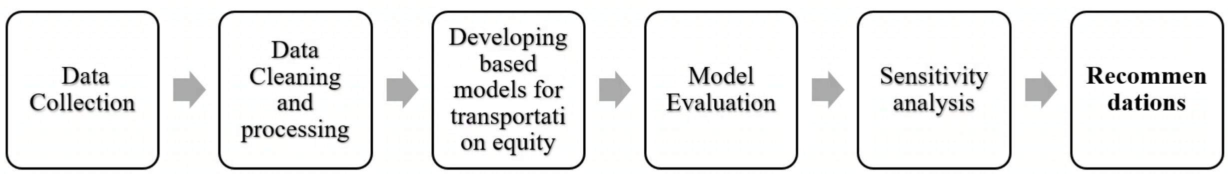

Figure 1. Methodology

DATA SOURCE

The 2022 Census data (Bureau, 2022), as reported by the United States Census Bureau, provides a comprehensive snapshot of the nation's demographic landscape. For this study, the model development utilized the 2022 Census data, and Maryland was chosen as the geographic area.

VARIABLES

Table 1 represents input variables used in the model development process. Distinguishing factors affecting horizontal and vertical transportation equity involves understanding the dimensions through which inequalities manifest in the transportation system. Horizontal equity focuses on ensuring individuals or groups with similar transportation needs or circumstances are treated similarly. Factors such as travel distance, travel time, and mode of transportation are key considerations. On the other hand, vertical equity addresses disparities between individuals or groups with different levels of advantage or disadvantage, often linked to socio-economic factors. Factors such as income, education, and access to resources may influence vertical equity considerations.

Vertical and Horizontal equity are considered for the output variables of the measurement and predictive model. These are continuous variables which are measured to be between 0 and 1, 0 represent a complete inequality and 1 indicates a perfect equality.

Table 1. Input Variables

S/N	Variable Name	Variable Label	Horizontal	Vertical
1	Number of persons in this household	NP	✓	✓
2	Vehicles (1 ton or less) available	VEH	✓	
3	Vehicle occupancy	JWRIP	✓	
4	Age	AGEP		✓
5	Presence of persons under 18 years in household	R18		✓
6	Presence of persons 60 years and over in household	R60		✓
7	Workers in family during the past 12 months	WIF	✓	
8	Work status of householder or spouse in family households	WORKSTAT		✓
9	Employment status recode	ESR	✓	✓
10	Access to the Internet	FACCESSINET	✓	
11	Ability to speak English	ENG	✓	✓
12	Household income (past 12 months)	HINCP		✓
13	Laptop or desktop	LAPTOP		✓
14	Smartphone	SMARTPHONE		✓
15	Class of worker	COW		✓
16	Self-care difficulty	DDRS	✓	✓
17	Hearing difficulty	DEAR	✓	✓
18	Vision difficulty	DEYE	✓	✓
19	Independent living difficulty	DOUT	✓	✓
20	Ambulatory difficulty	DPHY	✓	✓
21	Veteran service-connected disability rating (checkbox)	DRATX		✓
22	Cognitive difficulty	DREM	✓	✓
23	Health insurance coverage recode	HICOV		✓
24	Means of transportation to work	JWTRNS	✓	✓
25	Educational attainment	SCHL	✓	✓
26	Grade level attending	SCHG	✓	
27	Sex	SEX		✓
28	Disability recodes	DIS		✓
29	Number of vehicles calculated from JWRI	DRIVESP	✓	✓
30	Time of arrival at work - hour and minute	JWAP	✓	
31	Time of departure for work - hour and minute	JWDP	✓	
32	Travel time to work	JWMNP	✓	
33	Usual hours worked per week past 12 months	WKHP	✓	
34	Number of own children in household	NOC	✓	
35	Total person's income (signed, use ADJINC to adjust to constant dollars)	PINCP		✓
36	Family income (past 12 months, use ADJINC to adjust FINCP to constant dollars)	FINCP		✓
37	Income-to-poverty ratio recode	POVPIP		✓
38	Recoded detailed race code	RAC1P		✓
39	Available for work	NWAV	✓	

MODEL DEVELOPMENT

Logistic regression method is applied to calculate the vertical and horizontal equity measurements. The 40 input variables for vertical equity from Table 1 is used for the development of the equity measurement models, and the following steps are applied.

Step 0, label-encoded categories were grouped into relevant and meaningful clusters that align with socio-economic factors involving combining related categories or creating new composite variables.

Step 1, define “u” as sum of the values of all the variables for a specific household i.e.

$$u_i = x_{i1} + \cdots + x_{in}$$

Step 2, The equity measurement is defined as a continuous variable which takes values between 0 and 1, where 0 represents absolute inequality and 1 represent perfect equality. We use logit formula to measure that.

$$M_i = \frac{e^{u_i}}{\sum e^{u_i}} \tag{1}$$

The effect of all input variables is considered equal in this model, i.e. no weight is assigned to any specific variable.

Step 3, the average vertical/ horizontal equity for each state is calculated.

Step 4, the equity measure is normalized.

Step 5, the variables vertical and horizontal equity are added to the data set for each household.

After measuring the vertical and horizontal equity, these measures are incorporated into the data set, to create a new dataset for the development of the predictive model, which can predict Vertical or horizontal equity for the new data sets. To develop the predictive model, the data set is split into training and test sets. 70% percent of the data set is considered for the training purpose and the other 30%, which was not used in the training process, is used for the evaluation process. The problem is considered as a supervised regression problem, meaning, the data set is labeled, the input variables are known, and the outcome, which is the commute equity, is a numeric continuous variable. Linear regression, XGBoost regression, and Decision tree regressor and Random Forest algorithms are used to build the predictive models. After model development, sensitivity analysis is performed.

PREDICTIVE MODELS FOR VERTICAL AND HORIZONTAL TRANSPORTATION EQUITY

Checking for collinearity and using correlation matrices in predictive model development for transportation equity is crucial. High collinearity can lead to multicollinearity, introducing instability and hindering the interpretation of individual variable impact. Examining the correlation matrix helps identify highly correlated features, enabling informed decisions on retention or removal. Eliminating such features mitigates redundancy, enhancing model interpretability and generalization. This ensures a more robust and reliable predictive model for transportation equity.

After adding and normalizing the vertical and horizontal equity measures a new data set is created which is used for building the predictive model using Decision Tree regressors and Linear Regression, Random Forest and XGBoost models. Evaluation of these models for vertical and horizontal equity are provided in the Table 2 and 3 respectively.

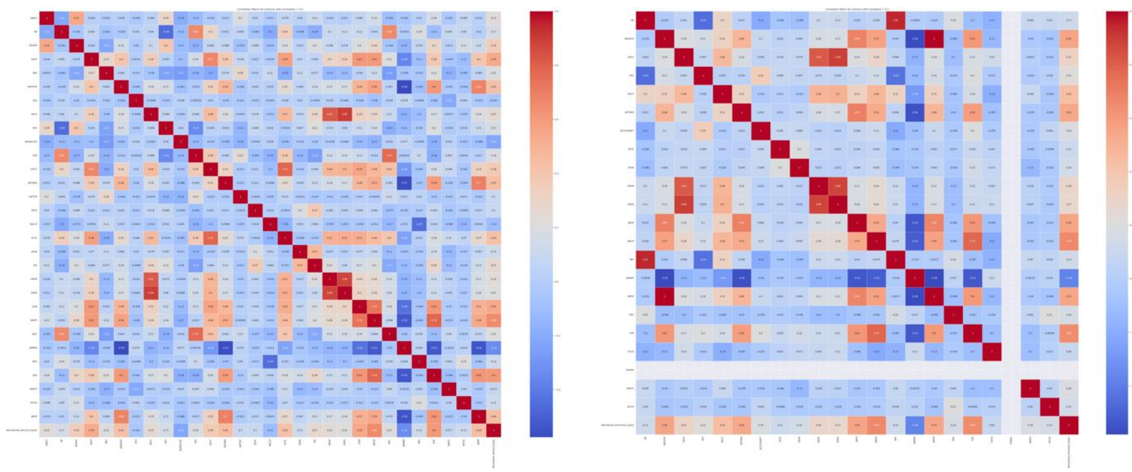

Figure 2. Correlation Matrix for a) Vertical Equity b) Horizontal Equity

Table 2. Vertical Equity Model Evaluations

Model	R-Squared	Mean Squared Error	Mean Absolute Error
Decision Tree	0.920	0.0010	0.014
Linear Regression	0.717	0.0050	0.043
Random Forest	0.962	0.0007	0.009
XGBoost	0.973	0.0005	0.009

Table 3. Horizontal Equity Model Evaluations

Model	R-Squared	Mean Squared Error	Mean Absolute Error
Decision Tree	0.948	0.0008	0.008
Linear Regression	0.765	0.0040	0.032
Random Forest	0.970	0.0005	0.006
XGBoost	0.985	0.0002	0.005

Analyzing graphs that showcase the predicted versus actual values plays a pivotal role in gauging the effectiveness of each regression model. These visual representations provide a firsthand look into how well the models align their predictions with the real observed values. For vertical equity the Decision Tree model exhibits a commendable R-squared value of 0.920, indicating a strong correlation between predicted and actual values. The Mean Squared Error and Mean Absolute Error further support its accuracy, with values of 0.001 and 0.0138, respectively. Meanwhile, the Linear Regression model, although having a respectable R-squared of 0.717, displays a higher Mean Squared Error and Mean Absolute Error at 0.005 and 0.0431. Comparatively, the Random Forest and XGBoost models outperform others, boasting higher R-squared values of 0.962 and 0.973, along with remarkably low Mean Squared Error and Mean Absolute Error values. Visually assessing the predicted versus actual value graphs for each model allows me to discern the nuances in their performance, aiding in the informed selection of the most effective model for my specific regression task as shown in Figure 3.

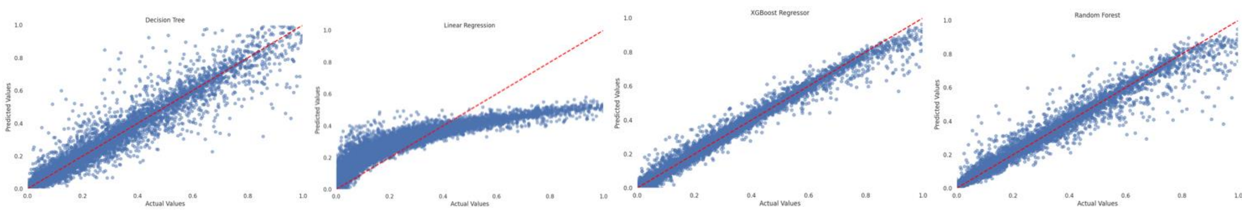

Figure 3. Actual vs Predicted values for Vertical Equity models.

For Horizontal equity, the Decision Tree model demonstrates an impressive R-squared value of 0.948, signifying a robust correlation between predicted and actual values. Its commendable performance is further validated by the low Mean Squared Error and Mean Absolute Error, recorded at 0.0008 and 0.008, respectively. In contrast, the Linear Regression model, while achieving a respectable R-squared of 0.765, exhibits higher Mean Squared Error and Mean Absolute Error values, measuring at 0.0040 and 0.032. Comparatively, the Random Forest and XGBoost models surpass others, boasting superior R-squared values of 0.970 and 0.985, accompanied by remarkably low Mean Squared Error and Mean Absolute Error values of 0.0005/0.006 and 0.0002/0.005, respectively. Examining the visual representations of predicted versus actual value graphs for each model in Figure 4 helps us identify performance nuances, facilitating the informed selection of the most effective model for our regression task.

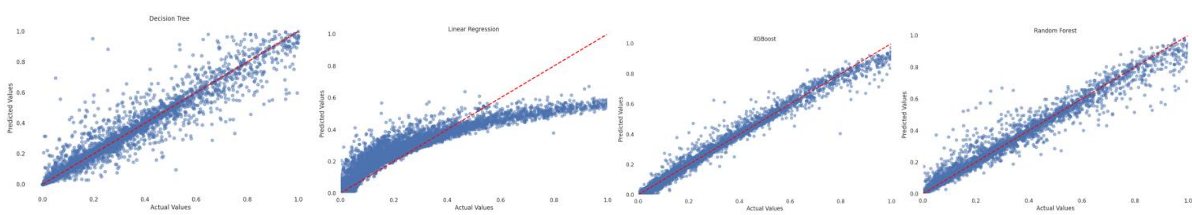

Figure 4. Actual vs Predicted values for Horizontal Equity Models

The top 10 features identified by each model—Decision Tree, Random Forest, Linear Regression, and XGBoost—provide unique perspectives on their predictive priorities, shedding light on key factors influencing their predictions. In the Decision Tree model, "Employment status" emerges as the most crucial feature, signifying its central role in shaping predictions. This underscores the significance of employment-related variables in the decision-making process of the Decision Tree algorithm. For the Random Forest model, "Employment status" retains its importance, and additional factors such as "Military service" and "Disability" contribute significantly to prediction outcomes. This highlights the model's ability to capture a broader range of influential features, including those related to military service and disability status. Linear Regression prioritizes "Household income" as its primary feature, emphasizing the role of economic indicators in its predictive framework. This suggests that Linear Regression places a strong emphasis on household income when making predictions related to transportation equity. In XGBoost, "Employment status" stands out as a pivotal factor, with a substantial importance score of 51.7%. This reaffirms the central importance of employment-related variables in both XGBoost and Random Forest models. Shared influential features include the "Presence of persons under 18 years in household," "Military service," and "Disability," collectively contributing significantly to the predictive power of both models. Additionally, XGBoost emphasizes the importance of "Income-to-poverty ratio recode," while Random Forest prioritizes "Veteran service-connected disability rating" and "Household income." These insights collectively illuminate the multifaceted nature of transportation equity, where employment, familial structure, military service, and economic indicators play crucial roles.

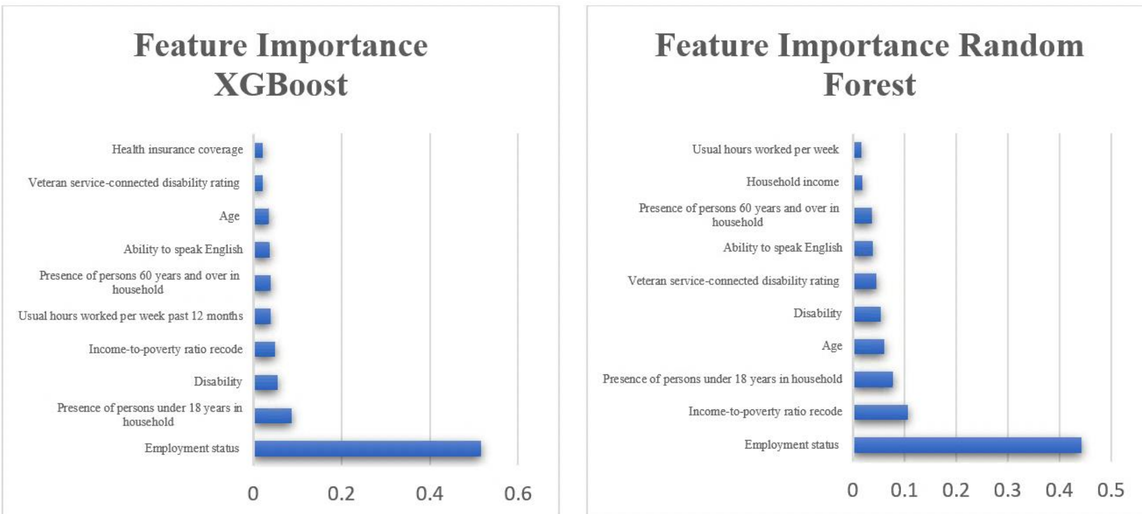

Figure 5. Feature importance for vertical equity.

For horizontal equity, in the Decision Tree model, "Employment Status" emerges as the top feature, followed by "Veteran service-connected disability rating" and "Grade Level Attending". The Random Forest model assigns considerable importance to "Employment Status", "Vehicle occupancy "and "Means of transportation to work". Conversely, the Linear Regression model prioritizes "Number of vehicles in the household" and "Vehicle Occupancy" and "Means of transportation to work". Lastly, the XGBoost model highlights "Employment Status ", "Veteran service-connected disability rating", and "Travel Time to Work" as its top features. The diversity in feature importance underscores the distinct ways in which each model evaluates and weighs the significance of input variables. These findings offer valuable insights for understanding their decision-making processes and contribute to the interpretation of their predictions.

Sensitivity analysis plays a crucial role in understanding the robustness and responsiveness of our predictive model to variations in input features. By systematically altering the values of the top features within a specified range, we aimed to discern how these changes influence the model's predictions. This exploration provides valuable insights into the relative importance of each feature and how sensitive our model is to fluctuations in their values. The resulting plot vividly illustrates the percentage change in the target variable corresponding to modifications in each feature, allowing us to identify key drivers and potential areas of concern.

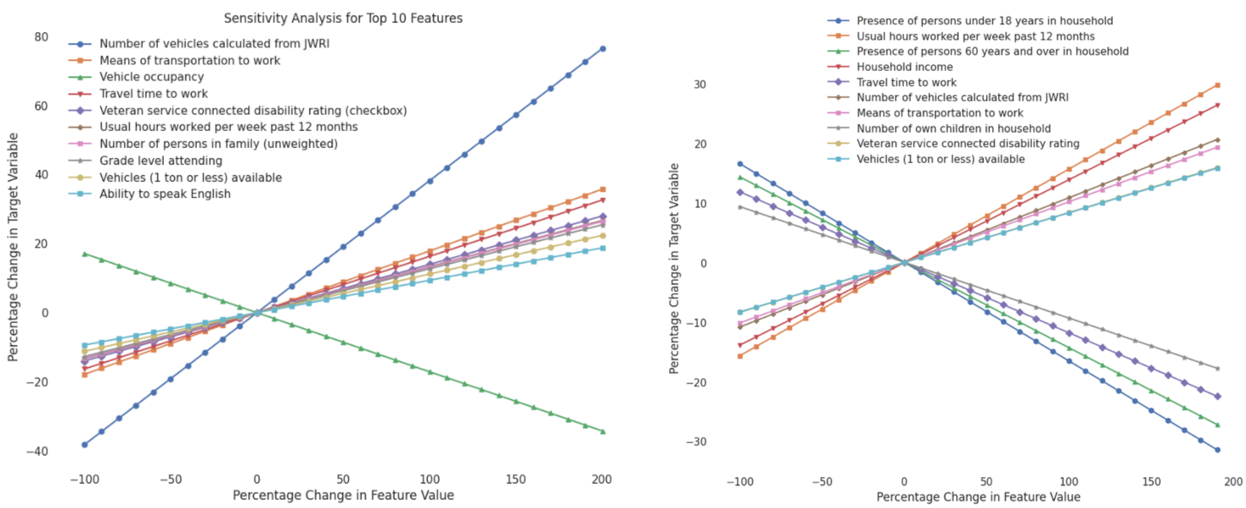

Figure 6. Sensitivity Analysis for a) Vertical Equity b) Horizontal Equity

The presented figures showcase the outcomes of sensitivity analysis conducted on our predictive models. The x-axis represents the variations in input variables, where 0 denotes the baseline with no changes in their values. Negative values signify percentage decreases, ranging from -100% to -50% with -100% representing complete elimination. Conversely, positive values indicate percentage increases of 50% and 100%. The y-axis illustrates the corresponding fluctuations in the output variable, providing a visual depiction of our model's responsiveness to varying input values. Notably, the analysis underscores the heightened sensitivity of the measure of vertical equity to alterations in key factors: Household Income, Usual Hours Worked per Week, Military Service, Presence of Persons in Household Under 18 Years, Means of Transportation to Work, Presence of Persons 60 Years and Over in Household, Number of Vehicles in Household. These factors exert a substantial influence on the measure of vertical equity, as demonstrated by the plot. The sensitivity analysis, with the white-background legend for clarity, elucidates the significant impact of these features on equitable outcomes. Significantly, the examination underscores the increased sensitivity of the horizontal equity measure to changes in crucial factors. These factors, such as Household Income, Usual Hours Worked per Week, Military Service, Presence of Persons in Household Under 18 Years, Means of Transportation to Work, Presence of Persons 60 Years and Over in Household, and Number of Vehicles in Household, wield considerable influence over the vertical equity measure, as depicted in the plot. The sensitivity analysis, enhanced by a clear white-background legend, brings to light the substantial impact of these features on the attainment of equitable outcomes. It underscores the critical role of these factors in shaping transportation equity and reinforces the importance of targeted interventions in promoting fair and just outcomes in the studied context.

CONCLUSION

In the pursuit of comprehensively assessing commute equity across Maryland, this study harnessed the potential of machine learning, utilizing household census data as a foundation. Our exploration into vertical and horizontal equity involved the development and evaluation of predictive models, including Decision Tree, Linear Regression, Random Forest, and XGBoost. Notably, XGBoost emerged as the preeminent performer for vertical equity prediction, demonstrating an exemplary R-Squared value of 0.973 alongside the lowest mean squared error (0.0005) and mean absolute error (0.009). This underscores the model's adeptness in capturing nuanced relationships within the vertical equity framework, affirming its efficacy in predicting and understanding vertical equity dynamics. Similarly, in the context of horizontal equity, our analysis reaffirms XGBoost's prominence, exhibiting superior predictive prowess with a remarkable R-Squared value of 0.985, and minimal mean squared error (0.0002) and mean absolute error (0.005). This consistent excellence across various metrics underscores XGBoost's robustness and reliability in forecasting both vertical and horizontal equity aspects. Beyond model performance, the study identified pivotal factors influencing equity, encompassing employment status, household income, income-to-poverty ratio, employment type, mode of transportation, vehicle occupancy, and travel time to work. In summary, our research successfully culminated in the development of a proficient machine learning program, trained on 2022 Census households' data from Maryland. The program, characterized by high accuracy of 97%, not only measured horizontal and vertical equity in commuting but also shed light on key factors contributing to fairness in commuting dynamics. This study thus advances our understanding of equity in the commuting landscape, providing valuable insights for future research and policy considerations.

ACKNOWLEDGMENT

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Using the 2017 NHTS to Investigate the Effect of Household Income on Bicycling Activities

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ABSTRACT

This study examines the relationship between household income and cycling activities in the US, using 2017 National Household Travel Survey (NHTS) data. Contrary to expectations, lower-income households engage in more bike trips and bike-sharing than higher-income ones. This pattern holds for both utilitarian and recreational cycling, suggesting it serves as an essential mode of transportation for low-income individuals. Bikesharing usage is also higher among this group, particularly in the lowest income bracket, highlighting its potential as an affordable and convenient option. However, racial disparities exist in bikesharing, with white individuals participating more than black or African American individuals, indicating potential inequities in access to resources and infrastructure. While sociodemographic factors like age, gender, and education show no significant difference in bike-sharing usage, suggesting its potential for diverse users, further research is needed to address observed disparities and promote equitable access to cycling and bike-sharing for all.

INTRODUCTION

Cycling's role in city transportation systems has gotten much attention in recent years (Azimi et al. 2019). With the recent increase in using bike and bike-share systems, a significant number of U.S cities and communities are investigating the use of bikes to increase the transportation system's environmental, social, and health results. Moreover, bike sharing is believed to be one of the solutions to improve urban mobility, enhance public health, and save the natural environment and energy. According to the most recent National Household Travel Survey (NHTS), bicycling accounts for around one percent of daily trips in the United States.

Low-income and minority communities are less likely to own vehicles, relying on non-motorized modes of transportation more frequently. Prior study has found that rural and minority communities are subjected to disproportionately high travel costs (Probst et al. 2007). Age, disability, lack of awareness of programs, small children, lack of safety and bicycling infrastructure, and bike share characteristics such as location, time constraints, cost, ease of use, and availability of bikes are the most prominent barriers to bike usage (Bateman et al. 2021). While minorities and lower-income groups make up a tiny percentage of total users, surveys have shown that they generally have positive views of bike-share systems and demonstrate an equal interest in becoming bike-share users as other groups (McNeil et al. 2018; Bateman et al. 2021). Therefore, there is a need to investigate the relationship between bicycling activities and income level.

Few studies have explored the effect of household income on different types of bike activities or focused on different sociodemographic attributes that affect bike trips (Sadeghvaziri, Javid, and Jeihani 2023; Sadeghvaziri et al. 2023). There are several data related to bike travel behavior. However, to the best knowledge of the authors, few bike-related studies investigated the relationship between different income groups and bicycling activities. There is still a need to investigate these factors through comprehensive data. The main goal of this study is to explore the bicycling activities among different household income groups. To reach this goal, the following objectives will be undertaken. Investigating the number of bike trips, number of bike trips for exercise, and bike share program usage among different income groups and exploring the bikeshare program participation among different sociodemographic groups and income levels. This research contributes to shaping the future of mobility by providing a deeper understanding of bike-travel behavior among households with different income groups in the U.S.

LITERATURE REVIEW

This section examines the existing literature on bike travel behavior in the U.S. With the recent surge in the usage of bicycles and bike-share systems, a growing number of cities and communities in the U.S. are looking into using bikes to improve the transportation system's environmental, social, and health outcomes (Fukushige, Fitch, and Handy 2021). With the increased interest in raising bicycle mode share, various academics have looked at the factors that influence bicycling, such as the built environment's effects, individual and household socioeconomic characteristics, and the availability and type of bicycle facilities (Wang, Akar, and Guldmann 2015).

Both the NHTS 2017 and NHTS 2009 datasets revealed an upward trend in income and the number of bike journeys (Sadeghvaziri and Tawfik 2020). In 2009 bikers who ride frequently were younger (36.4 years vs. 44.7 for non-bikers) and more likely to be employed (72.6 percent compared to 61.1 percent of non-bikers) (McGuckin 2012). In 2017, Young males were the most frequent users of bicycles, scooters, Segway, and skateboards for various activities, including social and recreational activities, shopping and errands, and business travel (Krizek and McGuckin 2019). Moreover, the average American made only 2 more bike trips and five more miles cycling in 2009 compared with 2001 (Pucher et al. 2011, 2001–2009). Grasso et al. (2020) indicate that people of color, Hispanics, the less-educated, females, low-income earners, and the unemployed are underrepresented in system membership in Baltimore Bike Share System (Hull Grasso, Barnes, and Chavis 2020). According to the NHTS 2017 and NHTS 2009 datasets, the number of senior people who walk, cycle, or take public transportation increases as their income rises (Sadeghvaziri and Tawfik 2020). Moreover, in 2009, people who walk frequently had a greater level of education than non-walkers, but they were less likely to be employed. Bicyclists who ride frequently are not more likely to have higher education (McGuckin 2012).

Bicycles could also save money and costs. For example, the result of a study suggests that if residents of Minnesota's urban Twin Cities (Minneapolis and St. Paul) replaced half of their short automobile journeys with bike trips during the warmer months, the anticipated cost savings from lower mortality and health care expenditures would be $146 million per year. Despite these advantages, only 0.6 percent of Americans commute by bicycle, with no indication of racial, ethnic, or socioeconomic inequalities (Swanson 2012). Also, bicycles are sometimes considered as the last choice for those who cannot afford a car or public transportation (Flanagan, Lachapelle, and El-Geneidy 2016). However, according to cycling advocates, low-income and minority neighborhoods in the U.S. have disproportionately limited access to bike lanes, and areas with a higher proportion of low-income households tend to use bike-share less (Braun, Rodriguez, and Gordon-Larsen 2019). One aspect is a lack of bike-sharing stations in neighborhoods with people of race and lower incomes, but this does not fully explain the discrepancies in usage. Other potential roadblocks include the cost, a lack of payment choices, a lack of bank and credit card accounts, and a lack of bike-sharing experience (McNeil, Broach, and Dill 2018).

According to several studies, bike lanes have tended to be created in socioeconomically advantaged regions in a total of five U.S. cities, including Birmingham, Chicago, Minneapolis, Oakland, and Portland (Flanagan, Lachapelle, and El-Geneidy 2016; Braun, Rodriguez, and Gordon-Larsen 2019; Hirsch et al. 2017). Block groups with higher proportions of black and Hispanic residents and lower SES (i.e., lower-income and educational attainment, higher poverty levels) were less likely to have bike lanes, were further from the nearest bike lane, and had lower bike lane coverage and reach (Braun, Rodriguez, and Gordon-Larsen 2019). Moreover, Andersen & Hall, 2015 examines data from the 2013 American Community Survey (ACS) and shows that the wealthiest quartile accounts for 20% of bicycle commuting in the U.S., while the poorest quartile accounts for 39% (Anderson and Hall 2014).

Overall, bike-sharing has several advantages such as it is less expensive than taking public transportation or renting a car; it is a good way to show visitors around; it eliminates the need for individual bike ownership; it is an excellent choice for occasional bikers, and it is better than driving or taking public transportation. Bike share indeed has many benefits, but it also has its drawbacks, such as the fact that shortages on the docks can be a problem or going too far can be expensive. Without a doubt, the micro-mobility business has the potential to reach underserved regions of our communities, thereby assisting in the creation of more egalitarian transportation networks for everybody. Shared mobility modes such as e-scooters and e-bikes, unlike traditional bike-share systems, are not geographically confined by docking infrastructure, allowing consumers to make first- and last-mile connections.

The findings in this growing body of research imply that low-income and minority groups may have disproportionately limited access to cycling infrastructure like bike lanes. Therefore, there is a need to investigate bicycling activities and household income in the U. The results of this study will contribute to investigate how the location of bike lanes is selected during the planning and advocacy process to understand why these inequalities exist. Moreover, previous studies only focus on just a few cities and specific areas, while this study focuses on the whole U.S.

DATA AND METHODOLOGY

Data

The data was obtained from the 2017 NHTS, Which was developed by FHWA and is one of the main source of data about travel behavior of the Americans (NHTS 2017). In this study, the person data set, which includes personal characteristics of each respondent from each household was used. Table 1 shows the variables used in this study and their description. In this study, the household income variable is aggregated into three categories, including “less than $35,000,” or “low-income class,” “$35,000 to $99,999” or “middle-income class,” and “$100,000 or more,” or “high-income class.”

Table 1. Variables Used in This Study

Variable	Description	Question in Survey
BIKESHARE	Count of Bike Share Program Usage	In the past 30 days, how many times did you use a bike share program (e.g., Bikeshare, Zagster, or CycleHop)?
NBIKETRP	Count of Bike Trips	In the past 7 days, how many times did you ride a bicycle outside including bicycling to exercise, or to go somewhere (e.g., bike to a friend's house, bike around the neighborhood, bike to the store, etc.)?
BIKE4EX	Count of Bike Trips for Exercise	In the past 7 days, how many of these bicycle rides were strictly to exercise?
R_AGE	Age	Please tell me your age.
R_SEX	Male	Please tell me your gender.
	Female	
HHFAMINC	Inc_0_35 = Less than $35K	Your total household income.
	Inc_35_99 = Between $35K and $99K	
	Inc_100More = More than $100K	
HHVEHCNT	Count of household vehicles	How many vehicles are owned, leased, or available for regular use by the people who currently live in your household?
EDUC	Less than a high school graduate	What is the highest grade or degree that you earned?
	High school graduate or GED	
	Some college or associates degree	
	Bachelor's degree	
	Graduate degree or professional degree	
R_RACE	B= Black or African American	Which of the following describes your race?
	W= White	
	A= Asian	

The 2017 NHTS person data contains a total of 264,234 data of participants who took part in the survey. However, we opted to exclude those who answered "DON'T KNOW" or "REFUSED" to any variable in Table 1. The total number of remained data is 17,484. As it can be seen from Table 1, 42% of participants are high-income class, 40% are middle-income class and 18% are low-income class. Figure 1 and Figure 2 show the percentage of participants among different income groups.

The analysis was conducted in R. A one-way analysis of variance (ANOVA) with post-hoc Tukey HSD (Honestly Significant Difference) test was used to compare the means among different income groups, and whether the means are statistically different (Mishra et al. 2019). All statistical analyses are conducted at the 95% level of confidence.

Moreover, to compare the number of bikeshare program usage and different bike trips, descriptive analysis and one-way ANOVA test is used. Because our objective is to investigate these variables, we opted to exclude those who answered "DON'T KNOW" or "REFUSED" to any variable in Table 1. The total number of remaining data is 17,484.

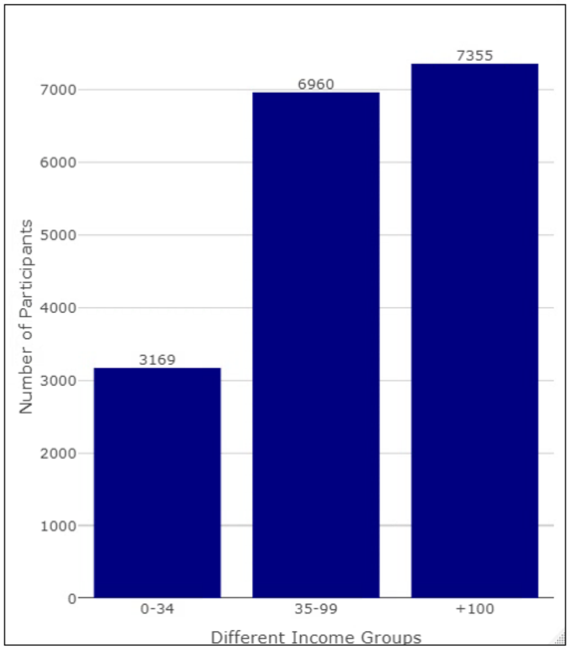

Figure 1. Unweighted number of the participants among different income groups

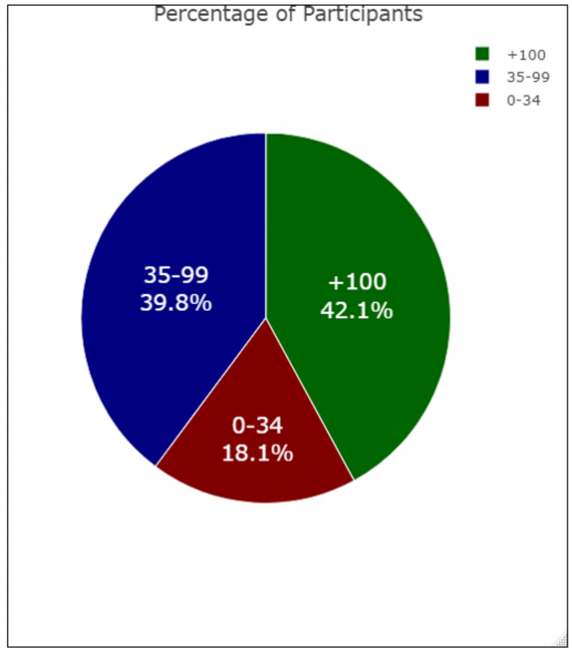

Figure 2. unweighted percentage of the participants among different income groups

ANALYSIS RESULTS

Bike Trips and Bike Share Usage Among Different income groups

In this section, three variables, including bike share program usage in the past 30 days (BIKESHARE), number of bike trips in the past 7 days (NBIKETRP), and number of bike trips for exercise in the past 7 days (BIKE4EX) are investigated. Figure 3, Figure 4, and Figure 5 show the average of these three variables among different income groups.

Figure 3 shows the average number of bikeshare trips in the past 7 days, by income group. The lowest income group (0-$34,999) had the highest average number of bikeshare trips, at 0.66 trips per day. The highest income group ($100,000+) had the lowest average number of bikeshare trips, at 0.38 trips per day. Figure 4 shows the average number of bike trips in the past 7 days, by income group. The pattern is similar to Figure 3, with the lowest income group having the highest average number of bike trips and the highest income group having the lowest average number of bike trips. Figure 5 shows the average number of bike trips for exercise in the past 7 days, by income group. The low-income group had the highest average number of bike trips for exercise.

Moreover, an ANOVA with post-hoc Tukey HSD test is used to investigate whether there is a statistically significant difference between bikeshare usage, number of bike trips and bike for exercise among different income groups. Table 2 shows the results of the test.

Bikeshare and sociodemographic information

An ANOVA with post-hoc Tukey HSD test is used to investigate whether there is a statistically significant difference between bikeshare usage and sociodemographic information.

The result showed that there is no significant difference in bikeshare usage among different age groups, gender, and education. However, the results showed a significant difference among different races and bikeshare usage. Table 3 showed the result in detail (W: White population, B: African American Population, A: Asian population).

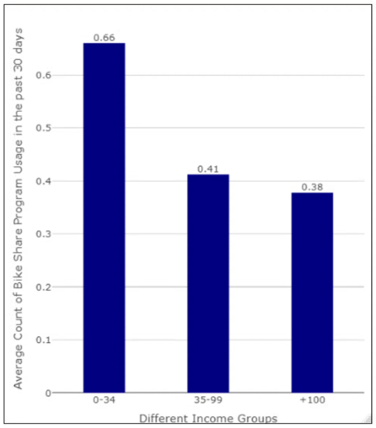

Figure 3. Average Count of Bike Share Program Usage in the past 30 days (BIKESHARE)

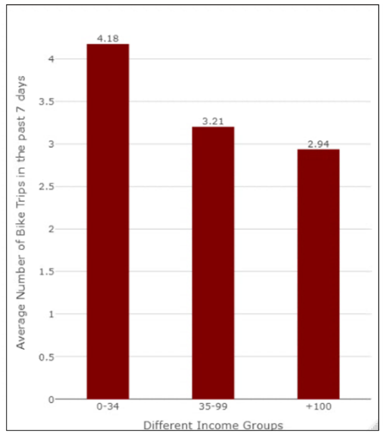

Figure 4. Average Number of Bike Trips in the past 7 days (NBIKETRP)

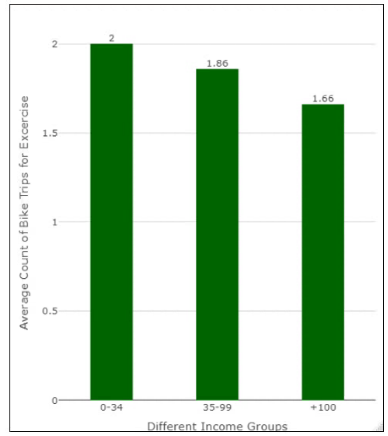

Figure 5. Average Number of Bike Trips for Exercise in the past 7 days (BIKE4EX) among different income groups

Table 2. ANOVA with pos-hoc Tukey HSD Test Among Different Income Groups

Income Groups	Bike Share			Number of Bike Trips			Bike for Exercise		
	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code
35-99 - 0-34 = 0	-0.24793	0.000626	***	-0.97389	< 1e-05	***	-0.14198	0.0139	*
+100 - 0-34 = 0	-0.28231	6.74E-05	***	-1.23956	< 1e-05	***	-0.3403	< 1e-04	***
+100 - 35-99 = 0	-0.03437	0.787132		-0.26567	0.000183	***	-0.19832	< 1e-04	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1									

Table 3. ANOVA with post-hoc Tukey HSD Test for Different Races

Different Races	Low-income Class			Middle-Income Class			High-Income Class		
	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code
W - B == 0	-0.7802	0.000307	***	-0.50287	0.00424	***	-0.6582	0.0111	*
A - B == 0	-0.3108	0.68751		-0.02284	0.99425		-0.3318	0.436	
A - W == 0	0.4694	0.35463		0.48004	0.01347	*	0.3264	0.0947	
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1									

DISCUSSION

This study has investigated the relationship between household income and bike-related trips in the United States. The findings reveal several key takeaways:

1. Lower-income households engage in more bike trips and bike share usage than higher-income households. This contradicts the common perception that cycling is primarily a recreational activity for affluent individuals. It suggests that low-income individuals may rely on bikes as a necessary mode of transportation due to factors like limited access to cars or public transportation.

2. The pattern is consistent for both utilitarian and recreational bike trips. Lower-income households show higher engagement in both bike trips for exercise and for other purposes like commuting or errands. This suggests that cycling is not just a leisure activity for them but an integral part of their daily lives.

3. Bike share usage is higher among lower-income households, particularly in the low-income class. This finding aligns with the notion that bike share programs can provide affordable and convenient transportation options for low-income individuals who may not own bikes.

4. Race plays a role in bike share usage, with White individuals using bike share programs more than Black or African American individuals. This disparity highlights potential inequities in access to bike share infrastructure and resources, which should be addressed to promote equitable mobility.

This study is not without limitations. The data used is from a single year (2017), and future research could explore trends over time and across different regions. Additionally, the study relies on self-reported data, which may be subject to recall bias. Future research directions could include investigating the specific reasons behind the observed differences in bike activity across income groups and races.

SUMMARY AND CONCLUSIONS

This study used data from the 2017 National Household Travel Survey to examine the association between household income and bike-related activities in the US. The results showed that lower-income households utilize bike shares and embark on more bike journeys than higher-income households. This pattern is consistent for both utilitarian and recreational bike trips, indicating that riding is a regular activity for low-income people rather than merely a luxury. Additionally, bike share usage is higher among lower-income households, particularly in the low-income class, highlighting its potential as an affordable and convenient transportation option.

Additionally, there may be racial disparities in access to resources and infrastructure as evidenced by the fact that White people use bike sharing more frequently than Black or African American people. Although the program's potential for diverse users is suggested by the lack of significant differences in bike share usage observed when controlling for sociodemographic factors like age, gender, and education, more research is required to determine the reasons for these disparities and to investigate strategies for promoting equitable access to cycling and bike share programs for all.

This study challenges the perception of cycling as solely a recreational activity for the wealthy, demonstrating its importance as a transportation mode for lower-income households in the U.S. These findings highlight the need for equity considerations when planning and implementing cycling and bike share initiatives. By addressing access barriers and promoting equitable infrastructure, we can ensure that everyone, regardless of income or race, can benefit from cycling for transportation, exercise, and recreation. Future research should delve deeper into the reasons behind the observed disparities and explore ways to create a more equitable and inclusive cycling environment for all.

Differences in bicycle usage among racial groups raise questions about equitable access to bicycling resources and infrastructure. Addressing these gaps needs a multidimensional approach that considers the intersectionality of race, income, and access to resources. Policymakers should focus on community engagement and outreach activities to better understand the challenges that minority communities encounter while using bicycle amenities. Targeted marketing initiatives, subsidized membership packages, and culturally relevant programming can all assist to close the gap and encourage diversity in the bicycling community.

Furthermore, the findings of this study highlight the need for transportation and urban planning strategies that prioritize equity and social justice. Implementing policies that prioritize the development of bicycle-friendly infrastructure in underserved communities might help to achieve larger goals such as eliminating environmental inequities and promoting healthier, more sustainable transportation options. Collaboration among government agencies, community organizations, and advocacy groups is critical to ensuring that cycling initiatives are inclusive and meet the different needs of all residents.

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Transportation Equity Analysis of Bikeshare Use among Different Sociodemographic Groups

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ABSTRACT

This study addresses a gap in the literature by investigating bikeshare program usage across different racial groups, specifically focusing on sociodemographic variables. Using the latest and most comprehensive national transportation data in the US, the National Household Travel Survey (NHTS), the research explores newly introduced bike-related variables and prioritizes analysis for white, African-American, and Asian populations by weighting the NHTS data. Results reveal that the African-American population has the lowest average number of bike trips compared to white and Asian populations. Among African-American and Asian populations, females show the highest 30-day average bikeshare program participation compared to males. Additionally, individuals with a household income exceeding $100,000 have the highest 30-day average bikeshare program participation in these groups. The study's primary contribution lies in offering a deeper understanding of bike-travel behavior among different races in the US, aiding authorities and transportation planners in equitable investment prioritization for bike infrastructure.

INTRODUCTION

Cycling, a low-cost and physically active means of transportation, has been suggested as a tool for promoting more equal health outcomes (Rachele et al. 2015; Braun, Rodriguez, and Gordon-Larsen 2019). Exercise is a well-established factor in promoting health. Also, bikeshare programs have emerged all over the United States to encourage people to ride their bikes as an active means of transportation that could enhance their health and quality of life. Active transportation benefits communities by reducing traffic, decreasing noise, and reducing pollution (Gössling et al. 2019; Rojas-Rueda et al. 2016). Cities worldwide are turning to non-motorized transportation, especially cycling, to help alleviate traffic congestion and pollution. This paradigm shift necessitates the construction of new infrastructure to support and increase local cycling rates. This requires developing new tools and methodologies for identifying and prioritizing communities for intervention through appropriately planned bike infrastructure. Public bicycle sharing systems, or "bikeshares," can make bicycling accessible to people from all socioeconomic backgrounds due to its low cost and convenience (Bateman et al. 2021). Over the last decade, the use of public bikeshare programs has increased in the U. S. Annual bikeshare rides rose from around 1.5 million in 2010 to over 45.5 million in 2018 (Bateman et al. 2021).

The National Household Travel Survey (NHTS) is conducted by the Federal Highway Administration (FHWA) and is the official source of public travel behavior in the U.S. It contains non-commercial travel daily in all modes and the characteristics of the travelers and their households and vehicles (NHTS 2017). According to the 2017 NHTS, Americans 5 and older walked or biked more than 42.5 billion trips. Non-motorized travelers 16 to 24 made up the smallest category, accounting for only 12% of all individuals surveyed. One in every six Americans (17%) reported going for a walk or riding a bike on a normal day. One-third (34%) of this group was between 40 and 64. A further 24% of those surveyed were between the ages of 25 and 39 (NHTS 2017). Both the 2017 and 2009 NHTS datasets revealed an upward trend in income and the number of bike journeys (Sadeghvaziri and Tawfik 2020). In 2009 bikers who ride frequently were younger (36.4 years vs. 44.7 for non-bikers) and more likely to be employed (72.6% compared to 61.1% of non-bikers) (McGuckin 2012). In 2017, young males were the most frequent users of bicycles, scooters, Segways, and skateboards for various activities, including social and recreational activities, shopping and errands, and business travel (Krizek and McGuckin 2019). Moreover, the average American made only two more bike trips and five more miles cycling in 2009 compared with 2001 (Pucher et al. 2011).

Although different data related to bikeshare programs are available, to the best knowledge of the authors, few bikeshare-related studies investigated the usage and popularity of these programs among different races and sociodemographic groups. Therefore, there is a need to investigate these factors through comprehensive data. The objective of this study is to study bike usage among different sociodemographic and socioeconomic groups using the 2017 NHTS data.

This paper is structured as follows. First, we conduct a literature review on three subjects, including studies that focused on bike trips using the NHTS data, studies on bike trips among different races, and bike trip frequency across the U.S. Second, we discuss the data and methodology used for this study. Third, we compare three variables - the average count of bikeshare program usage, the average count of bike trips, and the number of bike trips for exercise - among different races, using 2017 NHTS data. Fourth, we investigate the bikeshare program participation among different sociodemographic groups. Finally, we present the results and discussion.

LITERATURE REVIEW

Shared mobility services such as bikesharing, ride-hailing, carsharing, e-scooters, and other types of shared mobility have increased rapidly in recent years in cities. The global proliferation of bikesharing programs enhances physical activity, and bikeshare has been described as a social contagion phenomenon in which behavior spreads through imitation and compliance (Wang, Akar, and Guldmann 2015). Jiao et al. (2020) used 2017 NHTS data to find out if there is a link between using shared mobility services and the number of trips people take in a day. They found that bikesharing and carsharing do not appear to be associated with daily trip generation behavior on either weekends or weekdays (Jiao, Bischak, and Hyden 2020). In 2009, compared to 2001, women, children, and the elderly reduced their active travel, whereas men, the middle-aged, employed, well-educated, and those without a car increased theirs (Pucher et al. 2011). In 2017 the presence of another person(s) at the house decreased the number of active transportation trips. According to the 2017 NHTS and 2009 NHTS datasets, the number of senior people who walk, cycle, or take public transportation increases as their income rises (Sadeghvaziri and Tawfik 2020). Moreover, in 2009, bicyclists who ride frequently are not more likely to have higher education (McGuckin 2012).

Moreover, there is a vast body of literature related to biking to school in the U.S., which is critical for encouraging kids to engage in physical exercise. Age, gender, the distance between home and school, homeownership status, household size, number of household vehicles and drivers, and whether the household is in an urban or rural area all play essential roles in parents' decision to use active transportation modes for their children's school transportation (Sultana 2019). In 2017, almost 1% of kids rode their bikes to school. For these children, 82.8% of school trips were less than two miles. When the distance traveled was less than or equal to one mile, characteristics such as the child's school grade, the number of household automobiles per driver, and household wealth were linked to the decision to bike to school. Furthermore, in 2017, the percentage of students taking the school bus and driving decreased, while the percentage of students biking grew. Students who live closer to school are more likely to walk or ride their bikes to school. Females are more likely to drive to school and less likely to ride their bikes (Lidbe et al. 2020).

For most races, the presence of another person(s) at home resulted in fewer bike trips, particularly for Native Americans (Sadeghvaziri and Tawfik 2020). According to a study using 2009 NHTS data for California, compared to people of other races, African-Americans are far more likely to report biking seven or more times per week (McGuckin 2012). According to several studies, bike lanes have tended to be created in socioeconomically advantaged regions in a total of five U.S. cities, including Birmingham, Chicago, Minneapolis, Oakland, and Portland (Flanagan, Lachapelle, and El-Geneidy 2016; Hirsch et al. 2017). Block groups with higher proportions of Black and Hispanic residents and lower SES (i.e., lower-income and educational attainment, higher poverty levels) were less likely to have bike lanes, were further from the nearest bike lane, and had lower bike lane coverage and reach (Sadeghvaziri et al. 2023).

The NHTS and the American Community Survey (ACS) are two primary sources of national data on how many people bike and walk (Sadeghvaziri, Javid, and Jeihani 2023). The NHTS data showed that the number of trips made by bicycle in the U.S. more than doubled from 2001 (1.7 billion) to 2004 (4 billion) (NHTS 2017). For Citi Bike (2013-2018) in New York City, those who had taken at least one social trip were more likely to be older, have a higher household income, not own a car, be physically active, and have good health (Singhvi et al. 2015). In 2009, compared to people of other races, African-Americans were far more likely to report biking seven or more times per week (McGuckin 2012). Immigrants would still be more likely than native-born Americans to use bikeshare programs. In bicycle planning and advocacy, discussions regarding equity are becoming more critical. According to cycling advocates, low-income and minority communities in the U.S. have disproportionately limited access to bike lanes, while, areas with high poverty rates generate more biking trips (Yu 2014). The findings of a study conducted in Chicago, suggest that bikeshare stations in underserved areas account for around two-thirds of all annual trips made at all stations (Qian and Jaller 2020). Overall, there are several studies related to bikeshare programs. However, to the best knowledge of the authors, no study has ever investigated the current utilization of the bikeshare program, the number of bike trips, and the number of bike trips for exercise among different races.

DATA AND METHODOLOGY

This section first explains the data used in this study which was obtained from the 2017 NHTS dataset, and describes the variables used. Next, it simply explains the methodology to repeat the study for other researchers. The process of data preparation and statistical approaches (ANOVA with post-hoc Tukey HSD) are explained thoroughly.

Data

The NHTS is the most valid and the largest national transportation-related data in the U.S. The NHTS is a survey conducted by the FHWA, designed to better understand the travel behaviors and patterns of Americans. The NHTS is the main national source of data on how the travel behavior of the American public is changing as demographic, economic, and cultural changes take place (NHTS 2017). The NHTS dataset contains different datasets, including person-, household-, trip-, and vehicle-level data. The person dataset, which is used in this study, consists of the personal characteristics of each respondent from each household. The household dataset describes the household characteristics of each respondent. The trip dataset consists of trip characteristics for each trip that was taken on the travel day. The vehicle dataset describes the vehicle characteristics of each vehicle in the household.

In 2017, the NHTS added several new variables to the survey due to their increasing popularity and usage in cities across the U.S. In this study, some of these new variables are investigated, including “count of bikeshare program usage,” “count of bike trips for exercise,” “count of walk trips for exercise,” and “count of times of physical activities.” Other variables used in this study are “count of bike trips,” “count of walk trips,” “age,” “gender,” “household income,” “count of household vehicles,” “educational attainment,” and “race.”

Table 1 presents the variables used in this study, as well as their corresponding questions in the NHTS survey. The levels of educational attainment variable are “less than a high school graduate,” “high school graduate or GED,” “some college or associate degree,” “bachelor's degree,” and “graduate degree or professional degree.” Moreover, in this study, the household income variable is aggregated into three categories, including “less than $35,000,” “$35,000 to $99,999” and “$100,000 or more.” Also, the different races (and labels used for them in this study) are as follows: White (W), Black or African American (B), Asian (A), Multiple responses selected (M), American Indian or Alaska Native (I), Native Hawaiian or Other Pacific Islander (H), Some Other Race (O), DON’T KNOW (D), and REFUSED (R).

Methodology and Preparing the Data

Analysis was conducted in R. A one-way analysis of variance (ANOVA) with post-hoc Tukey HSD (Honestly Significant Difference) test was used to compare the means among different races, and whether the means are statistically different (Mishra et al. 2019).

The 2017 NHTS person data file contains a total of 264,234 data from participants who took part in the survey. Out of this, 214,237 of the data were collected from the White population, which is 81.1% of the entire dataset. A total of 19,426 of the data were collected from the Black or African-American population, which is 7.35% of the entire dataset. Moreover, 12,064 of the data were collected from the Asian population, which is 4.57% of the entire dataset. This study focuses on these three races, which are the largest race groups in the U.S. and contain more than 90% of the entire dataset. Figure 1 and Figure 2 show the unweighted number and the unweighted percentage of participants in different races in the NHTS data, respectively.

The 2017 NHTS data used complex strategies to ensure the collected data represents the U.S. population so that disproportionate sampling across a region does not artificially inflate the response rate. Accordingly, the applied weight provided in the person dataset was used in this study to weigh the variables to ensure the results represent the U.S. population.

After weighting the data, the percentage of the White population decreased while the percentage of the African-American and Asian population increased. Figure 3 and Figure 4 show the weighted number and the weighted percentage of participants in different races in the NHTS data, respectively.

Table 1. Variables Used in This Study

Variable	Description	Question in Survey
BIKESHARE	Count of Bikeshare Program Usage	In the past 30 days, how many times did you use a bikeshare program (e.g. Bikeshare, Zagster, or CycleHop)?
NBIKETRP	Count of Bike Trips	In the past 7 days, how many times did you ride a bicycle outside including bicycling to exercise, or to go somewhere (e.g., bike to a friend's house, bike around the neighborhood, bike to the store, etc.)?
BIKE4EX	Count of Bike Trips for Exercise	In the past 7 days , how many of these bicycle rides were strictly to exercise?
NWALKTRP	Count of Walk Trips	In the past 7 days, how many times did you take a walk outside including walks to exercise, go somewhere, or to walk the dog (e.g., walk to a friend's house, walk around the neighborhood, walk to the store, etc.)?
LPACT	Count of Times of Light or Moderate Physical Activity in Past Week	During a typical week how many times do you do light or moderate physical activity for more than 30 minutes?
R_AGE	Age_24Less = Less than 24	Please tell me your age.
	Age_25_64 = Between 25-64	
	Age_65More = More than 65 years	
R_SEX	Sex_M = Male	Please tell me your gender.
	Sex_F = Female	
HHFAMINC	Inc_0_35 = Less than $35K	Your total household income.
	Inc_35_99 = Between $35K and $99K	
	Inc_100More = More than $100K	
HHVEHCNT	Count of household vehicles	How many vehicles are owned, leased, or available for regular use by the people who currently live in your household?
EDUC	E_L_HS = Less than a high school graduate	What is the highest grade or degree that you earned?
	E_G_HS = High school graduate or GED	
	E_College = Some college or associates degree	
	E_Bachlor = Bachelor's degree	
	E_Grad = Graduate degree or professional degree	
R_RACE	B= Black or African American	Which of the following describes your race?
	W= White	
	A= Asian	
	M= Multiple responses selected	
	I= American Indian or Alaska Native	
	H= Native Hawaiian or other Pacific Islander	
	O= Some Other Race	
	D= DON'T KNOW	
	R= REFUSED	

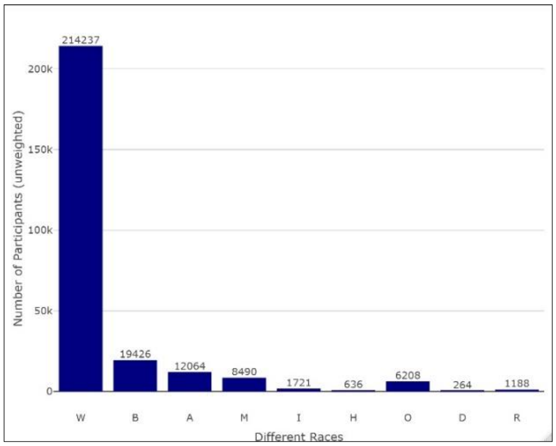

Figure 1. Unweighted number of participants among different races

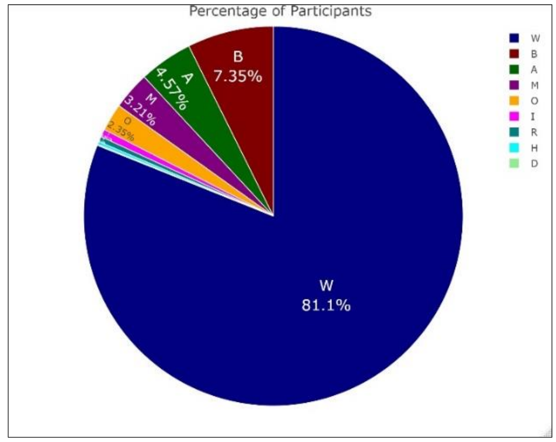

Figure 2. Unweighted percentage of the participants from different races

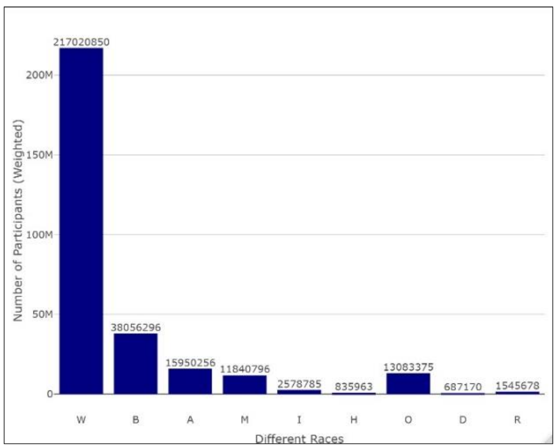

Figure 3. Weighted number of the participants among different races

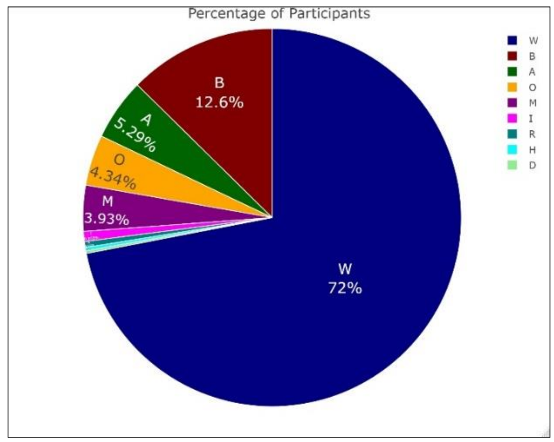

Figure 4. Weighted percentage of the participants among different races

To compare the number of bikeshare program usage and different bike trips, descriptive analysis and a one-way ANOVA test is used. Because our objective is to investigate these variables, we opted to exclude those who answered “DON’T KNOW” or “REFUSED” to any variable in Table 1. The total number of remaining data is 8,243. Next, the data of these individuals become weighted, and the total number of the weighted population is 10,215,180. Also, bikeshare program participation among different sociodemographic groups is investigated, using ANOVA with post-hoc Tukey HSD test. All statistical analyses are conducted with a 95% level of confidence.

ANALYSIS RESULTS

Bike Trips and Bikeshare Usage Among Different Races

Figure 5, Figure 6, and Figure 7 present bike usage among three races. The white population had the lowest 30-day average of bikeshare program participation and the lowest 7-day average of bike trips for exercise. The Black population had the lowest 7-day average of bicycle rides. Asian population had the highest 30-day average of bikeshare program participation, a 7-day average of bike trips, and a 7-day average of bike trips for exercise.

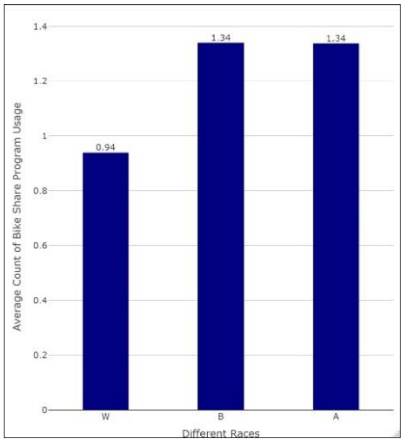

Figure 5. Average Count of Bikeshare Program Usage in the past 30 days (BIKESHARE)

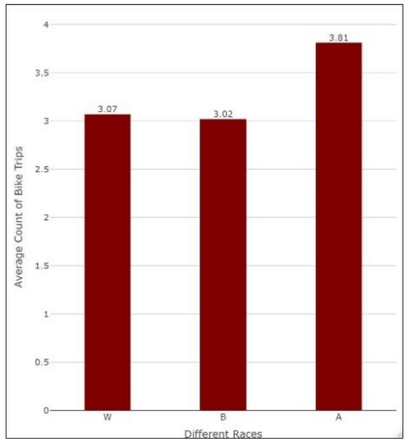

Figure 6. Average Number of Bike Trips in the past 7 days (NBIKETRP)

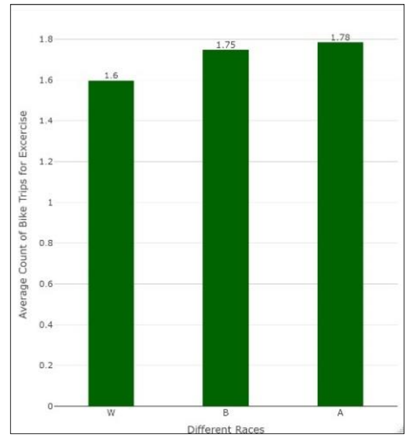

Figure 7. Average Number of Bike Trips for Exercise in the past 7 days (BIKE4EX)

To determine which groups significantly differ from each other, we used an ANOVA with post-hoc Tukey HSD test. Table 2 presents the results of the Tukey test in detail. From Table 2 one can conclude that there are significant differences between the Black and White populations; and the Asian and White populations in or number of bikeshare program usage. Also, it can be concluded that a significant difference exists in the number of bike trips between the Black and White populations; and between the Asian and White populations. Finally, there is a significant difference in the number of bike trips for exercise between the Black and White populations.

Table 2. ANOVA with post-hoc Tukey HSD Test Among Different Races

Races	BIKESHARE			NBIKETRP			BIKE4EX		
	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code	Estimate	Pr(>|t|)	Signif. Code
W - B	-0.84	<0.001	***	-0.58	0.00	**	-0.48	0.00	***
A - B	-0.28	0.34		-0.07	0.95		-0.36	0.07	.
A - W	0.56	<0.001	***	0.51	0.01	**	0.12	0.55	
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1									

Bikeshare Program Participation and Sociodemographic Groups

To investigate which sociodemographic groups among different races are significantly different in the 30-day average bikeshare program participation, we used an ANOVA with post-hoc Tukey HSD test, as shown in Table 3. In detail, among the white population, the 25 to 64 years old group had the highest 30-day average bikeshare program participation compared to other age groups.

Table 3. ANOVA with post-hoc Tukey HSD Test for Sociodemographic Characteristics and Bikeshare Program Usage

Variable	Levels	White			Black			Asian		
		Estimate	Pr(>|t|)	Code	Estimate	Pr(>|t|)	Code	Estimate	Pr(>|t|)	Code
Age	Age_25_64 - Age_24Less	0.45	<2e-16	***	-0.44	<2e-16	***	1.16	<1e-10	***
	Age_65More - Age_24Less	0.18	<2e-16	***	-0.57	<2e-16	***	0.24	<1e-10	***
	Age_65More - Age_25_64	-0.27	<2e-16	***	-0.13	<2e-16	***	-0.93	<1e-10	***
Sex	Female - Male	-0.38	<2e-16	***	0.72	<2e-16	***	0.75	<2e-16	***
Education	E_G_HS - E_L_HS	0.06	<2e-16	***	-1.05	<1e-08	***	1.07	<2e-16	***
	E_College - E_L_HS	0.25	<2e-16	***	-1.37	<1e-08	***	4.58	<2e-16	***
	E_Bachlor - E_L_HS	0.12	<2e-16	***	-0.77	<1e-08	***	1.34	<2e-16	***
	E_Grad - E_L_HS	0.51	<2e-16	***	-0.68	<1e-08	***	0.61	<2e-16	***
	E_College - E_G_HS	0.19	<2e-16	***	-0.31	<1e-08	***	3.51	<2e-16	***
	E_Bachlor - E_G_HS	0.06	<2e-16	***	0.28	<1e-08	***	0.28	<2e-16	***
	E_Grad - E_G_HS	0.44	<2e-16	***	0.38	<1e-08	***	-0.46	<2e-16	***
	E_Bachlor - E_College	-0.13	<2e-16	***	0.60	<1e-08	***	-3.24	<2e-16	***
	E_Grad - E_College	0.25	<2e-16	***	0.69	<1e-08	***	-3.97	<2e-16	***
	E_Grad - E_Bachlor	0.39	<2e-16	***	0.10	<1e-08	***	-0.74	<2e-16	***
Income	35_99 - 0_34	-0.09	<2e-16	***	-0.29	<2e-16	***	0.08	1.14E-06	***
	100 - 0_34	-0.38	<2e-16	***	2.14	<2e-16	***	1.05	<1e-07	***
	100 - 35_99	-0.30	<2e-16	***	2.43	<2e-16	***	0.97	<1e-07	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Additionally, the male population had a higher 30-day average bikeshare program participation compared to females. Among African-American population, individuals younger than 24 years old had the highest 30-day average bikeshare program participation compared to other age groups. The female population had a higher 30-day average bikeshare program participation compared to males. Among the Asian population, the 25 to 64 years old group had the highest 30-day average bikeshare program participation compared to other age groups. The female population had a higher 30-day average bikeshare program participation compared to males.

DISCUSSION

It was revealed that after weighting the data, the percentage of the White population decreased while the percentage of the rest of the races increased. It can be understood that more data were collected from the White population, 81.1%, than the actual percentage of the entire U.S. population, which is 73%. Therefore, the data were not collected proportionally among different races. While African-American population is 13% of the U.S. population, they are only 7.35% of the NHTS original (unweighted) data. More efforts should be made to accurately represent racial groups in the next NHTS dataset. The comparison of a number of bikeshare program usage showed that the White population's usage of bikeshare programs is significantly lower than all other races. Also, the White population have the lowest average number of bicycle rides that were strictly for exercise compared to African-American and Asian population. However, African-American population has the lowest average number of bicycle rides compared to the White and Asian population.

Table 4 presents the highest and lowest socio-demographic groups among different races. In detail, individuals aged 25 to 64 had the highest 30-day average bikeshare program usage among the White population compared to other age groups. In comparison to females, males had a higher 30-day average bikeshare program participation. Compared to other educational attainment groups, those with a "Graduate degree or professional degree" had the greatest 30-day average bikeshare program usage. Furthermore, when compared to other income groups, those with a household income of less than $35,000 had the greatest 30-day average bikeshare program participation.

Table 4. Highest and Lowest Bikeshare Program among Different Races

Variables		White	Black	Asian
Age	**Highest**	25 to 64	Less than 24	25 to 64
	Lowest	Less than 24	65 or more	Less than 24
Sex	**Highest**	Male	Female	Female
	Lowest	Female	Male	Male
Education	**Highest**	Graduate degree or professional degree	Less than a high school graduate	Some college or associates degree
	Lowest	Less than a high school graduate	Some college or associates degree	Less than a high school graduate
Income	**Highest**	Less than $35,000	More than $100,000	More than $100,000
	Lowest	More than $100,000	Less than $35,000	Less than $35,000

Furthermore, individuals younger than 24 years old had the highest 30-day average bike sharing program usage among African-Americans compared to other age groups. In comparison to males, females had a higher 30-day average bikeshare program participation. Compared to other educational attainment groups, those with "less than a high school graduate" had the greatest 30-day average bikeshare program participation. Furthermore, compared to other income groups, those with a household income of more than $100,000 had the greatest 30-day average bikeshare program participation. Moreover, individuals aged 25 to 64 had the highest 30-day average bike sharing program engagement among Asians. In comparison to males, females had a higher 30-day average bikeshare program participation. Compared to other educational attainment groups, those with "some college or associate degree" had the greatest 30-day average bikeshare program attendance. Those with household incomes of more than $100,000 had the greatest 30-day average bikeshare program participation among all income groups.

SUMMARY AND CONCLUSIONS

This paper is a first approximation of exploring bikeshare program usage among different races using the weighted 2017 NHTS data. The main goal of this study was to investigate the number of bikeshare program usage among different races. To reach this goal, the first objective was to compare the “bikeshare program usage,” “number of bike trips,” and “number of bike trips for exercise” among White, African-American, and Asian populations. To see whether there were any significant differences among different races, one-way ANOVA with post-hoc Tukey HSD tests was used for each of the three aforementioned variables.

The second objective was to investigate bikeshare program participation among different sociodemographic groups using ANOVA with post-hoc Tukey HSD test. To be able to draw a valid conclusion, we used the latest NHTS dataset and R software. Additionally, to have a dataset that is representative of the entire U.S. population, we weighted the 2017 NHTS data based on the weights provided by the FHWA. After weighting the NHTS data, the percentage of the African-American population increased. This showed that the NHTS survey needed to collect more data from African-American population. Comparison among different races indicated that the White population’s usage of bikeshare programs is significantly lower than other races. Also, the White population have the lowest average number of bicycle rides that were strictly to exercise. However, African-American population has the lowest number of bike trips. Moreover, the Asian population has the highest average in all three variables.

The results of our investigation on NHTS data are supported by previous studies outcomes that showed different sociodemographic groups are not using the bikeshare programs equally. Due to their relatively low cost and convenience, bikeshare programs can promote mobility to users of diverse sociodemographic profiles, including low-income and racial minorities. It is recommended that future NHTS surveys will include questions related to the reason for not using bikeshare programs. These questions can reveal whether the non-users are not using the bikeshare programs due to lack of interest or unavailability of infrastructure. Outreach initiatives to reach low-income residents that have limited access to docked and dockless bikeshare systems (especially among African-American and Asian populations that have the lowest number of bikeshare programs) may increase participation. Moreover, discounted annual membership for income-qualifying individuals can increase bikeshare programs among minorities since our findings highlighted that among African-American and Asian populations, individuals with income less than $35,000 have the least number of bikeshare program usage compared to other income groups.

One of the limitations of this study is the concern about the high number of individuals who answered either DON'T KNOW or REFUSED, and because so many in the dataset did, we recommend adding different choices (e.g., I do not have a bike, I do not exercise, I do not know the meaning of bikeshare, etc.) that can provide more insight into the respondent's reason for selecting either of two aforementioned choices. Another limitation of this study is that the NHTS survey does not consider different types of bike-related questions. With the increase of vast types of questions, the travel behavior of a bike rider could be investigated more thoroughly. For future studies, spatial analysis of the accessibility to bike-related infrastructures can be conducted to identify the areas where the residents have less usage of bikeshare programs.

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Equity Considerations in Benefit-Cost Analysis: A Necessity or an Overreach?

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ABSTRACT

This paper addresses the urgent need to incorporate equity considerations into benefit-cost analysis (BCA) in US transportation and infrastructure projects, potentially leading to an equity-based BCA. Utilizing a comprehensive meta-analysis, the paper explores the factors influencing equitable outcomes, examining aspects such as assumptions and considerations, the extent of benefits and costs, treatment of long-term and indirect effects, and the integration of environmental and social concerns. Additionally, the paper underscores these factors' importance in the discussion on reforming BCA practices. It also examines the current concept of efficiency in BCA, emphasizing the potential for redistribution through taxes and transfers and the theoretical possibility for policy beneficiaries to compensate those worse off through a costless, lump-sum transfer, ensuring overall societal improvement. The paper provides policy and practice implications, recommendations for enhancing BCA practices in transportation and infrastructure projects, and suggests ways to promote more informed decision-making.

I. INTRODUCTION

In the realm of transportation and infrastructure projects within the United States, Benefit-Cost Analysis (BCA) stands as one of the most fundamental tools in the decision-making process. It plays a pivotal role in guiding decision-makers as they evaluate the viability of such projects, offering a structured approach to assess the relationship between benefits and costs. Throughout its history, BCA has provided a systematic method for optimizing societal welfare, focusing primarily on economic efficiency and cost-effectiveness. Yet, the evolving landscape of societal values, coupled with a heightened emphasis on equity and fairness, has precipitated a critical reexamination of BCA's adequacy in capturing the diverse aspirations of a just and equitable society.

The traditional emphasis on economic efficiency in BCA has been underpinned by the presumption that optimizing overall societal welfare inherently promotes equity. Such presumption finds support in the underlying rationale that non-tax policies should refrain from considering their distributional effects, as the necessary redistribution can be efficiently managed through tax and transfer mechanisms (Liscow 2021). However, contemporary societal discourse and evolving priorities have underscored the limitations of this approach. While economic efficiency remains a vital objective, it is increasingly evident that this criterion alone does not fully encompass the broader range of societal objectives, particularly those linked to equity and distributive justice.

Transportation and infrastructure projects, given their substantial impact on communities and individuals, have come under increased scrutiny in the context of equity in the past few years. The impact of these projects cannot be underestimated. They shape access to education, healthcare, employment opportunities, and essential services for millions of citizens. They have the potential to catalyze the growth and enhancement of neighborhoods and communities, ultimately contributing to their overall betterment. Thus, there is a growing recognition that the methodologies employed to evaluate such projects should be capable of reflecting the diverse needs and values of the society they serve. Equity considerations in BCA extend beyond the traditional focus on efficiency, involving a comprehensive examination of how benefits and costs are distributed across various segments of society. Such considerations encompass not only whether transportation and infrastructure projects disproportionately affect vulnerable or disadvantaged populations but also whether they contribute to the reduction of societal disparities. This perspective acknowledges that fairness and distributive justice should be central components of project evaluation, alongside the goal of economic efficiency.

Utilizing the meta-analysis methodology, this research investigates whether equity considerations should be explicitly integrated into BCA. It grapples with essential, complex questions: is it practical and feasible to balance equity with efficiency within the framework of BCA? Are there potential pitfalls in introducing equity considerations that might detract from BCA's primary goal of optimizing societal welfare efficiently? These questions underscore the critical challenge of striking the right balance, weighing the ethical and practical implications, and navigating the complexities that emerge when considering the potential for redistribution through taxes and transfers. The challenge is further compounded by the fact that BCA traditionally leans toward a purely quantitative approach, emphasizing numerical measurements, while equity considerations often introduce a qualitative dimension, necessitating an assessment of non-monetary, ethical, and distributive aspects. Harmonizing these distinct qualitative and quantitative elements within a unified framework poses a multifaceted challenge for both researchers and policymakers.

The goal of this research is to ultimately address the core question of whether equity should be explicitly integrated into BCA within U.S. transportation and infrastructure projects. While recognizing the growing importance of equity considerations, this inquiry raises a fundamental debate on whether the traditional BCA framework, firmly rooted in the pursuit of economic efficiency, is the optimal platform for addressing equity concerns. The central challenge lies in assessing whether the benefits derived from the integration of equity into BCA align with broader societal goals and whether they outweigh potential drawbacks that may emerge from diverting BCA's core focus from efficiency. This research, relying on contemporary sources, aims to evaluate the necessity of incorporating equity into BCA and its potential implications, contributing to the ongoing discourse on BCA's role in fostering a just and equitable society.

II. LITERATURE REVIEW

a. Overview of Benefit-Cost Analysis (BCA)

The United States Department of Transportation (USDOT) defines BCA as a systematic process for identifying, quantifying, and comparing expected economic benefits and costs of proposed infrastructure projects (U.S. Department of Transportation n.d.). It is designed to provide a benchmark to evaluate and compare potential transportation investments, adding rigor to the project evaluation process. When discounted future benefits are equal to or exceed discounted life-cycle costs, a project is considered economically efficient.

The BCA process typically involves several key steps, including defining the problem the project addresses, measuring and valuing benefits and costs, calculating benefit-cost measures, and interpreting and presenting results. The process is designed to be systematic and structured, providing a directed overview of procedures and relevant concepts (Kaplan n.d.).

b. Historical Development of BCA in Transportation and Infrastructure Projects

The origin of BCA dates back to 1708 in France with the work of the Abbé de Saint-Pierre, who conducted the first formal benefit– cost study. This study measured the incremental benefits of road improvements, focusing on increased trade and reduced transport costs. These early works, however, did not draw attention from other countries. However, in 1822, Pierre-Simon Girard, a French mathematician and engineer, attempted to measure the benefits of a canal project, combining hydraulics and economics. This was followed by Henri Navier in 1830, who set up a benefit–cost principle stating that public works should only be provided if total benefits exceeded total costs. By 1844, Jules Dupuit introduced the concept of consumer surplus, providing a theoretical basis for BCA.

In the U.S., water resources development began in the early 19th century. However, the modern economic analysis of project value began during the New Deal era with the establishment of national resource planning organizations and the introduction of the 1936 Flood Control Act, which is often considered the beginning of BCA in the U.S.

The Water Resources Committee of the National Resources Planning Board (NRPB) contributed significantly to the development of BCA in the U.S. By the 1950s, where it became the principal basis for project evaluations by related agencies. The inconsistencies in methods used by various agencies led to the creation of the Green Book in 1950, a book that established uniform methods for economic analysis of river basin projects (Jiang & Marggraf 2021).

c. Theoretical Underpinnings of Equity in BCA and Existing Research

Traditionally, BCA has been viewed as insensitive to distributional considerations. The standard form of BCA sums up unweighted individual willingness-to-pay and willingness-to-accept amounts, a method that is indifferent to how a policy’s income costs are distributed among the population.

Kaldor-Hicks efficiency is one of the most prominent arguments that defends the current BCA practice. Kaldor-Hicks dictates that a policy is considered efficient if those who benefit from it could hypothetically compensate those who are worse off, leading to a situation where everyone is ultimately better off. It does not account for distributional considerations and instead assumes that redistribution can happen through taxation, making the approach hypothetical.

Another common rationale is the Social Welfare Function (SWF) which was introduced in the 1930s and 1940s by Abram Bergson and Paul Samuelson and further developed by Amartya Sen. The method employs a unique "utility" indicator as a means to characterize how well-being is distributed within a population and to evaluate the effects of a particular policy on this distribution. Various forms of SWFs are utilized to capture different normative perspectives on comparing these distributions of well-being. To illustrate, one of these SWFs, the utilitarian approach, focuses on aggregating the overall well-being of the population, essentially summing up the total. In contrast, another approach, known as the "prioritarian", SWF assigns greater significance to changes that benefit the less fortunate members of society (Adler 2021).

Economists use various approaches to incorporate distributional consequences into BCA, such as distributional weights and metrics based on the Lorenz curve. Empirical methods like the contingent valuation method (CVM) and hedonic property methods (HPM) are employed to quantify how non-market environmental benefits are distributed by income and ethnicity. These methods can reveal differential effects of policies on various demographic groups, indicating the importance of considering equity in BCA (Loomis 2021).

Research, such as the framework developed by the New Zealand Transport Agency, has explored integrating equity considerations into transportation BCA. This approach involves geospatial analysis to understand how costs and benefits are distributed across the population, ensuring that transportation projects address social equity effectively. This method was further developed in North Carolina for cross-modal measures like air quality and physical health (TRB n.d.).

d. Gaps in the literature

One of the primary gaps in the literature is the lack of established, standardized methods for quantitatively integrating equity considerations into BCA. This includes the challenge of measuring and valuing non-market impacts, such as social and community well-being, and how these impacts are distributed among different societal groups. The challenge also lies in examining short-term and long-term effects on infrastructure investments on underserved communities. There is a need for more interdisciplinary research that incorporates insights from sociology, psychology, and environmental science into the traditionally economic framework of BCA. Such approaches can provide a more holistic understanding of the impacts of infrastructure projects on different segments of society. From a public policy standpoint, there is a gap in literature focusing on the practical implications and how these theories can be implemented in real-world policy and decision-making processes.

III. METHODOLOGY

Relevant publications were identified through a comprehensive search of academic databases. Key search terms included "equity in benefit-cost analysis," "BCA and equity," "social equity in infrastructure projects," and "federally funded transportation projects and BCA." Initial screening was based on titles and abstracts, followed by a full-text review to ensure relevance to the research question. For each selected study, the following information was extracted: author(s), year of publication, study objectives, methodology, main findings, and specific insights related to equity in BCA.A thematic analysis was then conducted. This involved categorizing the literature based on themes such as methodologies for integrating equity, empirical findings, theoretical underpinnings, and policy implications.

IV. ANALYSIS AND DISCUSSIONS

This section embarks on a detailed analysis and discussion of the collected literature, focusing on the integration of equity considerations in BCA within U.S. transportation and infrastructure projects. This analysis aims to dissect the complex interplay between economic efficiency and social equity in BCA, drawing insights from various scholarly contributions.

a. Redistribution for Realists – Zachary Liscow

Zachary Liscow begins by highlighting the growing concern about inequality in the United States and the perception of a "rigged" economy. It criticizes the standard economic approach to addressing inequality using an example from the USDOT's grant distribution. Federal funding prioritizes saving time but assigns a higher value to the time of wealthier individuals, leading to an allocation that benefits the rich more than the poor. The author questions the logic behind this approach, given the importance of economic mobility. This skewed allocation reinforces income inequality as it makes it harder for lower-income individuals to access opportunities.

Liscow discusses the standard economic approach to policymaking, emphasizing that it views all policies as a unified whole. The primary goal of this approach is to maximize social welfare by recommending policies that efficiently allocate resources. It operates under the assumption that policies can be implemented coherently, as if overseen by a benevolent dictator. The critique presented in this article challenges this approach's assumption of "one-pieism," which implies that all policy ingredients are perfectly commensurable and interchangeable. It argues that this approach prioritizes two main outputs: maximizing the economic pie's size (efficiency) and achieving a fair distribution of resources. Additionally, it asserts that the standard approach prefers using taxes and cash transfers for redistribution, assuming that these are the most efficient means. The “one-pieism” argument is applied in two steps. First, it emphasizes the need to make non-tax policies efficient, adhering to the "Kaldor-Hicks" efficiency criterion, which evaluates the value individuals place on policy outcomes given their existing wealth distribution. The second aspect of "one-pieism," which is the concept of redistribution. The rationale behind using cash for redistribution via taxation is that it allows the poor to choose how to spend the money, increasing the likelihood that they use it in the way that benefits them the most. This approach also aims to minimize harm to the rich by reducing their cash income through taxes rather than removing legal entitlements they highly value. Cash is considered superior for redistribution because it offers flexibility and efficiency.

Liscow discusses a key challenge to redistribution, which is public resistance to using taxes for redistribution, partly due to the belief that individuals should keep a significant portion of their earnings, based on their pretax income, regardless of work incentives. This perspective contradicts the standard economic approach, which advocates for all redistribution through taxes. Policy silos, where different concerns apply to different areas, are essential for understanding public attitudes. People may support income retention in the tax domain while endorsing government support for necessities elsewhere. Ignoring these varied perspectives can lead to flawed policy recommendations.

Thus, there’s a mismatch between optimal tax theory and real-world taxation practices. While economists have explored how to achieve an ideal income distribution through taxes, this research is often overlooked outside tax scholars. Optimal tax theory suggests features such as a substantial cash to allow people to choose how to use their money. However, in practice, redistribution is far less extensive than what optimal tax theory would propose. This discrepancy raises questions about common views on taxation, with real-world policies differing significantly from the ideal outlined in optimal tax theory. Liscow proposes the "thousand points of equity" approach as a practical strategy for addressing inequality. This approach advocates for spreading redistribution efforts modestly across multiple policy domains rather than focusing intensively on a single area, such as taxation. This method aims to achieve equitable outcomes in a politically and socially feasible manner, utilizing opportunities for low-cost redistribution in various sectors, including transportation and housing. It combines efficiency with behavioral insights, striving for a more achievable and comprehensive approach to reducing inequality (Liscow 2021).

b. Equity in Regulatory Cost-Benefit Analysis – Zachary Liscow

In analyzing the various perspectives on the integration of equity in BCA, Zachary Liscow's paper "Equity in Regulatory Cost-Benefit Analysis" provides a pivotal critique of the traditional efficiency-focused approach in federal regulatory analysis. Liscow's findings underscore a key deficiency in how current policies, particularly in the USDOT, handle the valuation of time savings, which disproportionately favors wealthier individuals due to the higher monetary value placed on their time. Liscow also highlights a fundamental flaw in the approach that values an hour saved for wealthier individuals (like those using airports) much higher than an hour saved for lower-income individuals (like bus users). This practice not only reflects an efficiency bias but also exacerbates existing inequalities, as it directs resources towards projects that benefit the rich over those that serve the needs of the poor (Liscow 2021).

To address this imbalance, Liscow proposes three strategies:

- Measuring Distributional Impacts: This involves a systematic analysis of how proposed regulations differentially affect various income groups.
- Cleansing Measures of Costs and Benefits: This strategy advocates for equalizing the valuation of time across different income groups, thereby tilting spending back towards the poor.
- Using Distributional Weights: This method suggests applying heavier weights to benefits accruing to the poor than to the rich, thereby prioritizing regulations that disproportionately benefit lower-income groups.

c. Equity or Efficiency? The Battle for the Soul of Benefit-Cost Analysis– James Broughel

In "Equity or Efficiency? The Battle for the Soul of Benefit-Cost Analysis" by James Broughel, the crucial role of benefit-cost analysis (BCA) in US federal regulatory processes, especially for significant regulations, is highlighted. Despite its widespread acceptance, the article points out unresolved issues, notably the disagreement over the measure of human welfare, often surfacing in debates about the "social discount rate (SDR)." These debates, while appearing technical, are fundamentally rooted in value differences and reflect broader discussions about public policy goals. The lack of consensus on these issues can cast doubt on the credibility of BCAs for public programs, potentially leading to skepticism and criticism of their conclusions as arbitrary or misleading. Broughel's article underscores the complexity of the ongoing BCA debate in regulatory policy. The debate in BCA centers on competing goals: some economists prioritize economic efficiency, focusing on overall wealth creation, while others emphasize equitable wealth distribution. This disagreement extends to SDR, where discussions revolve around intergenerational equity. Values play a substantial role, illustrated by parameters like the "rate of intergenerational inequality aversion," which varies based on individual values. The technical nature of these discussions may create an illusion of precision, but it conceals the subjective and normative aspects of BCA assessments, highlighting the complexity of its underlying goals and values.

The article highlights the challenges in assigning appropriate weights to costs and benefits, which are inherently subjective. Additionally, the exclusion of ordinary citizens from these value-based debates among experts raises concerns. It suggests that presenting benefits and costs without further weighting would enhance transparency in BCA reports. Discounting, instead of clarifying evaluations, introduces a layer of values related to intergenerational equity preferences, making it difficult to discern normative biases from reported figures. Current BCA practices face an additional issue concerning the inadequate consideration of capital affected by government policies. While many economists aim to account for the opportunity cost of capital using a discount rate, this approach may not be suitable, except in specific cases. Instead, economists propose using a "shadow price" to assess how capital returns would evolve over time. Shadow pricing is an economic technique used to estimate the value of a resource when there is no market price or when the market price does not reflect its true value, as seen with various aspects of the natural environment. Economists have recognized that the market price of capital does not fully capture its value. By estimating its value based on the returns it generates, analysts can shadow-price capital, similar to how financial analysts assess the value of stocks or bonds. Although these returns are not directly observable, they are just as real as the more easily quantifiable costs or benefits from policies. However, in practice, government agencies rarely use shadow prices, leading to the neglect of the unseen consequences of policies. Consequently, there is an imbalance in analysis, with an excessive focus on consumption compared to capital and investment considerations (Broughel 2019).

d. Factoring Equity into Benefit-Cost Analysis– Matthew Adler

In Matthew Adler's article titled "Factoring Equity into Benefit-Cost Analysis," the central theme revolves around the incorporation of equity considerations into BCA within regulatory review processes. The article begins by highlighting President Biden's memorandum, which emphasizes the importance of accounting for the distributional consequences of regulations in BCA. It underscores the pressing need to address distributional inequities in the United States concerning race, gender, socioeconomic factors, and more.

Adler delves into the role of quantitative BCA in regulatory review, noting that while directives like Executive Orders 12866, 13563, and Circular A-4 acknowledge distribution, practical regulatory analysis often overlooks it. Standard BCA, characterized by the aggregation of unweighted willingness-to-pay and willingness-to-accept values, has been criticized for its insensitivity to distributional concerns.

The article then explores two normative rationales for BCA within welfare economics: Kaldor-Hicks efficiency and SWFs. While the Kaldor-Hicks approach focuses on hypothetical efficiency and poses challenges due to its lack of real-world applicability, SWFs, coupled with distributional weights, offer a framework to effectively integrate equity considerations into BCA. By shifting away from the problematic Kaldor-Hicks foundation, policymakers can refine BCA to better accommodate equity concerns, aligning regulatory analysis more closely with real-world distributional impacts (Adler 2021).

e. Inequality and Regulation: Designing Rules to Address Race, Poverty, and Environmental Justice - Daniel A. Farber

Daniel Farber's "Inequality and Regulation: Designing Rules to Address Race, Poverty, and Environmental Justice" primarily addresses two significant aspects in the realm of regulatory practices. Firstly, Farber challenges the traditional approach in BCA by advocating for a uniform value of statistical life (VSL). He argues that this is not just a pragmatic solution but is grounded in a principle he terms "harm egalitarianism." This principle posits that all individuals, regardless of their economic status or other personal characteristics, have equal entitlements to protection against harm. This approach redefines the concept of equality in the context of regulatory decision-making, particularly when assessing the value of life and health across different socioeconomic groups. Secondly, Farber explores the integration of environmental justice concerns into regulatory processes. He suggests that a more effective way to address these concerns is by concentrating on differences in exposure and vulnerability in the cost-benefit analysis of regulations. This focus, according to Farber, offers a promising path for expanding protection for disadvantaged groups, especially in environmental contexts. His argument pivots around the idea that understanding and addressing the disparities in pollution exposure and vulnerability among different communities can lead to more equitable regulatory outcomes. This approach also seeks to indirectly address broader issues of racial and economic inequalities through more nuanced and targeted regulatory measures.

f. The Equality–Equity Dilemma in Cost–Benefit Analysis Comment on Daniel Farber’s Inequality and Regulation: Designing Rules to Address Race, Poverty, and Environmental Justice – Daniel Hemel

Daniel J. Hemel's commentary in "The Equality–Equity Dilemma in Cost–Benefit Analysis," focuses on the complexities and challenges of integrating equity considerations into BCA, particularly in the context of regulatory decisions that affect different racial and socio-economic groups. Hemel acknowledges the importance of Farber's proposals but points out a fundamental tension, which he terms the equality–equity dilemma. This dilemma arises from the conflict between using equal-dollar Value of Statistical Life and implementing disparate-impact analysis in regulations. To assess the net benefits or burdens for specific groups, regulators would need to use willingness-to-pay numbers that are specific to those groups. However, since willingness to pay varies by income, which in turn correlates with race, this approach would necessitate income- and race-differentiated VSLs. Hemel notes the potential challenges this poses, including the risk of misinterpretation and public backlash, as well as the possible message of disrespect to the groups the analysis aims to protect. Hemel further explores the implications of this dilemma for regulatory policy, suggesting that addressing equity through BCA might require moving away from the principle of equal-dollar VSLs. He emphasizes the need for a careful balancing of ethical principles in regulatory decision-making, recognizing the moral complexities inherent in prioritizing equity. Hemel highlights that while Farber's approach of focusing on unequal exposure and vulnerability is a step in the right direction, it must be navigated thoughtfully to ensure that the goals of racial and economic justice are effectively met. This involves grappling with the deeper question of how to weigh and integrate different ethical considerations and objectives in the context of regulatory analysis and decision-making.

V. SYNTHESIS OF FINDINGS

The synthesis of findings from the selected academic literature offers an overview of the current discourse on integrating equity into BCA in U.S. transportation and infrastructure projects. This section aims to weave together the diverse perspectives and insights from scholars like Zachary Liscow, James Broughel, Matthew Adler, Daniel A. Farber, and Daniel Hemel. Their contributions illuminate the complexities and nuances of incorporating equity considerations into BCA, challenging traditional notions of efficiency and broadening the scope to include social justice and equitable outcomes.

The collective works emphasize the need for a nuanced balance between efficiency and equity in BCA. Traditionally, BCA has focused predominantly on economic efficiency, often at the expense of social equity. The argument presented in these resources is for an expanded framework that equally values equitable outcomes. This shift does not undermine the importance of economic considerations but rather enriches the analysis by integrating social impacts, especially on marginalized communities. Such an approach recognizes that the most cost-effective solutions may not always align with equitable outcomes and seeks to bridge this gap.

Additionally, a consistent theme in the literature is the importance of considering how different demographic groups are impacted by infrastructure projects. This approach challenges the traditional one-size-fits-all methodology of BCA, advocating for a more detailed examination of the distribution of costs and benefits among various societal groups. This nuanced understanding, as highlighted by Farber and Hemel, is crucial for addressing systemic inequalities and ensuring that BCA is responsive to the complexities of social justice. It calls for a methodology that is sensitive to the diverse needs and circumstances of different communities, thereby promoting fairness and legitimacy in the decision-making process.

Integrating equity into BCA has significant implications for policy and practice. The synthesis suggests that this integration could catalyze changes in how infrastructure projects are evaluated and implemented. It highlights the need for new methodologies that can effectively measure and incorporate long-term and indirect social effects, such as environmental sustainability and community well-being. The literature points towards a collaborative, interdisciplinary approach, involving economists, sociologists, and urban planners, to develop a more comprehensive BCA framework. Such a framework would not only balance efficiency and equity but also ensure that infrastructure investments contribute to a more equitable and just society.

The combined insights from Zachary Liscow, James Broughel, Matthew Adler, Daniel A. Farber, and Daniel Hemel converge on the necessity of integrating equity into BCA but differ in their approaches and emphases. Liscow and Adler both stress the importance of directly incorporating equity considerations into BCA, with Liscow focusing on the redistributive impacts of infrastructure projects and Adler emphasizing equity as a core part of the cost-benefit assessment. Broughel's perspective complements these views by advocating for a broadened BCA framework that weighs both economic benefits and social impacts, thus resonating with the holistic approaches suggested by Liscow and Adler. Farber takes a more specific stance, arguing for BCA regulations that explicitly address race, poverty, and environmental justice, which aligns with Hemel's emphasis on the balance between equality and equity. Hemel's viewpoint highlights the challenge of designing regulatory frameworks that are both equitable and efficient, echoing the broader theme of balancing economic efficiency with social equity that underpins the collective suggestions of all authors. This reveals a shared recognition of the need for more nuanced and inclusive BCA methodologies yet indicates differing viewpoints on how best to achieve this integration of equity.

VI. ADDRESSING GAPS IN THE LITERATURE

A major gap in literature is the lack of a standardized methodology for incorporating equity into BCA. This results in inconsistencies across projects and undermines efforts to achieve equitable outcomes. Developing universally accepted methods to quantify and include social equity impacts is essential for progress in this field.

There is a notable scarcity of data on the long-term socio-economic impacts of infrastructure projects. Most studies focus on immediate or short-term effects, leaving a gap in understanding the enduring consequences of these projects on different population groups. Additionally, the literature often overlooks the perspectives and needs of marginalized communities in BCA processes. Ensuring that these groups are adequately represented, and their concerns addressed is crucial for equitable decision-making.

VII. CONCLUSION

This paper has delved into the intricate debate surrounding the integration of equity considerations into BCA for U.S. transportation and infrastructure projects. Drawing upon the perspectives and findings of key scholars in the field, this research has illuminated the complexities, challenges, and potential pathways for incorporating equity into BCA. While significant strides have been made in recognizing the importance of equity in decision-making processes, this paper has also identified critical gaps in the literature that need to be addressed to advance the field further.

The synthesis of the literature underscores a growing acknowledgment within the academic and policy-making communities that traditional BCA, primarily focused on economic efficiency, may no longer suffice in addressing the multifaceted needs of contemporary society. This paper argues for a more holistic approach to BCA, one that balances efficiency with equity and considers the broader impacts of infrastructure projects on different population groups, particularly marginalized communities. Such an approach not only ensures fairer outcomes but also contributes to building a more equitable and just society.

However, the journey towards fully integrating equity into BCA is fraught with challenges. The lack of standardized methodologies, insufficient data on long-term impacts, under-representation of marginalized voices, and the need for a deeper integration of environmental and social justice concerns represent significant hurdles. This paper calls for continued research and dialogue in these areas, urging scholars, policymakers, and practitioners to collaborate in developing innovative methodologies and inclusive decision-making processes.

In conclusion, this paper contributes to the ongoing discourse on BCA's role in fostering equitable outcomes in transportation and infrastructure projects. It highlights the necessity of re-envisioning BCA practices to align with broader societal goals and the imperative of making informed, equitable decisions that resonate with the values of a diverse and evolving society. The insights and recommendations presented in this research offer a foundation for future studies and practical applications, paving the way towards more inclusive and responsive infrastructure planning and development.

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Pedaling toward Equity: Investigating Gender Disparities in Chicago's Bikeshare Ridership

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ABSTRACT

This study examines gender differences among bikeshare users in Chicago, focusing on a dataset of over 21 million Divvy bikeshare trips between 2013 and 2019. Using a binary regression model, the research investigates the association between gender and trip attributes. Results indicate that women tend to take longer bikeshare journeys than men. As a "dependent" or "subscriber" user, a rider is more likely to be a man. While both genders exhibit similar ridership patterns on weekdays, women show a greater tendency to use bikeshare on weekends compared to men. Peak ridership for both genders occurs between 8 a.m. and 5 p.m., suggesting recreational or weekend use. The study suggests the potential development of a more accessible and equitable bikeshare system by incentivizing weekday passes and ensuring adequate bikes and docking stations during rush hours. These findings contribute to informed decision-making, supporting initiatives to address gender gaps in Chicago's bikeshare system.

INTRODUCTION

Micromobility has received increasing popularity in recent years as a sustainable mode of transportation. It is changing user's behavior, and because of the convenience it offers, it has seen rapid growth (Department of Transportation 2021). Bikesharing has swiftly become well-established as a new mode of transportation that may increase cycling, enhance urban mobility, and increase the use of public transportation, with over 343 million trips conducted in the United States since 2010. These systems can assist communities in enhancing their sustainability, livability, and safety (NACTO 2015).

In several locations throughout the world, bikesharing is expanding quickly as a sustainable and green alternative type of transportation (Fishman 2016; O'brien, Cheshire, and Batty 2014). In the U.S., there have been more than 70 cities and college campuses with bikeshare programs since 2008, and more are expected to be added in the future. With the recent increase in bike use and bikeshare systems, numerous American cities and communities are looking at the use of bikeshare to enhance the transportation system's environmental, social, and health outcomes. The demographics of bikeshare users are a common focus for researchers and academics who are interested in bikeshare users. In addition to ethnicity and educational attainment, aspects such as gender and income in relation to underlying population averages are factors that are taken into consideration (Fishman 2016).

Equity promotes equality. Gender equality necessitates the equal enjoyment by men and women of socially valued goods, opportunities, resources, and rewards. Where gender disparity exists, women are typically excluded or disadvantaged in terms of decision-making and access to economic and social resources. Therefore, a critical aspect of promoting gender equality is the empowerment of women, with a focus on identifying and redressing power imbalances and giving women more autonomy to manage their own lives. Gender equality does not imply that men and women become identical; rather, it means that access to opportunities and life changes is neither reliant on, nor limited by, their gender ("United Nations Population Fund" 2005).

Gender gap analysis is also an important topic in urban studies and transportation (Pojani 2014). Moreover, access to bikeshare stations and use of bikeshare systems is still unevenly distributed. Gender equality in bikeshare access is one of the most significant topics that has encouraged academics in recent years to evaluate users' accessibility and travel patterns according to their gender (Javid and Sadeghvaziri 2023b; 2023a). Gender disparity in bikeshare ridership is a complex and pressing issue in many urban environments (Fishman, Washington, and Haworth 2013). According to previous studies, women are often underrepresented among bikeshare users compared to men, but the underlying reasons for this disparity have not been thoroughly investigated. In order to obtain a thorough knowledge of the issue, this study will look at several variables that might explain the gender gap in Chicago's bikeshare usage. The goal of this study is to investigate the gender disparities and travel behavior in bikeshare ridership in the city of Chicago. Two specific research questions will be addressed in this work: 1) What is the difference between women and men in terms of bikeshare trip duration? 2) What is the difference between women and men in terms of bikeshare ridership and time of the day and day of the week?

This study intends to shed light on the underlying issues and provide suggestions for developing more inclusive and equitable bikeshare systems by looking at variables impacting the ridership gender gap. Policymakers, urban planners, and bikeshare operators should develop focused policies to advance gender equity and establish an inclusive urban transportation system by recognizing possible obstacles and limitations experienced by women.

LITERATURE REVIEW

The number of analyses of bikeshare system usage is quickly growing, and many research projects employ openly accessible "big data" sets produced from docking stations (Javid and Sadeghvaziri 2023b; 2023a). Researchers are using open data to examine sociodemographic usage characteristics, assess system demand's geographical and temporal aspects, and investigate the impacts of additional important variables, such as local landscape, weather, and seasons. Using different types of data, previous studies suggest that some demographic groups—including individuals of color, families with low incomes, women, the elderly, and those with less education—are underrepresented among bikeshare users (McNeil, Broach, and Dill 2018).

Regardless of gender, many modes of transportation are intended for transporting people worldwide. However, different forms of public transport have been used unevenly among different gender groups (Sadeghvaziri 2022). In nations with low rates of general bicycle ridership, such as the UK, the U.S., and Australia, between 65% and 90% of bike trips are made by males (Fishman 2016). Furthermore, research showed that the proportion of trips made by females varied from 14% to 41%, depending on where the bikeshare stations were located. According to prior studies, women prefer cycling in traffic-free areas (Fishman 2016). These studies also show that women avoid driving in heavy traffic, prefer to utilize bikesharing services, and are less likely to use bikeshare for commuting purposes (Kaufman et al. 2015).

Hirsch et al. (2019) used a web-based panel survey to examine the equity in the use of bikeshare services. Their survey results revealed that users were disproportionately young, male, White, resided closer to the city center, and were already more likely to have or use a bicycle (Hirsch et al. 2019).

Gender gaps existed in the mobility patterns of active transportation users as well (Mitra, Yao, and Ritchie 2021). Being female decreases the likelihood of cycling (Acheampong and Siiba 2018), and males have a higher chance of commuting and traveling by bike, but a lower chance of walking (Quinn et al. 2016). Previous studies also show that women are more sensitive than men in terms of using bikeshare and weather (Bean, Pojani, and Corcoran 2021). Cyclists, particularly women, were the most likely to change their commute modes in winter (Nahal and Mitra 2018). The majority of the literature on traditional docked bikeshare systems has suggested that males are more likely to be bikeshare users (Chen, van Lierop, and Ettema 2020). Exciting potential for additional studies exists because of the lack in the body of literature regarding the analysis of gender differences in bikeshare ridership. Filling these gaps can help policymakers, urban planners, and bikeshare operators develop targeted strategies to promote gender equity in Chicago's bikeshare system and beyond. Scholars can help create a more inclusive and accessible urban transportation landscape for all genders by filling the gaps that have been discovered in previous research.

DATA AND METHODOLOGY

This study focused on Chicago as the case study. Chicago, located in the state of Illinois, is the third largest city in the U.S. (About Chicago 2022). Chicago has a population of 2,665,039 residents, of which 51.2% are female. The three largest groups in Chicago are White (45.3%), Black or African American (29.2%), and Asian (6.8%). In 2022, Chicago had 17.1% of residents living below the poverty level (U.S. Census Bureau 2022). Chicago has the second-highest percentage of commuters riding their bikes to work, with an average trip time of 23 minutes. Chicago has 303 miles of bike lanes, more than 13,000 bike racks, and 19 miles of lakefront bicycle paths (City of Chicago 2022). The Chicago bikeshare system began with efforts made by Alta Bicycle Share. After that, on June 28, 2013, Divvy launched with 750 bikes at 75 stations in Chicago. The Chicago metropolitan area's Divvy bicycle sharing program now serves the cities of Chicago and Evanston. The Chicago Department of Transportation owns the infrastructure, which Lyft has been running since 2019. Divvy has operated 16,500 bicycles and over 800 stations as of September 2021, covering 190 square miles. Figure 1 shows the Chicago city boundary, bike lanes, and the spatial distribution of Divvy bikeshare stations currently in service, which include 1,402 stations (Chicago Data Portal 2022).

Data was retrieved from the Chicago Data Portal. The data is a list of individual Divvy bikesharing trips, including the origin, destination, and timestamps for each trip. Trips are included when there is a starting and end date. Trips using a subscriber pass will include some basic demographic data (gender and age) associated with the account. The data is for the period of 2013 to 2019. Following this timeframe, Divvy bikeshare's datasets do not include demographic data (Chicago Data Portal 2022).

The initial dataset consisted of 21,242,740 trips of which 324,623 were used for this study. Trips were eliminated based on different factors and criteria utilized by previous studies (Qian and Jaller 2021; Yan et al. 2021; Tokey, Shioma, and Jamal 2022). The dataset was cleaned by excluding trips that had any of the cases shown in Table 1.

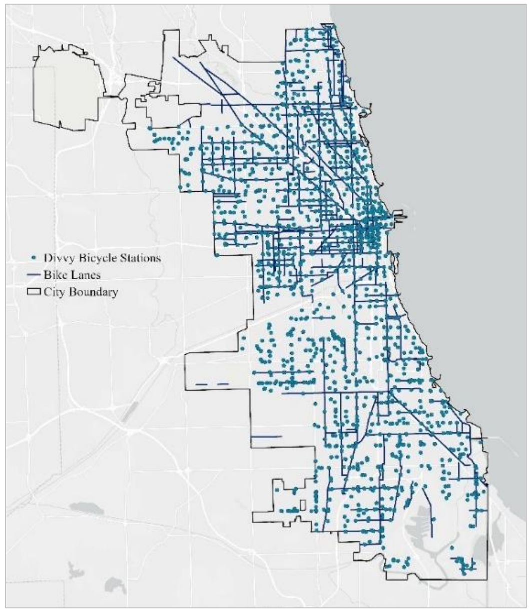


Figure 1. Bikeshare Stations and Bike Lanes in Chicago

Table 1. Criteria for Trip Removal from the Dataset

Criteria	Number of Trips removed	% of Initial Trip Dataset
Trip of less than one minute	161,660	0.76%
Trip duration more than two hours	162,963	0.77%

After the initial cleaning of the data, there were a total of 21,079,777 trips made between 2013 to 2019 in Chicago. Table 2 shows information about the final dataset, demographic, and travel factors among riders. The demographic information, such as age and gender, was collected only from users with a subscriber pass. Based on the dataset, 77.37% of the riders are subscribers. Among subscribers, only 25.13% are female. Moreover, the majority of the trips are in the 1- to 10-minute interval (42.35%).

Lastly, a binomial logistic regression model was developed using "Gender" as the dependent variable and trip information (e.g., trip duration, time of the day, etc) as independent variables. A binomial logistic regression (often referred to simply as logistic regression) was developed to predict the probability that an observation falls into one of two categories of a dichotomous dependent variable based on one or more independent variables that can be either continuous or categorical (Laerd Statistics 2023). Equation 1 shows the mathematical equation of the Binary Logistic Regression model:

$$\log(p / (1 - p)) = \beta0 + \beta1x1 + \beta2x2 + ... + \beta pxp \quad (1)$$

Where p is the probability of the outcome variable, $\beta0$ is the intercept, $\beta1$, $\beta2$, ..., βp are the coefficients associated with each predictor variable (x1, x2, ..., xp), and log is the natural logarithm. The logistic regression model is used to estimate the values of the coefficients β0, β1, β2, ..., βp based on the observed data. These coefficients indicate the direction and strength of the relationship between each predictor variable and the outcome variable. The coefficients are typically exponentiated to obtain odds ratios, which indicate the increase or decrease in the odds of the outcome variable associated with a one-unit increase in the predictor variable.

Table 2. Dataset Information

Variable	Levels	Frequency	Percentage
Year	2013	751,168	3.56%
	2014	2,439,927	11.57%
	2015	3,164,365	15.01%
	2016	3,574,618	16.96%
	2017	3,809,739	18.07%
	2018	3,564,510	16.91%
	2019	3,775,450	17.91%
Month	Jan	500,782	2.38%
	Feb	545,341	2.59%
	Mar	853,854	4.05%
	Apr	1,292,678	6.13%
	May	2,039,970	9.68%
	Jun	2,658,515	12.61%
	Jul	3,168,654	15.03%
	Aug	3,187,971	15.12%
	Sep	2,770,640	13.14%
	Oct	2,137,928	10.14%
	Nov	1,170,190	5.55%
	Dec	753,254	3.57%
Day of the Week	Sun	2,663,358	12.63%
	Mon	3,094,280	14.68%
	Tue	3,148,849	14.94%
	Wed	3,072,375	14.57%
	Thu	3,084,180	14.63%
	Fri	3,106,066	14.73%
	Sat	2,910,669	13.81%
Time of the Day	Morning (6 a.m. - 12 p.m.)	7,388,773	35.05%
	Midday (12 p.m. – 6 p.m.)	10,050,127	47.68%
	Evening (6 p.m. – 12 p.m.)	3,116,172	14.78%
	Night (12 am – 6 am)	524,705	2.49%
Trip Duration	1 to 10 minutes	8,926,291	42.35%
	10 to 20 minutes	6,926,618	32.86%
	20 to 45 minutes	4,391,548	20.83%
	45 minutes and more	835,320	3.96%
Membership Status	Subscriber	16,308,730	77.37%
	Customer	4771047	22.63%
Gender	Female	4,098,218	25.13%
	Male	12,210,512	74.87%

ANALYSIS RESULTS

Figure 2 shows the duration of the trips between women and men. The results show that the mean trip duration was about 19 minutes; the majority of trips (75.21%) were under 20 minutes. The mean trip duration for women was 14 minutes, and 12 minutes for men.

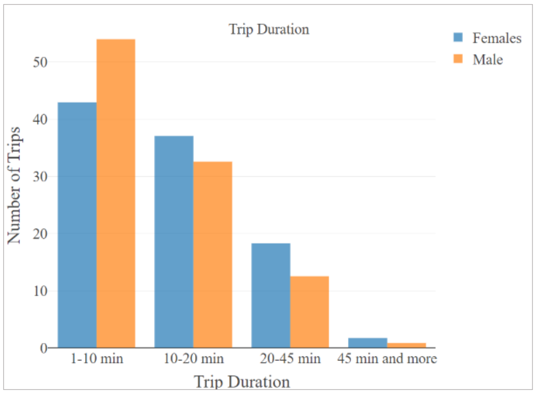


Figure 2. Bikeshare Trip Duration

Figure 3 and Figure 4 show that for both men and women, almost half of the trips (49.15%) took place mid-weekdays. On average, 46% of the trips made by women were on mid-weekdays, and this percentage was 50% for men. The highest ridership occurred on Tuesdays. Moreover, on average, women made more trips on weekends compared to men (more than 6%).

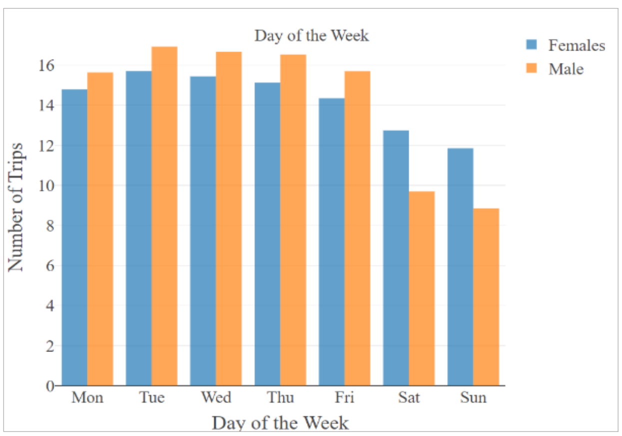


Figure 3. Day of the Week Ridership

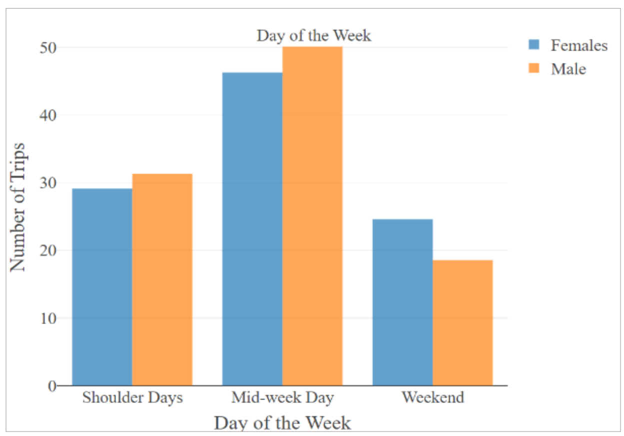
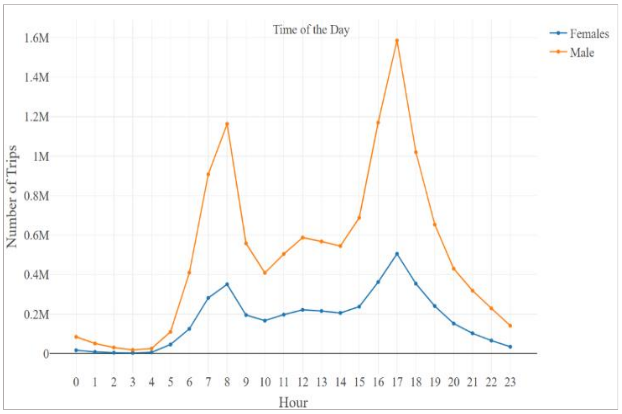


Figure 4. Weekend/Weekdays Bikeshare Ridership

Figure 5 shows that 5 p.m. and 8 a.m. had the highest usage of bikeshares in Chicago for both women and men. The pattern of usage in a day was the same for both women and men. Moreover, Figure 6 shows that middays (12 p.m. – 6 p.m.) had the highest ridership (45%) in a day.

Many studies have used statistical models to develop policies to improve traffic safety, investigate and forecast travel behavior, and pinpoint deficiencies in equity and transportation policies (Jeihani, Javid, and Sadeghvaziri 2022; Javid, Sadeghvaziri, and Jeihani 2022; Sadeghvaziri et al. 2016; Mokhtarimousavi, Azizinamini, and Hadi 2020). Therefore, this study developed a binary logistic regression to investigate the relationship between gender and travel variables. The dependent variable is Gender (Women/Men). All other variables were considered independent variables. Table 3 presents the results of the final models.



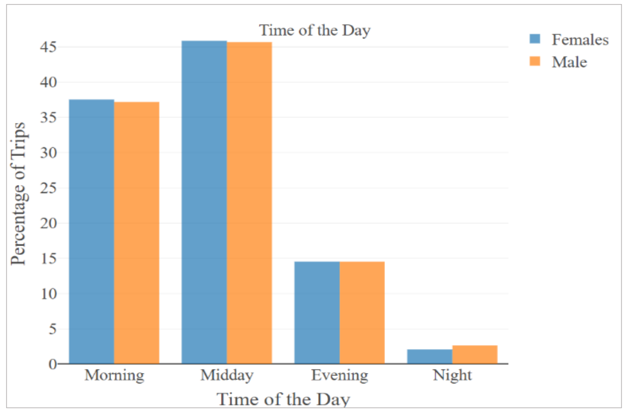


Figure 5. and Figure 6. Time of the Day Bikeshare Ridership

Table 3. Binary Logistic Regression Model Results

	Estimate	Std. Error	z value	Pr(>|z|)	Signif. Codes
(Intercept)	1.10E+00	3.73E-03	295.274	<2e-16	***
Trip Duration	-3.40E-04	9.96E-07	-341.665	<2e-16	***
User Type: Dependent	7.62E+00	3.20E+00	2.385	0.0171	*
User Type: Subscriber	1.90E-01	3.40E-03	55.89	<2e-16	***
Day of the Week: Mid-day weeks	-2.18E-01	1.14E-03	-191.626	<2e-16	***
Day of the Week: Weekends	-1.28E-01	9.48E-04	-134.8	<2e-16	***
Time of the Day: Midday	3.72E-02	1.27E-03	29.34	<2e-16	***
Time of the Day: Evening	3.20E-02	1.78E-03	18.011	<2e-16	***
Time of the Day: Night	2.86E-01	4.01E-03	71.413	<2e-16	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 (Dispersion parameter for binomial family taken to be 1) Null deviance: 18388019 on 16308729 degrees of freedom - Residual deviance: 18166843 on 16308721 degrees of freedom AIC: 18166861 - Number of Fisher Scoring iterations: 7					

DISCUSSION

The results of the study reveal significant insights that might help policymakers and bikeshare operators in their campaigns to encourage gender equality in riding. The trip duration was one of the key drivers of gender differences in bikeshare ridership. The average trip was 14 minutes for women and 12 minutes for men. These findings imply that, on average, women take longer bikeshare trips than men. The findings of the model showed that as the trip duration increased, the likelihood of a user being a man decreased significantly. This indicates that while utilizing the bikeshare system, female users are more likely to take longer trips than male riders, who overall, take shorter ones. Understanding these differences in journey length can assist planners of infrastructure better cater to the various demands of different riders.

Another significant element impacting gender disparities in bikeshare usage, according to our analysis, is user type. Notably, it was shown that being a “Dependent” or “Subscriber” user significantly increased the likelihood of a rider being male. While additional research is necessary to determine the precise reasons for this link, it may suggest that dependent users, who might be kids or people using a shared account—may have differing preferences when utilizing the bikeshare system. Moreover, interesting trends in gender differences were found that were related to the day of the week and the hour of the day. The analysis of the usage trends among days of a week reveals some similarities and some differences between men's and women’s bikeshare ridership. Similar patterns are seen in both genders, with Tuesdays seeing the highest ridership. Roughly half of the trips are made around the middle of the week. This shows that weekday bikeshare ridership is frequent and widespread across both genders. However, it is noteworthy to point out that women travel more frequently on weekends than men (more than 6%). This data may suggest that women are more likely to use bikeshare systems for recreational purposes or weekend activities, and it offers a chance for focused weekend promotions and incentives to attract more women riders. The model’s results also suggest that particularly on Saturdays and Sundays, the weekends revealed a more significant decline in the likelihood of a rider being a man as opposed to a woman. These results indicate the need to consider weekday-specific marketing and promotion efforts to engage women users further, as women's ridership may be substantially greater on weekends.

The examination of the time of day also uncovered interesting relationships. Similar trends between men and women are shown when daypart consumption habits are analyzed. The peak of the ridership is observed by both genders around 8 a.m. and 5 p.m., underlining the importance of these hours for bikeshare operators in order to satisfy demand during rush hours. The likelihood of being a male user increased throughout the middle of the day, whereas it also increased during the evening and nighttime. These patterns may reflect the various travel intentions and behaviors experienced by genders at various times of the day. The system’s inclusiveness might be improved by adjusting the bikeshare service hours and facilities to accommodate a variety of users’ demands during these times. Moreover, the months of June through October are generally considered to be the peak season for bikeshare trips in Chicago. The findings of this study have various ramifications for improving Chicago’s gender-equitable bikeshare ridership. Bikeshare operators can consider designing targeted marketing plans on the weekends to increase women’s ridership in order to enhance diversity and accessibility. More women may use bikeshare programs during weekdays if incentives are provided, including discounted weekday passes. Additionally, bikeshare providers may ensure they have enough bikes and docking stations at key locations to meet the commuting needs of both men and women during these hours by identifying the peak ridership at 5 p.m. and 8 a.m.

SUMMARY AND CONCLUSIONS

This study investigates gender discrepancies in bikeshare usage in Chicago with the goal of revealing underlying problems and offering recommendations for creating more inclusive and equitable bikeshare systems. In order to examine the association between gender and travel characteristics, this study used a dataset of over 21 million Divvy bikeshare rides between 2013 and 2019 in the City of Chicago. First, a descriptive analysis was conducted to investigate the trip duration, average trips in different months of the time period, and day of the week and time of the day for trips taken by both genders. Moreover, a binary logistic regression model was conducted to investigate the relationship between gender and travel variables.

The investigation uncovered multiple noteworthy results. Compared to men, women often take longer bikeshare trips, with average trip lengths of 14 minutes compared to 12 minutes for men. As a "Dependent" or "Subscriber" user, a rider is more likely to be a man. The months of June through October are generally considered to be the peak season for bikeshare trips in Chicago. Bikeshare usage by day of the week showed comparable patterns for both genders, with Tuesdays having the largest ridership and nearly half of the trips taking place in the middle of the week (Tuesday, Wednesday, Thursday). On weekends, however, women were more inclined to utilize bikeshare. The peak of the ridership is observed by both genders around 8 a.m. and 5 p.m., underlining the importance of these hours for bikeshare operators in order to satisfy demand during rush hours. The inclusion of the bikeshare system might be improved by modifying service hours and amenities to meet various gender-specific commuting habits throughout the day and at night.

Although this study offers insightful information, it is essential to acknowledge its limitations. It is possible that not all pertinent factors influencing gender discrepancies in bikeshare ridership were included in the dataset utilized for the study. To fully understand gender disparities, future studies might examine additional elements like trip purpose, neighborhood demographics, and bike infrastructure. The results of this study may not be directly applicable to other cities with various sociodemographic and cultural features because it specifically focused on the Chicago bikeshare program. Similar studies conducted in other metropolitan environments may offer more detailed knowledge of gender discrepancies in bikeshare use and support more specialized treatments.

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Unlocking Urban Sentiments about 15-Min City through Hashtags

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ABSTRACT

The 15-min city concept promotes active transportation and sustainable lifestyles by ensuring essential amenities within a 15-min radius from residences. While attracting significant interest, concerns about potential limitations on freedom of movement have been raised. This study aimed to gain broad insights into public perceptions and understanding of the 15-min city concept. Text mining and sentiment analysis techniques were applied to extract prevailing sentiments. The findings indicated that positive and negative sentiments were evenly distributed among the collected tweets, suggesting a balanced and diverse range of opinions. These opinions are what helps shape the policy and legislation, especially when prominent individuals with a large online presence endorse or reject a specific idea or theory. To further enhance the analysis, three different machine learning classifiers, namely naïve Bayes, logistic regression, and support vector machine, were employed to classify the sentiments expressed in the tweets. The framework developed in this study and the insights derived from the sentiment analysis offer valuable resources for policymakers and urban planners seeking to comprehend and embrace emerging urban concepts like the 15-min city.

INTRODUCTION

The 15-minute city concept, developed by Carlos Moreno, aims to create localized, healthy, equitable, and sustainable lifestyles by ensuring essential amenities within a 15-minute radius of residences. These amenities include access to groceries, healthcare, schools, parks, cultural institutions, and public transportation options, focusing on promoting active transportation through bike lanes and pedestrian pathways. Due to its potential benefits, the concept has gained immense interest from local authorities, urban planners, property professionals, and companies worldwide. However, as with any transformative idea, the 15-minute city has yet to be without its share of criticisms. Some campaigners have expressed concerns about potential limitations on freedom of movement and the challenges associated with implementing such a radical shift in urban planning. Despite these reservations, the 15-minute city holds immense promise in promoting equity, fostering stronger neighborhoods and communities, and bridging the gap between urban and suburban areas.

Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique that involves determining and extracting the emotional tone, attitude or opinion expressed in a piece of text. The goal of sentiment analysis employed in this study is to understand the subjective information conveyed by the text and classify it as positive or negative. Applications of sentiment analysis are diverse and include social media monitoring, customer feedback analysis, product reviews, and many others. It enables businesses and organizations to gain insights into public opinion, make data driven decisions, and respond effectively to customer feedback.

As the internet has evolved from traditional passive platforms to interactive spaces with user-generated content, social networks have become valuable data generation sources. Among these platforms, Twitter (now known as X; however, we used the previous name ‘Twitter’ in this paper) stands out as a prominent social media platform where millions of registered users actively share their opinions and perceptions. Leveraging knowledge discovery and data mining techniques on social networks, especially on Twitter, can prove instrumental in understanding public sentiment and reception towards emerging concepts such as the 15-minute city. Sentiment analysis and text mining on Twitter play a crucial role in gaining a comprehensive understanding of how the public responds to the 15-minute city concept. By tapping into social media data, researchers can uncover valuable insights into the level of acceptance, potential impact, and anticipated challenges associated with this innovative urban planning approach. Such knowledge can prove indispensable in informing decision-makers and policymakers, enabling them to create and implement more effective and inclusive policies for the future of urban development.

This paper’s analysis of sentiment towards the 15-minute city concept as expressed on Twitter is conducted using different machine learning models. In this study, sentiment analysis was conducted on Twitter data using the hashtag ‘#15minutescities’ to gauge public perceptions, opinions, and emotions related to this concept. This study aims to shed light on the overall sentiment landscape surrounding the 15-minute city idea by examining and interpreting the sentiments in a vast pool of user-generated content. This research contributes to understanding how the public perceives and engages with this innovative urban planning model and the potential implications it may have for the future of urban development. This study aims to examine the following two research questions:

- **Research Question 1:** How do Twitter users perceive the 15-minute city concept? What sentiments and opinions are expressed with the hashtag '#15minutescities,' and can machine learning models predict the sentiments accurately?
- **Research Question 2:** What are the potential implications of Twitter sentiment towards the 15-minute city concept for future urban development policies and decision-making?

The rest of this paper is organized as follows: the literature review section reviews of the relevant literature on the 15-minute city concept, sentiment analysis on social media platforms, and how public opinion shapes policy. The methodology section outlines the methodology employed in data collection and sentiment analysis. The results and discussion section presents our findings, offering insights into the sentiments expressed on Twitter regarding the 15-minute city. Finally, in the conclusion section, the paper summarizes the research and suggests avenues for future exploration in this dynamic and rapidly evolving field.

LITERATURE REVIEW

Several studies have assessed the 15-minute city concept. Stanley et al. (2015) examined the concept of a ’20-minute city’ proposed in Plan Melbourne to achieve sustainable Australian cities. It emphasized the importance of density, supportive public transport, and walking in creating a metropolitan area composed of smaller 20-minute cities. The paper encouraged stakeholders to contribute ideas for further development and progress in implementing the 20-minute city concept in Australia. Abdullah et al. (2022) assessed the knowledge and awareness of both planning and engineering students and practitioners regarding the concept of the 15-

minute city through a questionnaire survey in Lahore, Pakistan. Results revealed low awareness of the 15-minute city concept, with planning degree holders and attendees of more urban and transport planning seminars demonstrating higher awareness. Civil and Transportation Engineers exhibited lower awareness. Findings suggest the need to enhance awareness among professionals to promote sustainable solutions like the 15-minute city concept. Staricco (2022) developed a methodology to implement the 15-minute city concept, testing it in Turin, Italy. Results indicated that in dense European cities, the 15-minute target may not always be necessary as many services are already within walking distance, and service locations influence accessibility. The study suggests incorporating accessibility measures from regional sciences to enhance the operationalization of the 15-minute city concept. Papas et al. (2023) conducted a literature review on studies implementing the 15-minute city model in various large cities worldwide, focusing on Paris as an example. They found that this model facilitates socio-economic growth in neighborhoods and encourages citizens' participation in neighborhood redesign, emphasizing the need for a cultural change instead of just urban planning.

Much work has been done on the topic of sentiment analysis. Reddy et al. (2021) conducted sentiment analysis using methodologies such as logistic regression, evaluates web content from various sources, including social media, product reviews, and events, to classify sentiments and provide actionable insights for businesses seeking to enhance products and customer experiences in response to the growing volume of feedback data. They found that the Logistic Regression with grid search model proves to be the most effective in analyzing product reviews for polarity, showcasing the potential of natural language processing techniques to enhance business decision-making and marketing strategies. Shaziya et al. (2015) preformed sentiment analysis within the context of opinion mining, utilizing the Weka platform to classify 2000 movie reviews from the Cornell University dataset. Employing information gain for feature selection, the study demonstrates the enhanced performance of classifiers, specifically naïve bayes and SVM, through the reduction of the feature set. The research emphasizes the importance of feature selection, proposing an initial model with potential for further enhancement and exploration, particularly in preprocessing, tokenization, and the use of hybrid techniques in sentiment analysis.

How public opinion influence policy has been evaluated by several researchers. Mikael Persson (2021) evaluated the intricate a correlation between policy changes and the preferences of high socio-economic status citizens, yet the underlying mechanisms are not well-explored. This research investigates the role of political representatives in connecting public opinions and policy changes. The study confirms biases in policy responsiveness in Sweden, revealing that political representatives better represent the opinions of socioeconomically advantaged groups, raising questions about whether the underrepresentation of the less advantaged in policy changes is due to misperception, preferences, or information gaps, necessitating further research. Pacheco and Maltby (2017) examined how public opinion influenced the diffusion of Affordable Care Act (ACA) policy choices from 2010 to 2014, finding that gubernatorial ACA announcements and grant activity increased support for the ACA in nearby states, with gubernatorial announcements responding more significantly to shifts in ACA support. The results highlight the importance of considering both policy feedback and opinion learning mechanisms in understanding influence that public opinion has on policy implementation.

The literature review highlights the growing interest in the 15-minute city concept as a pathway to sustainable and connected urban environments. Studies have explored various aspects, including walkability, accessibility to essential services, and potential implementation in different cities worldwide. Several studies have also explored sentiment analysis of digital platforms and the level of influence that they have on policy decisions. Despite challenges and varying public opinion, the concept offers valuable insights for creating more liveable, resilient, and environmentally friendly cities in the future.

METHODOLOGY

After data collection, the data must be cleaned and translated to reduce noise and establish a consistent language across all samples. The cleaned text is then translated using the Google Translate API for non-English tweets (now known as posts), ensuring accuracy through a validation mechanism. Lastly, sentiment analysis and classification are carried out using machine-learning algorithms trained on a dataset of movie reviews. The algorithms, including naive Bayes, logistic regression, and support vector machine, are applied to the Twitter data to gain insights across diverse domains. The document term matrix is refined using the TF-IDF algorithm to optimize model performance and improve the accuracy of sentiment analysis.

Data Collection

This study used an opensource R package, ‘academicTwitter’ to collect the tweets associated with the hashtag ‘#15minutecities’. The data collection spanned from January 1, 2016, to May 30, 2023, and resulted in 20,773 tweets associated with the mentioned hashtag. Each of these tweets contained 31 columns providing various information, including 'tweet id,' 'text,' 'timestamp,' and 'sourcetweet_id.'

Data Preprocessing

This study showcased advanced data preprocessing techniques applied to the collected data. The dataset is strategically divided into quarters to expedite processing, ensuring efficient execution. Within these subsets, a new column with 'clean text' is processed by subsequent transformations. The following major steps are taken for the ‘clean text’ generation:

- By utilizing the regular expression pattern r'@(\w+)\s', which matches words preceded by the '@' symbol, mentions are identified. If the extracted mentions result in a list, they are joined into a single string using the 'join' method; otherwise, an empty string is assigned.
- Hashtags are extracted from the 'clean text' column and stored in a new column named 'hashtag'. The regular expression pattern r'#(\w+)\s' is employed to identify words preceded by the '#' symbol, indicating hashtags.
- In the subsequent step, regular expressions search for links within the 'text1' column. URLs beginning with 'http://' or 'https://' are captured and stored in a new column named 'links.' This process facilitates the organization and separation of links found within the text data. The researchers install and import the 'emoji' package to effectively handle emojis.
- The emoji library provides access to many emojis through Unicode standards. A function called 'extract_emojis' is defined to isolate English emojis from a given string. This function uses the emoji library to remove and store emojis from the text. This function is then applied to the 'text1' column, and the resulting emojis are stored in a new column named 'emoji.' This enables the identification and isolation of emojis within the text data.

- Other data cleaning includes removing mentions (words beginning with '@'), hashtags (words beginning with '#'), links, emojis, punctuation, and a specific prefix ('RT :').
- After cleaning the 'text_clean' column, it is further processed by replacing multiple consecutive whitespaces with a single whitespace, effectively condensing excessive whitespace within the text data. Finally, all the texts in the tweets are converted to lowercase for consistency.

Term Frequency – Inverse Document Frequency (TF-IDF)

TF-IDF is a numerical statistic that assesses the relevance of keywords to specific documents, enabling automatic identification and categorization Silge and Robinson (2017). Term frequency (TF) denotes the frequency with which a term, typically a word, appears within a document. The underlying principle assumes that terms appearing more frequently within a document are more important or relevant to that document. It is commonly calculated utilizing the following formula:

$$\mathrm{TF} = \mathrm{t} / \mathrm{d} \tag{1}$$

Where:

- t represents the number of occurrences of the term in the document.
- d represents the total number of terms in the document.

Inverse document frequency (IDF) evaluates the significance of a term across the entire collection of documents. The IDF value increases when a term is found in fewer documents throughout the collection, implying that the term offers greater informational value or distinctiveness. It is calculated as follows:

$$\mathrm{IDF} = \log(\mathrm{t} / \mathrm{D}) \tag{2}$$

Where:

- t represents the total occurrences of the term across the entire collection of documents.
- D represents the entire collection of documents. D is a set that contains all the documents being analyzed or considered.

Upon computation of both the TF and the IDF, the TF-IDF score for a given term in a document can be derived by multiplying the TF and IDF values. Higher TF-IDF scores for terms within a document indicate a heightened level of relevance or importance. In summary, TF-IDF is utilized in the models employed throughout the following sections to transform the text data into numerical features that capture the importance or relevance of terms within the documents. These TF-IDF features are then used for training the models and making predictions or classifications on new data. TF-IDF can be calculated using the equation below.

$$\mathrm{TF} - \mathrm{IDF} = \mathrm{TF} * \mathrm{IDF} \tag{3}$$

Classification Algorithms

Naïve Bayes (NB)

The Multinomial NB Classifier is a text classification method that uses probability and multinomial distribution. It converts text data into a nominal form to compute with integer values. This classifier is effective in analyzing and categorizing text by leveraging probabilities. It is a valuable tool for text classification tasks due to its probabilistic approach and efficient handling of text data. The formula used for NB models is based on Bayes' theorem, a fundamental theorem in probability theory Farisi et al. (2019). NB models are probabilistic classifiers that assume independence between the features given the class label. The formula for NB can be expressed as:

$$\mathrm{P}(\mathrm{y} \mid \mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{p}) = (\mathrm{P}(\mathrm{y}) * \mathrm{P}(\mathrm{x}_1 \mid \mathrm{y}) * \mathrm{P}(\mathrm{x}_2 \mid \mathrm{y}) * \ldots * \mathrm{P}(\mathrm{x}_\mathrm{p} \mid \mathrm{y})) / \mathrm{P}(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_\mathrm{p}) \quad (4)$$

Where:

- $P(y \mid x_1, x_2, \ldots, x_\mathrm{p})$ is the posterior probability of the class label y given the input features $x_1, x_2, \ldots, x_\mathrm{p}$.
- $P(y)$ is the prior probability of the class label y.
- $P(x_\mathrm{i} \mid y)$ is the conditional probability of feature $\mathrm{x_i}$ given the class label y.
- $P(x_1, x_2, \ldots, x_\mathrm{p})$ is the probability of the input features $x_1, x_2, \ldots, x_\mathrm{p}$ occurring together.

Logistic Regression (LR)

This experiment uses LR for classification due to its sigmoid activation and improved accuracy compared to NB algorithms Reddy et al. (2021). It is applied to binary logistic models with a dependent variable having two alternative values, represented as "0" and "1". The log-odds for the "1" value in the model are a linear combination of independent variables, which can be either binary or continuous. The corresponding likelihood for the "1" value ranges between 0 and 1, and the logistic function is used to transform log-odds into probabilities. The formula for LR can be expressed as:

$$P(y = 1 \mid X) = 1 / (1 + e\hat{} - (\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_\mathrm{p} X_\mathrm{p})) \quad (5)$$

Where:

- $P(y = 1 \mid X)$ represents the probability of the outcome variable (y) being 1 given the input features (X).
- e is the base of the natural logarithm (approximately 2.71828).
- $\beta_0, \beta_1, \beta_2, \ldots, \beta_\mathrm{p}$ are the coefficients or weights assigned to each input feature $X_1, X_2, \ldots, X_\mathrm{p}$, respectively.
- $X_1, X_2, \ldots, X_\mathrm{p}$ are the input features.

Support Vector Machine (SVM)

The SVM algorithm is employed for sentiment analysis of two pre-classified sets of tweets. SVM is a well-known supervised machine learning approach widely used for classification purposes. It has proven highly effective in various aspects of text categorization and has shown better performance than NB classifiers in many instances. The equation used for SVM is based on the concept of finding an optimal hyperplane that separates different classes in a dataset. SVM is a supervised learning algorithm for classification and regression tasks Feng et al. (2022). In the case of linearly separable classes, the formula for SVM is shown in Equation 6. The decision rule for SVM is given in Equation 7.

$$w^T * x + b = 0 \quad (6)$$

$$f(x) = sign(w^T * x + b) \quad (7)$$

Where:

- w is the weight vector perpendicular to the separating hyperplane.
- x is the input feature vector.
- b is the bias term, which determines the offset of the hyperplane from the origin.

If $f(x)$ is positive, the input sample x is classified as one class, and if f(x) is negative, it is classified as the other class. To determine the optimal hyperplane, SVM maximizes the margin (the distance between the hyperplane and the closest data points of each class). The support vectors are the data points on the margin or inside it.

Text Network Analysis

Text network analysis (TNA) is a powerful tool within text mining as it uncovers hidden trends in unstructured text data (Hunter, 2014; Kwayu et al. 2021). TNA uses nodes and edges to establish relationships between keywords within a corpus (a large, structured body of text). The nodes in this network correspond to individual keywords, while the edges represent their relationships or connections. The keywords' frequency and co-occurrence within the network are indicated by the sizes of the nodes and the edges, respectively.

RESULTS AND DISCUSSIONS

The training dataset comprises 40,000 movie reviews obtained from a modified dataset by Phadnis (2021) on IMDB reviews from Lakshmipathni (2019), each paired with a sentiment label indicating positive or negative sentiment. The dataset has intentionally been balanced, containing an equal number of positive and negative sentiment samples, with 20,000 reviews in each category. This balance ensures that sentiment analysis models trained on this data can effectively generalize both positive and negative sentiments.

Movie reviews hold considerable value for sentiment analysis tasks, particularly in analyzing sentiments in Twitter data, due to shared language patterns and sentiment expressions. Training models on movie reviews improve understanding of short texts and informal language, enhancing performance on Twitter data. Utilizing transfer learning with pre-trained models enables the adaptation of knowledge from movie reviews to Twitter data, fostering improved sentiment analysis capabilities. The movie review dataset has two columns: 'text' and 'sentiment.' The 'text' column captures the raw textual form of movie reviews, which can vary significantly in length and content. These texts authentically express diverse opinions and experiences various individuals share about the movies they have watched. The 'sentiment' column corresponds to sentiment labels, with 'pos' denoting positive sentiment and 'neg' denoting negative sentiment.

This movie review data is used to train and test models for application on the 15-minute cities dataset. The '15-minute data' is split into a 75% training and 25% test sets. This split ratio allows a significant portion of the data to be used for training sentiment analysis models. In contrast, a separate portion is utilized to evaluate their performance on unseen data. This approach aids in assessing the models' generalization capabilities and ensures reliable sentiment analysis results, even when applied to new, real-world data, such as Twitter posts. By leveraging appropriate models, such as SVM, NB, and LR, sentiment analysis models can effectively interpret sentiments expressed in textual data, including Twitter posts. Leveraging the well-balanced nature of the dataset and the chosen models, sentiment analysis provides meaningful insights into sentiments conveyed across diverse domains.

For this binary classification, this study used the following performance metrics to evaluate the model performance. Table 1 shows a breakdown of these performance metrics across the three models used in this study.

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{8}$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP}) \tag{9}$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN} \tag{10}$$

$$\text{F1} - \text{score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \tag{11}$$

Where,

- True Positive (TP) refers to the instances correctly predicted as positive by the classifier.
- True Negative (TN) represents the instances correctly predicted as negative by the classifier.
- False Positive (FP) refers to the instances predicted as positive but are negative.
- False Negative (FN) refers to the instances predicted as negative but are positive.

Table 1. Performance Metrics.

Performance Metrics	Naïve Bayes	Logistic Regression	Support Vector Machine
Accuracy	.8424	.8741	.8755
Precision	.8427	.8743	.8758
Recall	.8424	.8741	.8755
F1-score	.8424	.8741	.8755

Across all three classifiers, this study observed relatively high accuracy values (see Table 1), indicating that the models make correct predictions for a significant portion of instances in the evaluation set.

- The SVM classifier achieves the highest accuracy at 0.8755, followed closely by LR at 0.8741 and NB at 0.8424.
- In terms of precision, all three classifiers perform well. The SVM classifier achieves the highest precision of 0.8758, followed by LR at 0.8743 and NB at 0.8427. These precision scores indicate that the models have a high level of correctness when identifying positive instances.
- The recall values are also quite high for all three classifiers. The SVM classifier exhibits a recall of 0.8755, LR and NB have a recall of 0.8741. These scores indicate that the models can accurately capture a significant portion of the positive instances in the evaluation set.

- When considering the F1-score, this study observes similar values for all three classifiers. The SVM classifier, LR, and NB all have an F1-score of 0.8755. These scores suggest that the models balance minimizing FPs and capturing TPs.

Overall, the performance of the SVM classifier is consistently strong across all metrics, followed closely by LR and then NB. The SVM classifier's robust performance can be attributed to its ability to find an optimal hyperplane that maximizes the margin between classes in the feature space. LR, which uses a linear decision boundary, performs well and is particularly suitable for problems with linearly separable classes. It effectively learns the relationship between features and class labels. Although slightly lower in performance, NB relies on the assumption of independence between features. It performs well in scenarios where this assumption holds, such as text classification. The results indicate that SVM and LR classifiers tend to outperform NB in accuracy, precision, recall, and F1 score. The superior performance of SVM can be attributed to its ability to handle complex decision boundaries, while LR benefits from its simplicity and linear decision boundary assumption. Despite its simplicity and assumption of feature independence, NB still delivers reasonable performance but lags slightly behind the other two classifiers.

Training Data Influence

The performance of machine learning models heavily relies on the training data, influencing their results. Similar accuracy, recall, and F1 scores across different classifiers can occur due to various factors related to the distribution of classifications within the training set. Factors like balanced data distribution can lead to similar performance, while severe class imbalance or data representation issues can impact accurate classification. Proper preprocessing, addressing class imbalances, feature selection, and handling missing or noisy data are essential for optimal performance. Hyperparameter tuning and model selection further improve performance and enable differentiation between classifiers' capabilities.

Figure 1 shows the results of sentiment polarity analysis using SVM and LR models. It reveals a consistent shift in sentiment around 2022-2023, boosting the credibility of this observation. The convergence of results from both models strengthens the reliability of the identified sentiment shift during that period. Various factors like socio-political events, cultural changes, economic fluctuations, or technological advancements might contribute to this shift. These shifts indicate changes in the overall sentiment, reflecting how people perceive and feel about certain issues, topics, or entities. While these results don’t explain why the shift occurred, they can be used to document and understand when shifts in sentiment occurred. Future research within this subject could further identify causal relationships between these shifts and outside factors that could have contributed to the shift.

On the other hand, the NB model doesn't show a similar sentiment shift as observed in SVM and LR models from 2022-2023. This difference is likely due to inherent factors in the NB algorithm, such as its simplistic assumptions and limitations in capturing complex sentiment patterns. The NB algorithm assumes feature independence, which might not accurately reflect real-world situations, limiting its ability to capture nuanced shifts in sentiment over time. While the NB model performs slightly worse than SVM and LR models, this alone doesn't explain its failure to capture the sentiment shift. It's essential to consider the NB algorithm's predictive power and generalization limitations compared to more advanced models.

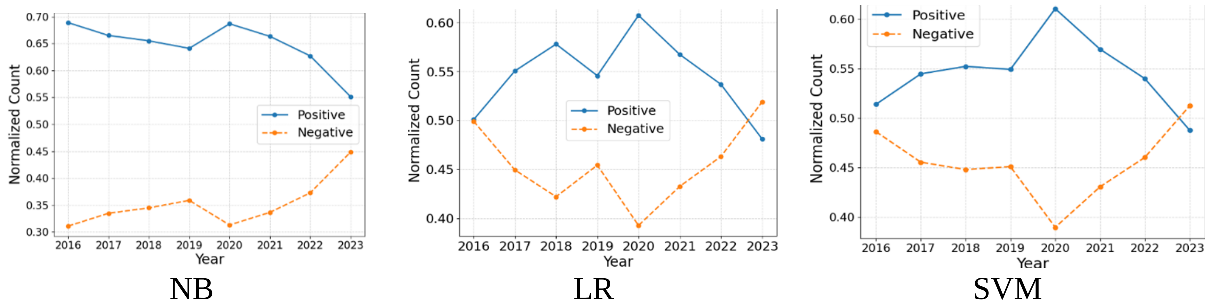


Figure 1. Normalized score by the algorithms used.

Figure 2 shows the confusion metrices for sentiment analysis across the three machine learning models, with 0 representing negative sentiment and 1 representing positive sentiment. The SVM model demonstrates a well-balanced performance with high TP and TN values, indicating its ability to classify both positive and negative sentiment instances accurately. However, it does have some misclassifications, with a moderate number of FP and FN predictions. The LR model also shows a balanced performance with high TP and TN values and exhibits slightly fewer FP and FN predictions than the SVM model, further demonstrating its effectiveness in sentiment classification. In contrast, the NB model achieves lower TP and TN values, indicating a slightly lower ability to classify both positive and negative sentiment instances accurately. It also has a higher rate of misclassifications, with a relatively higher number of FP and FN predictions. Based on the confusion matrices analysis, it can be concluded that the SVM and LR models perform better in sentiment classification than the NB model. Both models consistently demonstrate higher TP and TN values and produce fewer misclassifications (FP and FN) than the NB model.

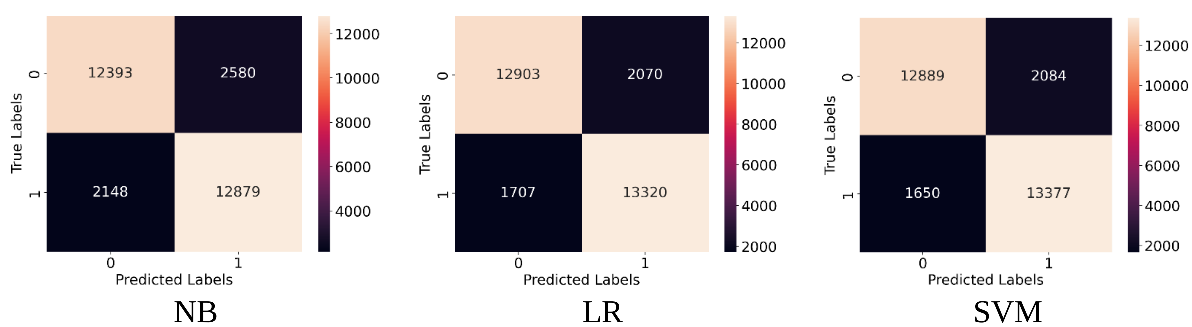
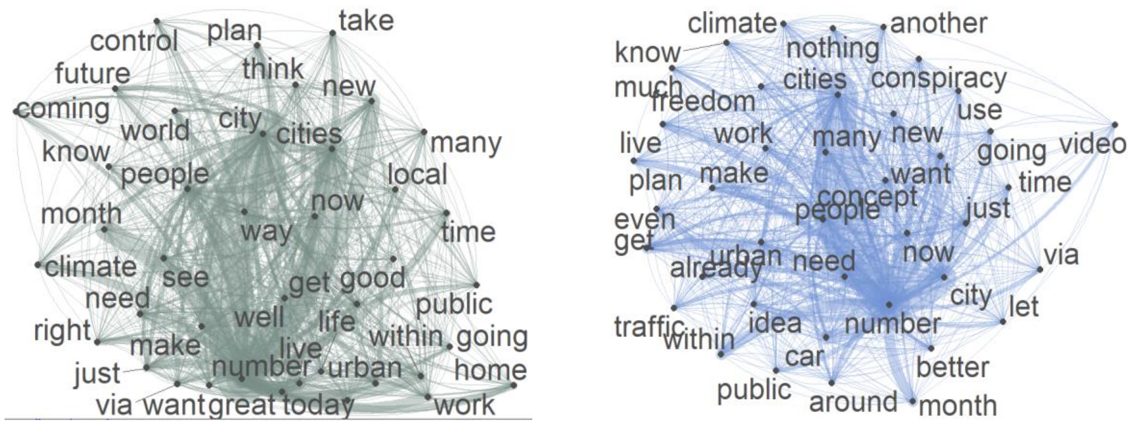


Figure 2. Confusion matrices by the used algorithms.

Figure 3 shows text networks of both positive and negative sentiments in 15-minute cities. In the positive sentiments, some significant keywords include *great*, *people*, *want*, *work*, *home*, *future*, and *plan*. Great is heavily connected with other keywords, suggesting those who view 15-minute cities in a positive light consider them to be a great concept. They also think that 15-minute cities will offer a good life with better access to both work and home, although they may require some planning for the future. For the negative sentiments, some of the main keywords include conspiracy, freedom, car, and concept, suggesting that those who view 15-minute cities in a negative light may consider the concept to be a conspiracy aiming to reduce their freedom and take away their cars.



Positive **Negative**

Figure 3. Text network of positive and negative sentiments.

CONCLUSIONS

This paper conducts a comprehensive sentiment analysis using three classifiers—SVM, LR, and NB—revealing notable sentiment shifts from 2022 to 2023. The consistent findings from SVM and LR enhance the credibility of observed patterns, emphasizing the potential applications of sentiment analysis beyond social media. Policymakers can leverage this approach to swiftly gauge public opinions on various subjects, facilitating a nuanced understanding of societal views and reactions to new ideas or theories. Understanding shifts in sentiment can allow for contextual understanding of the factors that lead consumers and members of society to hold views in any given direction. The study underscores the importance of selecting appropriate classifiers and considering factors like training data, preprocessing, and model selection for optimal sentiment analysis outcomes.

While using SVM, LR, and NB classifiers in this study demonstrates their strong performance and capabilities, it also has some limitations that should be considered. Firstly, the study's findings may lack generalizability, as the evaluation set might not fully represent all possible sentiment variations in different contexts. Given that our dataset was not labeled, we had to rely on transfer learning from movie reviews. A potential limitation with these reviews is that they tend to be longer in length than tweets. To address this, future research should focus on cross-domain evaluation, testing the classifiers on diverse datasets from various domains to ensure their applicability across different contexts. In addition, while SVM and LR models exhibit high performance, they may lack interpretability on their own, making it challenging to understand the reasons behind their predictions. Future research could focus on developing high accuracy and interpretability models to gain better insights into sentiment analysis results. Finally, investigating methods to handle noisy and mislabeled data can enhance the classifiers' performance and real-world applicability. Addressing these limitations and pursuing these future research directions will advance the field of sentiment analysis and enable its broader application in various domains.

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Fairness-Driven Multi-Objective Optimization for Evacuation Planning in Natural Disasters

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ABSTRACT

In the context of natural disasters such as earthquakes and tsunamis, efficient and equitable evacuation strategies are critical for safeguarding human lives. This paper introduces a multi-objective optimization model that seeks to minimize both the overall transportation distance for affected individuals and the average unutilized space in designated evacuation centers. The model explicitly incorporates fairness, ensuring that all residents are equally prioritized during the evacuation process. We tested the model's applicability using a real-world scenario in Seaside, Oregon, which is a vulnerable town to frequent natural hazards. The case study aims to address the specific logistical challenges associated with evacuating a population of approximately 6,000 residents under tsunami hazard. Our analysis indicates that the transportation mode and capacity are pivotal variables for achieving an effective and equitable evacuation procedure. This research extends the existing literature on disaster preparedness by emphasizing the crucial role of transportation logistics in ensuring successful and fair evacuations.

Keywords: tsunami evacuation, fairness, multi-objective optimization, Seaside, community resilience, disaster safety

INTRODUCTION

Tsunami evacuation planning represents a critical component in disaster management, particularly in coastal regions susceptible to such catastrophic events (Wang et al. 2016). The inherent unpredictability and potentially devastating impact of tsunamis necessitate efficient and effective evacuation strategies to minimize loss of life and property (Chen et al. 2022; Prayogo and Ikhsan 2020; Yavuz et al. 2020). Recent advancements in computational methods and optimization techniques have opened new avenues for enhancing evacuation plans (Prayogo and Ikhsan 2020). However, a significant challenge in this domain is balancing efficiency with fairness, ensuring that vulnerable populations are not disproportionately disadvantaged during evacuation processes (Aalami and Kattan 2020).

This paper introduces a novel approach to tsunami evacuation planning, employing multi-objective optimization to address the dual goals of evacuation efficiency and fairness. The concept of fairness in evacuation planning is multifaceted, involving equitable access to evacuation resources, uniformity in safety levels across different demographic groups, and the minimization of disparities in evacuation locations. Our methodology integrates various considerations into a cohesive optimization framework, aiming to provide a balanced evacuation plan among various evacuation points that does not favor one objective at the expense of another (Aalami and Kattan 2020; Oh et al. 2021; Vahdani et al. 2022).

The multi-objective optimization model employed in this study is based linear programming techniques. These methods are well-suited to handle the complex, often conflicting objectives inherent in evacuation planning (Forcael et al. 2014; Khalilpourazari and Pasandideh 2021). Our model is designed to be flexible, capable of accommodating various constraints and parameters specific to different coastal regions. This adaptability is crucial for the application of the model in diverse geographic and demographic settings (Gupta et al. 2022; Oregon Seismic Safety Policy Advisory Commission (OSSPAC) 2013; Wood et al. 2010). The proposed optimization model can suggest evacuation routes to optimize both transportation distance and fairness. This aspect is particularly important in the context of tsunamis, where conditions can change rapidly and unpredictably by network disruptions (Akkermans and Van Wassenhove 2018; Mostafizi et al. 2017; Ogawa et al. 2019).

Though are significant among of studies in literature where researchers from different backgrounds worked on natura hazard evacuation plan (Aalami and Kattan 2020; Aránguiz et al. 2018; Chen et al. 2022; Forcael et al. 2014; Khalilpourazari and Pasandideh 2021; Yavuz et al. 2020), there is still a gap in maintaining fairness in evacuation plans. In addition to the theoretical development of the optimization model, this paper also presents a case study to demonstrate its practical application. The case study involves a coastal region known for its high tsunami risk, providing a realistic context for evaluating the effectiveness of the proposed approach. Through analysis, we illustrate how the model can be used to generate evacuation plans that not only meet efficiency criteria but also significantly improve fairness outcomes compared to conventional methods.

OPTIMIZATION MODELING APPROACH

This section outlines a comprehensive Fairness-based Multi-objective Optimization Model (MOO) for emergency facility center location and evacuation planning. This model incorporates various sets, parameters, decision variables, and constraints to address the complexities of emergency evacuation scenarios. Here's an overview of the model components and their implications:

Sets

$\mathcal{A}$: Set of arcs/links
$\mathcal{N}$: Set of locations
$\mathcal{M}$: Set of transportation modes $\{\text{Ambulance, Car, Walk, etc.}\}$
$\mathcal{N}^{\mathrm{d}}$: Set of emergency facility centers or assembly areas $\{\text{Location 1}, \ldots, \text{Location n}\}$
$\mathcal{N}^{\mathrm{s}}$: Set of locations where people are waiting for evacuation
$\mathcal{N}^{\mathrm{o}}$: Set of locations containing no people
$\mathcal{D}$: Set of peoples' need $\{\text{Accesbility Issues, Only Evacuation, etc.}\}$

Parameters

k_{id}: Number of people waiting at location $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
b_{id}: Capacity of the emergency facility centers or assembly area $i \in \mathcal{N}^d$ for their need $d \in \mathcal{D}$
c_{ij}: Length of arc $(i,j) \in \mathcal{A}$
τ^+_{id}: Cost of having people not evacuated from location $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
τ^-_{id}: Cost of having empty space at each emergency facility center or asembly location $i \in \mathcal{N}^d$ for their need $d \in \mathcal{D}$
ρ_{id}: Cost of not meeting the minimum required service level at node $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
α_{id}: Minimum required service level at node $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
y_{ij}: Binary variable equals to 1 if the arc $(i,j) \in A$ is active after disruptions due to the natural hazard, otherwise equals to 0

Decision Variables

x_{ijmd}: The number of people transferred using arc $(i,j) \in A$ using transportation mode $m \in \mathcal{M}$ who were demanding $d \in \mathcal{D}$
ϕ^+_{id}: Positive deviation from the total percentage of people move than the actual supply of people from the area $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
ϕ^-_{id}: Negative deviation from the total percentage of people move than the actual number of people from the area $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
s^+_{id}: Excessive number of people at each supply node $i \in \mathcal{N}^s$ for their need $d \in \mathcal{D}$
s^-_{id}: Empty space at each emergency facility center or assembly area $i \in \mathcal{N}^d$ for their need $d \in \mathcal{D}$
δ_{id}: Binary variable equals to 1 if the node $i \in \mathcal{N}^s$ did not get the minimum required service level, otherwise equal to 0 for their need $d \in \mathcal{D}$
γ_d: Total percentage of extra people in the evacuaion points with their need $d \in \mathcal{D}$

Fairness-based Multi-objective Optimization Model (MOO)

The optimization problem for emergency facility center location and hazard evacuation planning involves multiple objectives, which must be considered simultaneously to find the best solution. The first objective function (OF1) seeks to minimize the total cost/distance of all the people to move from their location to assembly points. It consists of four terms: the first term represents the transportation cost/distance, the second term represents the cost of having excessive demand, the third term represents the cost of unmet demand, and the fourth term represents the cost of not meeting the minimum required service level. The second objective function (OF2) aims to balance the spatial distribution of the people to the emergency facility centers or assembly areas.

$$Minimize\ OF1 = \sum_{m\in\mathcal{M}}\sum_{d\in\mathcal{D}}\sum_{(i,j)\in\mathcal{A}} x_{ijmd}\, c_{ij} + \sum_{t\in\mathcal{T}}\sum_{d\in\mathcal{D}}\sum_{i\,\in\,\mathcal{N}^d} s_{id}^{+}\tau_{id}^{+} + \sum_{d\in\mathcal{D}}\sum_{i\,\in\,\mathcal{N}^s} s_{id}^{-}\tau_{id}^{-} + \sum_{d\in\mathcal{D}}\sum_{i\,\in\,\mathcal{N}^s} \rho_{id}\,\delta_{id} \tag{1}$$

$$Minimize\ OF2 = \frac{\sum_{i\,\in D}\sum_{i\,\in\,\mathcal{N}^d}(\phi_{id}^{+} + \phi_{id}^{-})}{|\,\mathcal{N}^s\,|} \tag{2}$$

The optimization model is subject to several constraints that ensure the model's feasibility and consistency with the real-world problem. Equations (3 – 5) in the optimization model are the flow balance constraint ensures the balanced flow of evacuee through the transportation network.

$$\sum_{m\in\mathcal{M}}\sum_{j:(i,j)\in\mathcal{A}} x_{ijmd} - \sum_{m\in\mathcal{M}}\sum_{j:(j,i)\in\mathcal{A}} x_{jimd} = b_{id} + s_{id}^{-}, \qquad \forall\, i \in \mathcal{N}^d, \qquad \forall d \in \mathcal{D} \tag{3}$$

$$\sum_{m\in\mathcal{M}}\sum_{j:(i,j)\in\mathcal{A}} x_{ijmd} - \sum_{m\in\mathcal{M}}\sum_{j:(j,i)\in\mathcal{A}} x_{jimd} = k_{id} - s_{id}^{+}, \qquad \forall\, i \in \mathcal{N}^s, \qquad \forall d \in \mathcal{D} \tag{4}$$

$$\sum_{m\in\mathcal{M}}\sum_{j:(i,j)\in\mathcal{A}} x_{ijmd} - \sum_{m\in\mathcal{M}}\sum_{j:(j,i)\in\mathcal{A}} x_{jimd} = 0, \qquad \forall\, i \in \mathcal{N}^o, \qquad \forall d \in \mathcal{D} \tag{5}$$

Constraints (6) ensures that the number of people moving (x_{ijmd}) through each arc in the network is limited by the maximum capacity (u_{ij}) of that arc and the arc functionality (y_{ij}) after disruptions due to the impact of natural hazard.

$$\sum_{m\in\mathcal{M}}\sum_{d\in\mathcal{D}} x_{ijmd} \leq u_{ij}\, y_{ij}, \qquad \forall\,(i,j) \in \mathcal{A} \tag{6}$$

Constraints (7) are formulated to ensure that all emergency facility centers, and assembly areas will receive at least the minimum required service level (α_{id}).

$$\sum_{m\in\mathcal{M}}\sum_{j:(i,j)\in\mathcal{A}} x_{ijmd} - \sum_{m\in\mathcal{M}}\sum_{j:(j,i)\in\mathcal{A}} x_{jimd} \geq k_{id}(1 - \delta_{id})\alpha_{id}, \qquad \forall\, i \in \mathcal{N}^s, \forall d \in \mathcal{D} \tag{7}$$

According to Equation (7), the total percentage of having people at the disaster impacted location (γ_d) is equal to the sum of extra non evacuated people in each affected location (s_{id}^{+}) divided by the total number of people for all type of evacuees' demand (k_{ik}).

$$\frac{\sum_{i\,\in\,\mathcal{N}^d} s_{id}^{+}}{\sum_{i\,\in\,\mathcal{N}^d} k_{id}} = \gamma_d, \qquad \forall\, i\ \in \mathcal{N}^s, \qquad \forall d \in \mathcal{D} \tag{8}$$

Equation (9) is developed to calculate the absolute deviation in which (ϕ^{+}_{id}) and (ϕ^{-}_{id}) represent the positive and negative deviations from the total percentage of non-evacuated people.

$$\frac{s^{+}_{id}}{k_{id}} - \gamma_d + \phi^{-}_{id} - \phi^{+}_{id} = 0, \qquad \forall\, i \in \mathcal{N}^s, \qquad \forall d \in \mathcal{D} \tag{9}$$

Constraints (10 – 16) present the domain of the decision variables.

$$x_{ijdm} \in \mathbb{Z}^{\geq 0}, \qquad \forall\, (i,j) \in \mathcal{A}, \qquad \forall d \in \mathcal{D}, \qquad \forall m \in \mathcal{M} \tag{10}$$

$$s^{+}_{id} \geq 0, \qquad \forall\, i \in \mathcal{N}^{s}, \qquad \forall d \in \mathcal{D} \tag{11}$$

$$s^{-}_{id} \geq 0, \qquad \forall\, i \in \mathcal{N}^{d}, \qquad \forall d \in \mathcal{D} \tag{12}$$

$$\phi^{+}_{id} \geq 0, \qquad \forall\, i \in \mathcal{N}^{d}, \qquad \forall d \in \mathcal{D} \tag{13}$$

$$\phi^{-}_{id} \geq 0, \qquad \forall\, i \in \mathcal{N}^{d}, \qquad \forall d \in \mathcal{D} \tag{14}$$

$$\gamma \geq 0 \tag{15}$$

$$\delta_{id} \in \{0,1\}, \qquad \forall\, i \in \mathcal{N}^{s}, \qquad \forall d \in \mathcal{D} \tag{16}$$

ILLUSTRATIVE EXAMPLE: SEASIDE, OREGON

Seaside, Oregon, is a popular coastal city that attracts millions of visitors each year. However, like many coastal communities, Seaside is vulnerable to tsunamis, and city officials have implemented a comprehensive evacuation plan to ensure the safety of residents and visitors in the event of a disaster (Cox et al. 2022; Pal et al. 2022; Park et al. 2017). The Seaside tsunami evacuation plan includes designated evacuation routes, evacuation maps, and public education campaigns to ensure that residents and visitors are aware of the risks and how to evacuate safely. The plan also includes the identification of assembly areas and emergency facility centers, such as schools and parks, that can provide shelter and emergency services in the event of a disaster. Moreover, Seaside has collaborated with neighboring communities and local, state, and federal agencies to develop a coordinated response plan that ensures effective communication and resource allocation during an emergency. This collaboration has included the development of mutual aid agreements, joint training exercises, and the establishment of a regional emergency operations center to coordinate responses across jurisdictions (Gupta 2022; Gupta et al. 2024; Kameshwar et al. 2019; Sanderson et al. 2021; Wang et al. 2018).

There are eight designated assembly areas situated beyond the inundation zone, a crucial detail for ensuring the safety of evacuees (Mostafizi et al. 2017). The infrastructure of Seaside includes a single hospital and one fire station, a reflection of its small population size and the essential services available during an emergency(Kameshwar et al. 2019). Notably, the accessibility to these critical amenities is contingent on the functionality of 13 bridges, which connect the city's three sections divided by a river and a creek, indicating the importance of these bridges in the evacuation process (Cox et al. 2022; Kameshwar et al. 2019).

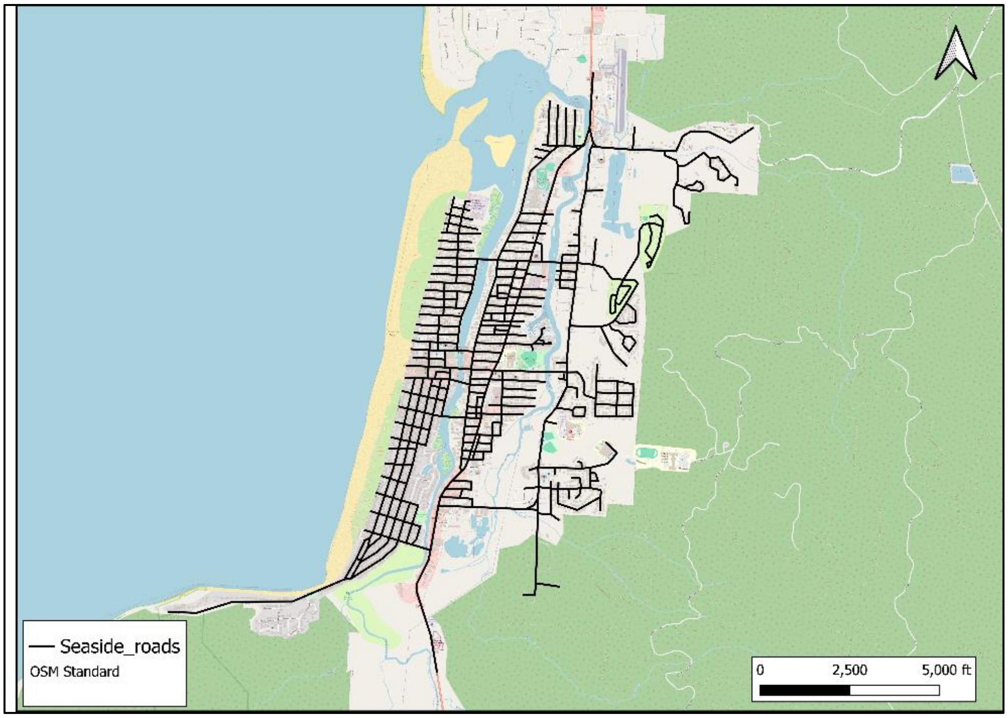

Figure 1: Transportation Network of Seaside, Oregon

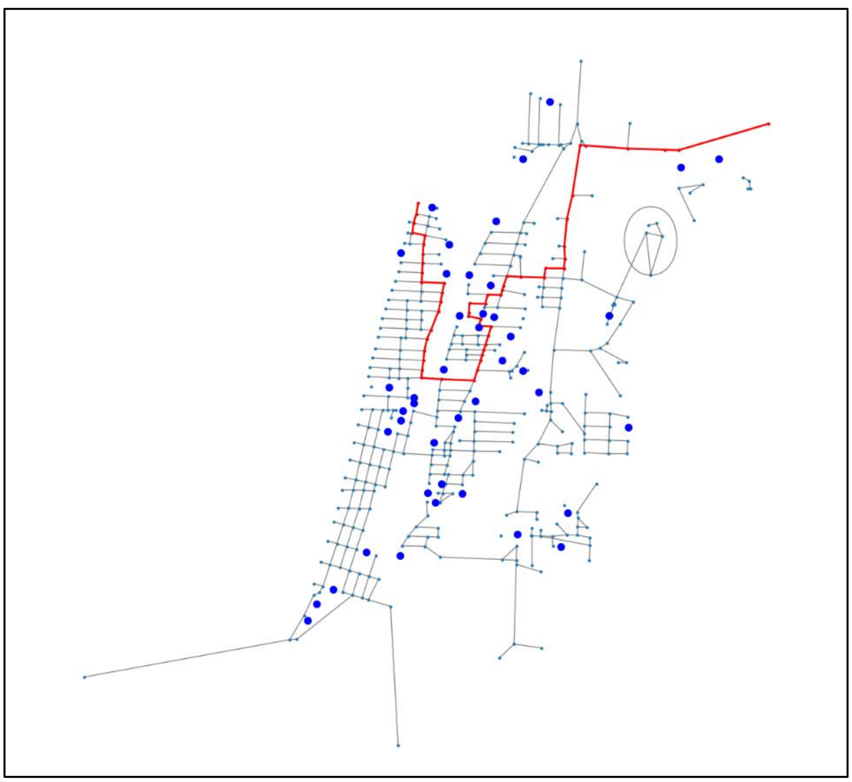

Figure 2: Example disruption scenarios (blue dots present disrupted node, red line present evacuation route)

RESULTS AND DISCUSSION

In the current study, we investigated the optimization of evacuation routes during a tsunami event across a range of scenarios involving varying degrees of infrastructure disruption. To this end, we modeled three distinct scenarios to evaluate the effectiveness of the evacuation routes, as delineated in Figure 2. Initially, the optimization model was applied under a no-disruption condition to establish a baseline for optimal routing prior to the tsunami impact. The findings from this baseline scenario indicate that the success of evacuation specifically, the number of evacuees reaching safety is closely tied to the capacity of the utilized evacuation routes.

Subsequent analyses introduced random disruptions, simulating the immediate effects of a tsunami's impact, as depicted in Figure 2(b). This scenario aimed to reflect the unpredictability of route availability during such a disaster. Finally, the model underwent validation through a sequential disruption scenario, illustrated in Figure 2(c), which aligns more closely with the progressive nature of a tsunami's impact on a community's infrastructure. Figure 3 presents how capacity of each link is impacting the number of people to be evacuated during tsunami.

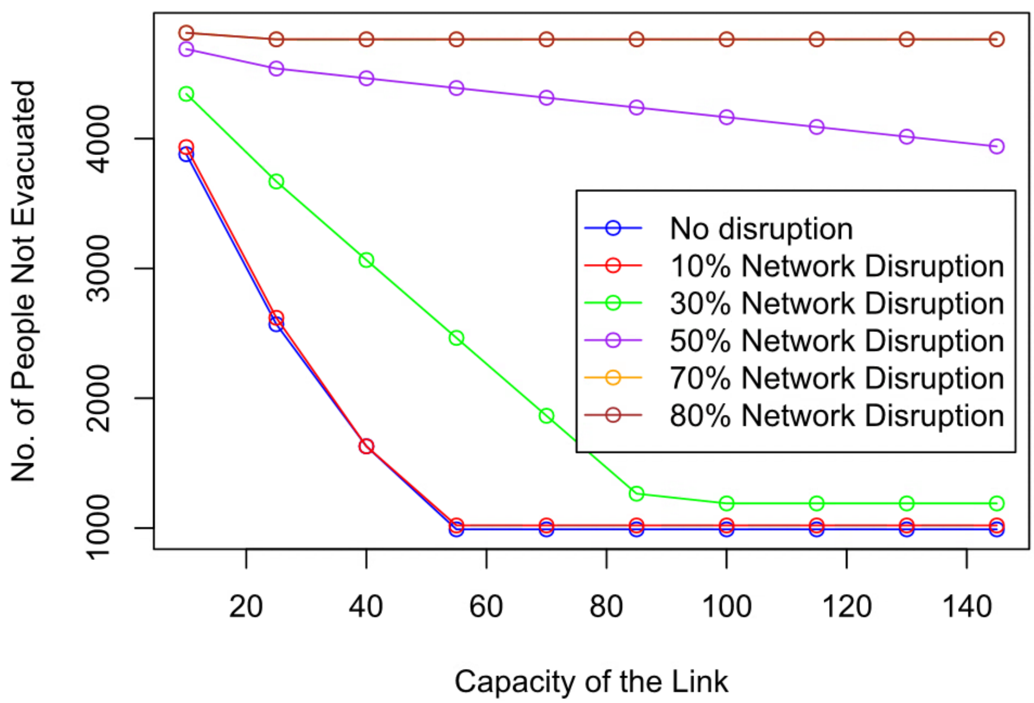

Figure 3: Impact on capacity of the links in evacuation

In this part of the study, we also examined the relationship between the first objective function, which focuses on minimizing the overall distance that evacuees have to travel, and the second objective of minimizing the total average deviation of evacuating people in the safe evacuation assembly locations. To analyze this relationship, we used the ε-method to run the model with both objectives and construct the Pareto frontier. The graph in Figure 3 presents the results of a multi-objective optimization using the epsilon constraint method, showing the relationship between two conflicting objectives: cost (OF1) and deviation (OF2). The downward trend suggests that as we accept a higher average deviation, which could be related to the fairness or distribution of resources in the evacuation plan, the total cost associated with the evacuation decreases. This result is typical in multi-objective optimization where improving one objective may lead to a compromise in the other, and the epsilon constraint method allows for exploring the extent of these trade-offs.

Table 1 illustrates that incorporating fairness into tsunami evacuation planning significantly improves outcomes, especially at lower service levels. This trend highlights the importance of fairness in enhancing evacuation efficiency, demonstrating up to 61.66% improvement in scenarios with fairness compared to those without.

Table 1: Comparison of Number of Risky Locations with and without Considering Fairness

Minimum Service Level	With Fairness	Without Fairness	Percentage Improvement
40%	189	493	61.66%
50%	189	493	61.66%
60%	205	493	58.42%
70%	220	493	55.38%
80%	284	493	42.39%
90%	397	493	19.47%
100%	415	493	15.82%

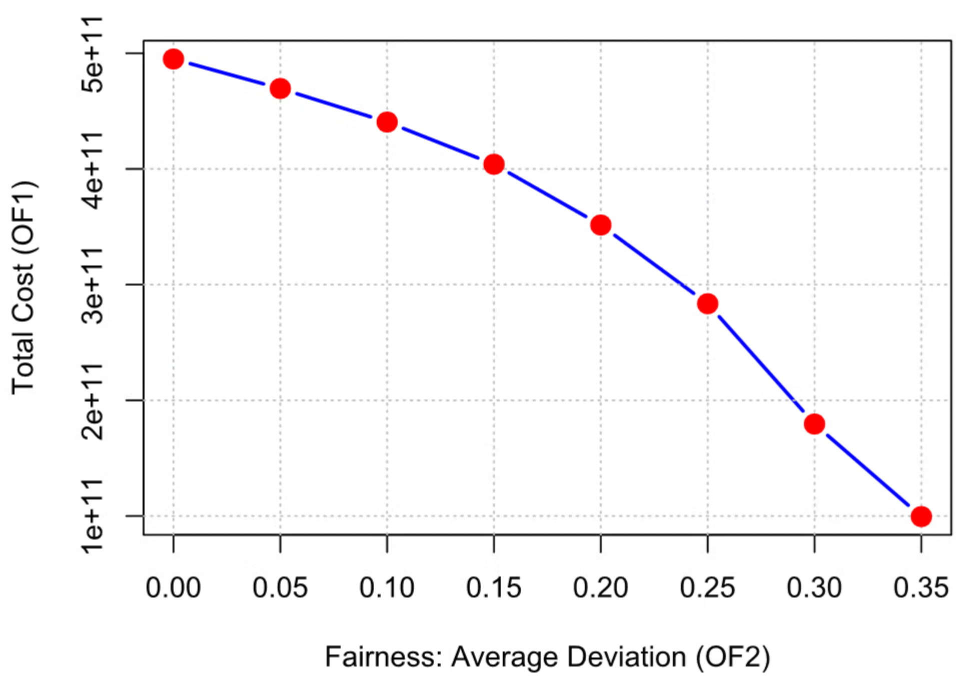

Figure 4: Pareto Frontier after Solving the Multi-objective Optimization Problem

CONCLUSIONS

In conclusion, this research has demonstrated that mathematical modeling is a critical tool in the design of tsunami evacuation plans, providing a means to identify optimal evacuation routes.

The balance between minimizing the number of individuals who are not evacuated and reducing the total distance traveled is crucial. Additionally, by integrating the concept of fairness into evacuation planning, the study has laid the groundwork for more equitable disaster response strategies. The implementation of these models can be adapted for diverse locations, showcasing their versatility and potential for widespread application.

Looking ahead, future work will aim to enhance the predictive power and responsiveness of evacuation models by incorporating real-time traffic data and addressing potential road blockages. An analysis of the temporal variations in supply and demand of evacuation nodes will be essential in preempting bottlenecks. Furthermore, as population dynamics shift, particularly in peak seasons, the development of additional shelters and the expansion of evacuation infrastructure will be imperative. Advancing fairness metrics and their integration into policy will also be key areas of focus, ensuring that the insights from mathematical models translate into effective and actionable evacuation guidelines.

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DECLARATION OF COMPETING INTEREST

Authors have no conflict of interest to declare.

DATA AVAILABILITY

Data will be made available on request.

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Risk Assessment Study for Mega Tunnel in Fault Zone of the Lesser Himalayas Using Finite Element Analysis

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ABSTRACT

Mechanized tunneling technology using a tunnel boring machine (TBM) has a great space in the modern era as it provides a safe and workable environment for the working crew and a high advance rate in favorable geologic conditions. Despite being a good solution in the favorable ground scenario, it will create a challenging situation for the weak and fragile rock masses. Himalayan mountain ranges are the most unstable region in the world, and seeking the researcher's attention for proposing a suitable methodology for successful tunneling operations using TBM. Complex geology, tectonically intricate zones, squeezing ground, faults, and ingress of water are some of the inevitable challenges in this region. The selection of appropriate TBM machines and other pressure parameters is a significant task. Keeping all in view, this research work proposed the study approach in the assessment of geo-risk evolved in TBM tunneling. A finite element-based program using Midas GTS Nx was used for the three-dimensional analysis of the mega tunnel. Mega tunnel refers to a large dimensional artificial passageway as an underground structure beyond 10 m in diameter. Soft computing models were prepared considering actual ground conditions and fault characteristics. Maximum vertical displacement of the surface considering plastic region up to three times of tunnel diameter (3D) was observed along with the crown settlement. Specification of single shield machine was considered as per literature at initial analysis. It was found that applied machine parameters were inadequate at the actual fault zone and led to excessive displacement of the ground, which may lead to blocking and jamming of the particular machine. The application of a combination of drilling thrust and cutter head torque provides a workable solution to avoid the above-mentioned risk. This research work anticipates a viable solution in the application of machine pressure parameters and provides insight for decision-making in the practical condition of the Lesser Himalayan region.

KEYWORDS: Fault zone, Risk assessment, TBM Tunnelling, Drilling thrust, Cutterhead torque

1. INTRODUCTION

Modern transport and infrastructure development depend significantly on the development of tunnels due to their ability to provide effective communication through difficult terrain. Mega tunnel, which is a larger diameter Tunnel than 10 m diameter [6,11] construction, poses special engineering challenges in areas like the Lesser Himalayas, which are known for their rugged topography as well as intricate geology. Compared to conventional drilling and blasting techniques, the introduction of Tunnel Boring Machines (TBMs) has revolutionized tunneling operations by allowing for faster excavation rates and less environmental impact. However, there is a chance that the interaction of TBMs with the Himalayan region's geology will affect the tunnels' structural stability. To ensure the security and longevity of mega tunnels in the Lesser

Himalayan region, which is noted for its seismic activity, steep slopes, and various rock formations, it is essential to have an in-depth understanding of the manner in which TBM-induced factors interact with the regional geology. The main objective of this risk assessment is to look into potential TBM impacts on the Mega Tunnel's structural stability in this difficult geological setting. Geologically speaking, the Lesser Himalayan region is complicated, with a mixture of sedimentary, metamorphic, and igneous rock formations. Tunnel designing and construction are complicated by the presence of fault lines, sheared zones, and varying rock strengths. A full understanding of how tunneling activities, particularly those utilizing TBMs, may affect the integrity of the tunnel construction is also necessary given the area's vulnerability to seismic disturbances. During excavation, tunnel boring machines produce a number of factors, such as ground settlement, vibration, stress redistribution, and pore pressure variations. These variables may have an impact on the stability of the tunnel lining and the surrounding rock mass. For the purpose of foreseeing possible dangers and developing suitable support systems, it is essential to comprehend the magnitudes and propagation patterns of these effects.

To ensure the safety of both tunnel users and the surrounding area, the structural integrity of a Mega Tunnel must be ensured at all costs. Failures or deformations in tunnel structures can result in expensive repairs, lost productivity, and potentially put lives in danger. This study seeks to shed light on potential risks connected to TBM operations and serve as a roadmap for the creation of mitigating measures. This research study aims to examine how TBM-induced parameters such as cutter head torque and thrust offered by the cylinders of the machine provide structural stability of the Mega Tunnel in accordance with risk minimization in the Lesser Himalayan region. It also benefited in avoiding TBM blocking/ Jamming in particular geology

2. RESEARCH SIGNIFICANCE

The results of this evaluation will advance our understanding of tunneling operations in difficult geological settings. The knowledge gathered can help engineers and decision-makers in the pre-planning phase of any project to ensure safe and dependable transportation infrastructure. Informing the torque and thrust computation and design to avoid TBM jamming/blocking while constructing Mega Tunnels in similar environments around the world. In conclusion, the Lesser Himalayan region's complicated geology and seismic activity make the evaluation of TBM-induced parameters on the structural stability of a Mega Tunnel extremely important. Engineers can advance sustainable infrastructure development in difficult terrains by improving the safety and durability of tunnel projects by thoroughly comprehending these relationships.

3. LITERATURE REVIEW

[1], In this study, a database of 262 different types of TBMs are statistically analyzed, and the correlations between the TBM diameter and installed thrust capacity, installed cutter head torque capacity, total TBM weight (machine + backup), a number of disc cutters, and maximum cutter head rotational speed are examined. Despite the strength of some of the ties, others are weak or moderate. For general/preliminary purposes, it is feasible to establish general trends and estimations for all TBM kinds. [2], TBM tunneling in the treacherous Himalayan terrain has not been promising. Only one of the four projects' planned HRT lengths was successfully built using TBM. The confidence and morale of engineers will undoubtedly increase with more triumphs of this nature. The timely completion of the projects depends on TBM's success. [4], deep tunneling

is extremely risky due to stress-induced strain burst and shear zone type fault sliding rock rupture. In a geologically and geomechanically heterogeneous setting, careful excavation is necessary. In addition to posing a serious risk to worker safety, rock bursts significantly slow the tunneling process. Failure scenarios must be foreseen in advance for excavation stability in order to reduce losses from rock bursting. Unseen and delicate shear and fault zones should be thoroughly investigated and assessed during the project's design and construction phases. A thorough characterization of the rock mass is necessary in such varied situations. [5], Poor ground conditions, significant water seepage, sinking ground, the collapse of existing ground structures, squeezing and swelling ground, segment cracks, and TBM jamming have all been associated with TBM risks.

The risk can be controlled through ground inspection, identifying the risk zone, close monitoring while tunneling, and appropriate rectification techniques. [7], the tunneling process may be modeled using the DEM technique, and the results show high agreement with those obtained using the EPB machine. The numerical outcomes demonstrate how ground characteristics and overburden affect the magnitude of torque and thrust. Torque and thrust rise as ground strength and overburden increase. [10], A crucial challenge is deciding on reaction plans to mitigate the dangers involved with TBM tunneling projects in challenging ground conditions. In order to detect, assess, and minimize key risk variables in challenging ground conditions in TBM tunneling projects, a new risk management method was provided in this research. This study uses risk analysis to objectively investigate the origins, effects, and relationships of project hazards and offers preventive and protective actions. Five types of potential risks were identified: ground deformation exceeding the TBM design allowance, rock bursting, poor TBM advance rate, installation of the rock support taking too long, and decreased cutter cuttability. [6], the tunneling process may be modeled using the DEM technique, and the results show high agreement with those obtained using the EPB machine. The numerical outcomes demonstrate how ground characteristics and overburden affect the magnitude of torque and thrust. Torque and thrust rise as ground strength and overburden increase. For overburden simulations, this relationship is linear with a significant regression. [9], optimistic pressure parameters of the TBM are important to evaluate for better face stability of Mega Tunnel. These pressure values allow the tunnel to be at a shallow depth and provide stability to the tunnel face.

In summary, the project TBM-driven Mega Tunnel faces many challenges at the planning and construction stage. This study would help to understand the measures to be applied at the planning stage of such a project for success in the Himalayan Region.

4. RESEARCH METHODOLOGY

The assessment was based on numerical modeling in correlation with field study data. Numerical simulations will be employed to predict the ground movement and ground collapse rate at applied cutter head torque and machine thrust and their implications for structural stability.

The research methodology adopted for the study is proposed as per the flowchart (Figure 1)

5. STUDY-SPECIFIC AREA

The selected study area is a key project in India. This project will improve connectivity, boost the local economy, and promote tourism. A significant component of the alignments that cross deep gorges and valleys include the Ganga and Alaknanda River valleys. The chosen tunnel site for data collection is in the northern Indian state (Figure 2). The alignment of the project passes through hazardous, difficult terrain. The Garhwal group, which comprises the majority of the Garhwal Lesser Himalayas, is where the project is situated. It is made up of a substantial sequence of mafic meta-volcanic and carbonate rocks that are contemporaneous with quartzite-based low-grade sediments that stretch from Nepal to the Tonnes Valley in the west to Himachal Pradesh and beyond. Its borders are the Main Central Thrust in the North and the Main Boundary Fault in the South. The Lesser Himalayan band is one of the structurally complex litho-tectonic units of the Himalayas. The Meso-Proterozoic-aged Garhwal Group, which is exposed from, overthrusts the Jaunsar Group, which is overthrust by the North Almora Thrust. The Garhwal Group is composed of formations known as Agast-muni, Rautgara, Pithoragarh, Nagnithak, and Berinag. The principal lithologies of the Rautgara, Berinag, and Nagnithak Formations include quartzite, metavolcanic, and basic intrusive, whereas the Pithoragarh Formation primarily consists of dolomite with slate. The Agast-muni Formation, which contains the metamorphosed succession of schist, schistose quartzites, and thin bands of dolomite, is thought to be the foundation of the Garhwal Group. The Mandakini valley is where it is mainly exposed. The seismogenic sources nearest to the project region are the Main center thrust, Main Boundary Fault, and North Almora thrust. The project area is seismically active and is situated in zone IV/V as a result of several earthquakes that have been registered in this region.

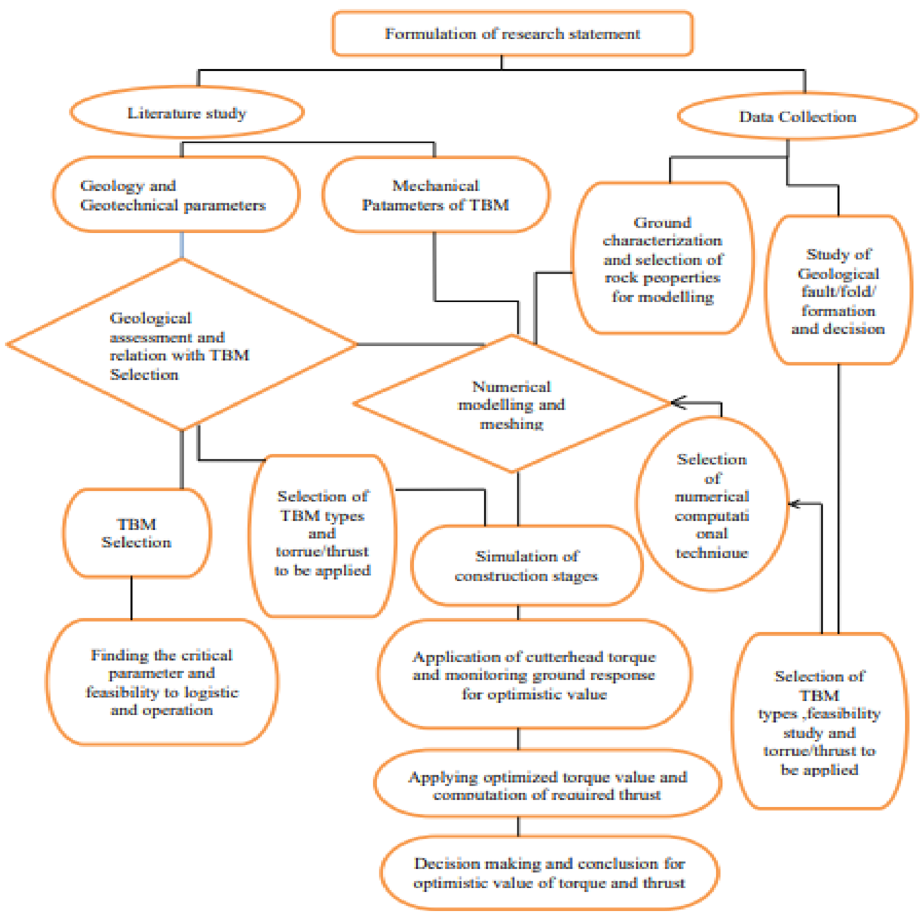

Figure 1: Research methodology flowchart

Figure 2: Alignment view of selected study location (Google Earth)

6. DATA COLLECTION

Data were gathered from an active site in the Indian state of Uttarakhand. Lesser Himalaya encompasses this region. The specific area chosen for the study features a high overburden, a fault zone, and a rock formation change (Figure 3, Figure 4). Single Shield TBM was chosen based on machine study, its viability for specific geology, and its logistical point of view, considering this crucial condition for determining needed thrust and torque estimation.

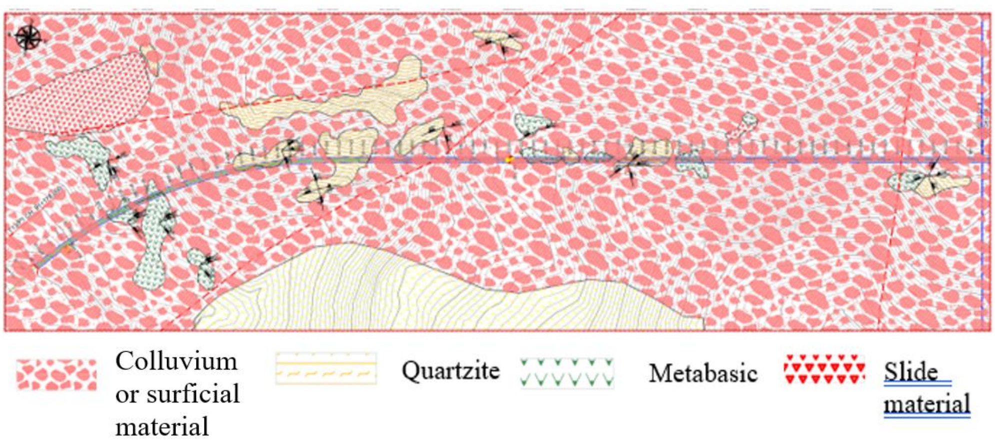

Figure 3: Geological plan of the selected tunnel alignment

7. GROUND CHARACTERIZATION AND ROCK MASS PROPERTIES AT THE SELECTED LOCATION

A particular segment considered a critical section contains two types of rock formation (Figure 5, Table 1), according to geological and geotechnical examination through a chosen alignment. It was primarily fractured and crushed quartzite in the preceding profile, but it abruptly transforms into a heavily crushed and broken rock mass with highly weathered Phyllites. For a detailed discussion of the rock qualities and ground types, see Table 1 and the Austrian code ONORM B2203/1994.

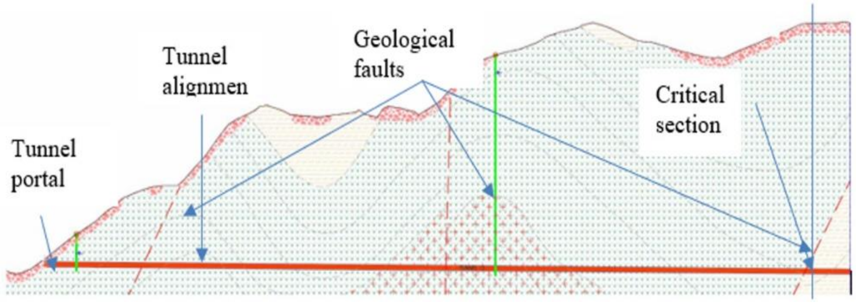

Figure 4: L-section of selected tunnel alignment and marked critical section

Figure 5: Rock Formation at the selected location.

Table 1: Rock properties at selected location

Sr.no.	Rock type	Overburden	UCS	GSI	RMR	Ko	ICE	Stress behavior of rock
1	Metabasic rock	369	40	30	35	1.5	3.56	Mostly Yeilding
2	Intensely fractured and crushed Quartzite	369	25	30	35	1.5	2.32	Mostly Yeilding

8. MODELLING AND DATA ANALYSIS

Finite element analysis was chosen as the preferred computational technique since the RMR of the rock mass of the chosen segment is less than 65[5]. The Midas GTS nx computational program is used to perform detailed engineering analysis [5,8,9]. The analysis's procedure is shown in (Figure 6)

The feasibility study was initially conducted for several tunnel diameters, ranging from 10 to 16 m at intervals of 2 m. Geological stress-strain trajectories in a specific segment considering the single shield TBM were studied to determine the size. It was optimized to a 12 m diameter tunnel with less crown displacement in the chosen segment. Continuum was used as a 3D model (D=tunnel diameter). The preparation of the geometry and the analysis advancement followed the flowchart.

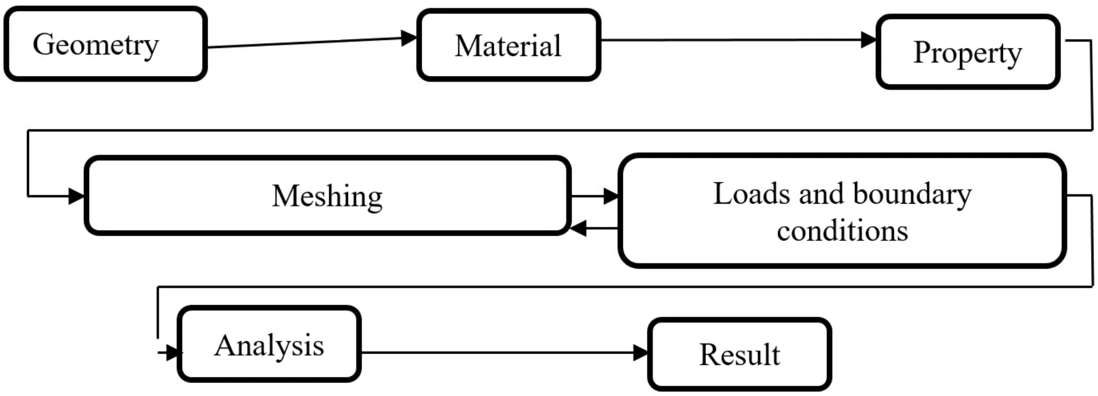

Figure 6. Workflow of Analysis

The cutter head torque was applied from 8000 kN.m to 20000 kN.m at an interval of 20000 kN.m after modeling and meshing it with actual rock attributes. The ground's collapse rate was seen to be at a minimum and was steadily reduced to minimize it. It was noted that the ground exhibits the lowest rate of collapse between 10000 and 14000 kN.m. and will continue until 15000 kN.m. Still, the conduct of the ground must be controlled to prevent collapse, which illustrates the necessity of calculating an optimized thrust to prevent tunnel jamming and blocking. The thrust provided by the thrust cylinder, which was required to elevate the machine and advance, was incorporated into the parametric analysis of the model. At 20,000 kN/m^2 intervals, the force was delivered between 3000N and 260000 kN/m^2. The modeling, meshing, and application of torque and thrust on the tunnel geometry model are shown in (Figure 7).

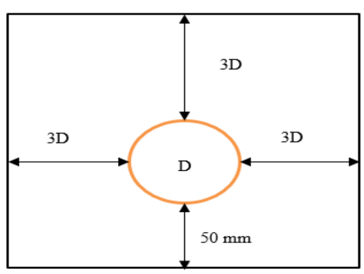

Figure 7a : Model geometry

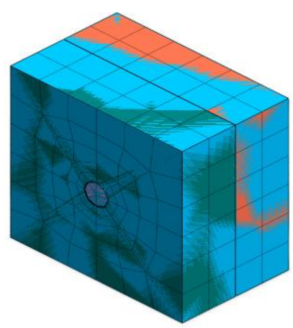

Figure 7b: Model Meshing

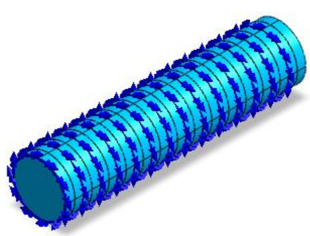

Figure 7c: Torque application

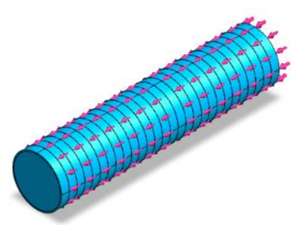

Figure 7d: Thrust application

Figure 7: Modelling, Meshing, and torque /Thrust application on Tunnel geometry

Model analysis was followed after applying torque and thrust on the tunnel geometry of the prepared model; construction stages were simulated as per requirement. The construction sequence should be such that it removes the ground with the rotation of the cutter head and moves the machine forward for the subsequent section by applying thrust through the machine's associated jack cylinders. The analysis also considered friction between the shield and the segment and machine-developed skin friction. In the following article, the author will discuss how the water pore pressure of the ground affects the tunnel's structural stability as it is being driven.

9. ESTIMATION OF TORQUE AND THRUST BY FEM

9.1 Effect of torque application: Tunnel excavation via TBMs, particularly in high-mountainous areas, torque optimization is crucial in high-mountain tunnel projects to avoid TBM jams. High mountain tunnels frequently cross numerous geological formations, including fault zones, soft soil, and hard rock. The cutting tools of the TBM may experience varying degrees of resistance from these circumstances. By eliminating excessive stress on the cutting tools, torque optimization enables the TBM to modify its drilling parameters, such as rotating force, to match the unique geological conditions. This lowers the danger of jamming [1,9].

The proposed research initially studied the effect of torque on ground collapse rate. Here the author defines Ground collapse rate as the rate of higher displacement of ground susceptible to collapse over the tunnel crown. As described in section 7 above, the model was prepared and analyzed for the requirement of torque, and the ground collapse rate was observed over the tunnel crown; it was observed that ground collapse shows stable behavior after 12000 kN.m. The author may consider the optimized torque value as 12000 kN.m but the cutting head is driven by strong motors that are part of TBMs. Without optimization, high torque application can result in increased energy use and component wear. By maximizing torque, the TBM can cut through rock or dirt effectively while reducing the likelihood of overheating or mechanical faults that could cause jamming. Hence, to see the behavior and control collapse trend, more models were analyzed, and results were plotted. It was shown that 11000 kN.m torque controls the collapse rate of ground but still, the displacement of the crown was not beyond the limit. This necessitates the determination of thrust application to uplift the tunnel and move the machine forward for ground excavation. This may avoid the TBM jamming scenario at the high overburden section. Figure 7a shows the ground collapse trend at various torque applications and optimized torque value susceptible to ground collapse.

9.2 Effect of thrust application: A TBM becoming clogged can cause delays, higher operating expenses, and even put the safety of the tunneling operation at risk. For smooth tunneling, thrust optimization is essential [1,9].

A TBM can efficiently cut through the ground by optimizing its thrust. The TBM can go forward steadily without becoming stopped when the thrust is adjusted properly, which aids in maintaining a constant excavation rate. The cutting tools and components may experience excessive wear and tear if a TBM is operated at the wrong thrust level. This contributes to both increased maintenance costs and downtime for repairs. When the TBM finds ground conditions that are too difficult for its current thrust level, blocks happen. The likelihood of running into obstructions that could cause blockages is decreased by optimizing thrust in accordance with the particular ground conditions. Safety issues for both employees and the overall tunneling project can arise from a clogged TBM. When a TBM becomes trapped, the tunnel may become unstable, debris may accumulate, and the tunnel may eventually collapse. Increasing thrust can reduce these dangers.

Projects involving tunneling are expensive and time-consuming. TBM obstruction delays may result in higher labor costs, longer project timeframes, and even legal repercussions. The project will be completed on schedule and within budget with thrust optimization. For the project to be successful in its entirety, efficient and consistent tunneling progress is required. Thrust optimization guarantees that the TBM can continue to excavate at a consistent rate, minimizing the possibility of unplanned stops.

As described in section 7, models were analyzed for thrust application and optimized the value at 200000 kN/m^2 (refer to figure 7b)

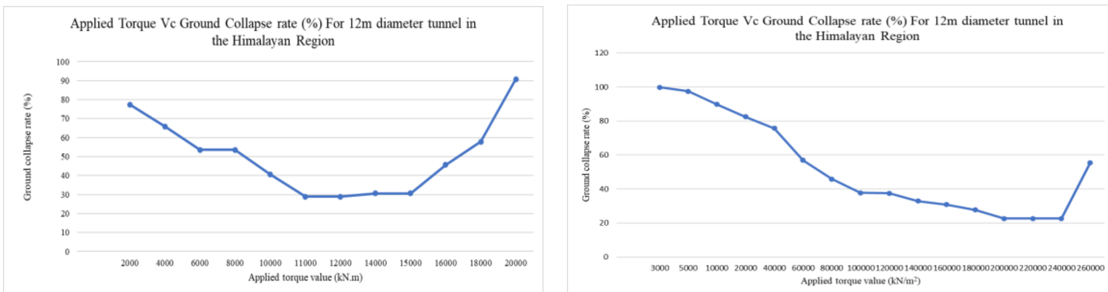

Figure 8: Effect of application of Torque and Thrust parameter on ground collapse

10. ESTIMATION OF TORQUE AND THRUST BY EMPERICAL METHOD

Cutterhead torque requirement can be estimated for open, single shield and double shield TBM was suggested as follows [1]

$$T_{open} = T_{4\text{-}open} = \sum_{I=1}^{Nc} ri.\ F_R.F_L \approx Nc.\ F_R.D/4.F_L$$

Where Topen is the total cutter head torque requirement, (RI) is the distance of (ith) cutter from cutter head center, (Nc) is a number of cutters, (F_R) is mean rolling force per revolution, (F_L) is loss due to friction and can be taken as 1.2.

[1], correlate the estimated cutter head torque and thrust by examining 262 TBM design parameters. This relation can be used to find the requirement of torque and thrust with suggested parameters and TBM diameter. For 12m diameter single shield TBM in weak ground required 12709.067 kN.m torque value and 199290.793 kN/m2 thrust for successful TBM tunneling operation, which is nearly equal to the estimated value by tunnel analysis with Finite Element Analysis (FEM).

10. RESULT AND INTERPRETATION

As discussed in the above section, the torque and thrust value to be applied on TBM to avoid blocking/ jamming determined for 12 m diameter. It was found to be in good agreement with the empirical method and statistical analysis of actual TBM [1]. As Mega Tunnel is a large diameter tunnel beyond 10m, to analyze its applicability for Mega Tunnel, Modelling was prepared for 10,12.14 and 16 m diameter tunnels. The results were plotted and found to be in good agreement with the statistical analysis of TBM data [1] (refer to Figure 8).

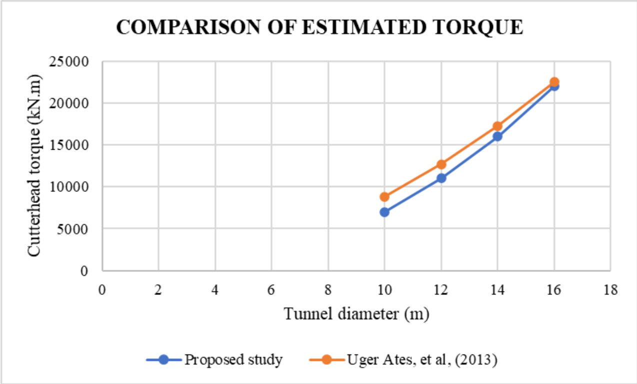

Figure 9a: Comparison of Estimated Torque

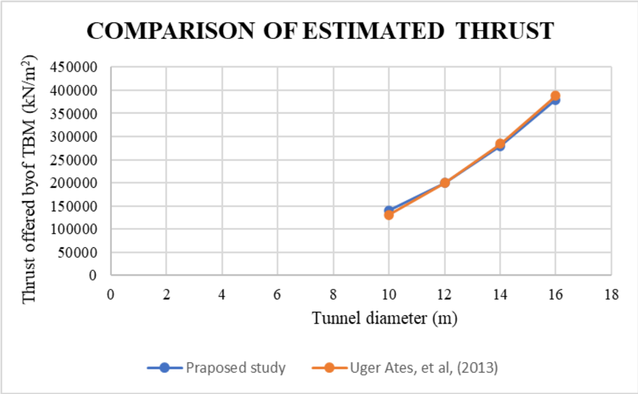

Fig 9b: Comparison of Estimated Thrust

Figure 9: Comparison of Estimated Torque and Thrust

11. CONCLUSIONS

In conclusion, the stability of a tunnel excavation process is a critical factor in ensuring the safety and efficiency of underground construction projects. By identifying and optimizing the torque and thrust values of TBMs, it is possible to achieve a stable excavation process that minimizes the risk of TBM blocking and jamming. Through a comprehensive analysis of geological conditions, ground behavior, and machine performance, Finite Element Analysis can provide a deterministic approach to determine the optimal torque at 15000 Kn.m and thrust settings at 160000 kN/m^2 that allow for smooth progress while avoiding excessive stresses on the machine and potential disruptions and found in good agreement with the study [1] in weak rock zone.

By avoiding expensive downtime caused by obstructions and failures, this strategy not only improves the overall safety of the tunneling operation but also increases productivity. The capacity to optimize TBM operations will become more and more crucial to the accomplishment of subterranean construction projects as technology develops and our understanding of ground mechanics grows. In the end, the incorporation of optimized torque and thrust values into tunneling procedures represents a major breakthrough in the creation of dependable, effective, and secure excavations that advance modern infrastructure.

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How Are the Post COVID-19 Travel Patterns Evolving? Results from a University Campus

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ABSTRACT

This paper aims to understand the post-COVID-19 travel patterns at the University of Texas at Austin (UT Austin). It constitutes a continuation effort of the 2022 study based on a travel preference survey distributed to the whole UT community during the spring of 2022. The 2022 travel preference survey was redistributed during the spring of 2023 to understand how travel patterns are evolving post-COVID-19. The survey questions include information about frequency, time, and purpose of commute as well as the mode of transportation used. They aim to analyze the shift in travel behavior as we gradually move to the new normal for operating conditions. The results of both surveys are compared and analyzed to help the Office of Sustainability at the University of Texas at Austin make informed decision regarding university transportation needs. Both surveys clearly illustrate the persistence of the hybrid mode of operation: 40% of undergraduate students, 40% of graduate students, 32% of faculty, and 27% of staff commuted five days a week to campus in 2023. Respondents expressed their tendency to use the car mode as it is the fastest way to get to campus and due to the lack of transit options available to them. This effort will help researchers and decision makers better develop travel demand modeling assumptions.

1. INTRODUCTION

As a response to the COVID-19 pandemic, enforced rules and health regulations led to a major change in travel behavior that still persists to this day. As the world emerges from the pandemic, it is evident that the way people commute is undergoing a fundamental shift. To measure that shift, this paper addresses the question: How the post-pandemic travel behavior is evolving at The University of Texas at Austin (UT Austin)?

Researchers around the globe including transportation researchers have been inspired to fast-track research on the various impacts of COVID-19 on transportation during 2020 (Bassil et al., 2022; Kim, 2021; Mack et al., 2021). However, the post-pandemic period has gained the attention of other researchers who have reported a long-term reluctance of some travelers to use shared occupancy modes and a persistence of the work from home mode (Currie et al., 2021; Shamshiripour et al., 2020). While change in travel behavior is certain, a major gap exists in quantifying how large and how long this change will persist and how it will impact travel patterns.

This paper constitutes a continuation of the effort to bridge this gap by examining post-pandemic travel behavior and patterns at The University of Texas at Austin (UT Austin). The research is based on data collected over two years from a travel preference survey distributed to the whole UT Austin community during Spring 2022 and Spring 2023.

2. BACKGROUND

Since the pandemic, individuals have commuted less (Aaditya & Rahul, 2023; Awad-Núñez et al., 2021; Bagdatli & Ipek, 2022; Javadinasr et al., 2022; Jiao et al., 2023; Schneider & Schinkowsky, 2021; Song et al., 2023; Srikanth et al., 2023; Ulahannan & Birrell, 2022)and indicated strong preferences for telecommuting and working from home (Javadinasr et al., 2022; Jiao et al., 2023; Schneider & Schinkowsky, 2021; Song et al., 2023). Various studies have considered survey data (Awad-Núñez et al., 2021; Bagdatli & Ipek, 2022; Schneider & Schinkowsky, 2021; Srikanth et al., 2023), smart-phone mobility data (Song et al., 2023), and even transit ridership data(Jiao et al., 2023) to characterize these changes in travel patterns. These changes in travel patterns, like avoiding shared modes and working from home to avoid COVID-19 infection, can affect some people's willingness to use specific modes in the long-term (Aaditya & Rahul, 2023). These changes in willingness, despite being in a post COVID-19 pandemic state, mean that travel patterns will likely look different from what they were before the pandemic.

2.1. Shared Modes vs. Private Modes

During COVID-19, private vehicles became increasingly attractive compared to shared modes because of the lower risk of contagion, and in the long-run still seem preferred by individuals (Aaditya & Rahul, 2023; Awad-Núñez et al., 2021; Bagdatli & Ipek, 2022; Srikanth et al., 2023; Ulahannan & Birrell, 2022). One study used a combination of online and in-person survey data collection to understand people's willingness to use a non-shared mode instead of a shared mode in a fully vaccinated, post-COVID-19 scenario (Aaditya & Rahul, 2023). This study found that willingness to use a non-shared mode was extremely high, and seemingly influenced by personal or family history of COVID-19, fear, and status of personal vehicle ownership. Overall, the perception of safety is an important factor in determining willingness to choose public transportation.

Another study sought to measure the willingness to adopt measures to improve safety conditions of public transport and shared mobility(Awad-Núñez et al., 2021). To understand this willingness, the researchers developed a survey with revealed and stated preference questions about mobility behavior pre-pandemic and possible adoption of different types of transport sharing services. Mostly because of contagion fears, survey results show preferences for non-shared modes, like driving a private car, walking, or biking.

Understanding preferences for shared modes post-pandemic can help inform transportation authority's decisions on service changes. Using an online discrete choice experiment (DCE) methodology, another effort sought to measure the utility of public transportation attributes, such as transportation type, fare cost, travel time, and additional travel time (Ulahannan & Birrell, 2022). The DCE method offers value because it attaches a monetary value to the tested attributes. Here, the results corroborate the results from the other studies in that individuals have a strong preference toward non-shared modes (taxis) when cost is not an issue.

2.2. Non-work-related Patterns

Evidently, the pandemic and post-pandemic period has created some large shifts in travel preferences, and non-work travel patterns also saw significant changes. Previous research has considered the impacts of COVID-19 non-work travel patterns and found significantly lower numbers of visitors during COVID-19 (Song et al., 2023). With the help of smartphone mobility data, this study focused on evaluating changes to major non-work destinations such as restaurants, supermarkets, drinking places, religious organizations, and parks during COVID-19. All categories showed significantly lower numbers of visitors and distance traveled during COVID-19. Besides the increase in distance traveled for general merchandise stores, distances traveled decreased as well. Only full-service restaurants, limited-service restaurants, and supermarkets were the stable categories. While this study was completed prior to the post-COVID period, it demonstrates how smartphone data could potentially help with characterizing travel patterns. Besides non-work travel, work-related travel is a huge component to identifying travel patterns post-COVID.

2.3. Work-related Patterns

A crucial element in investigating the changes in people’s travel behavior after COVID involves characterizing commute to work patterns. One survey-based study aimed to understand how working from home, mode choice, online shopping, and air travel have evolved since before the pandemic (Javadinasr et al., 2022). Using both descriptive and econometric methods, the results show a 30% increase in option to work from home compared to pre-pandemic times. In post-pandemic times, auto commuters are expected to drop by 9% and transit commuters by 31%. Lastly, 41% of people flew for business-related purposes pre-pandemic expect to fly less in this post-pandemic period.

Other studies have also considered how work-related commutes have changed during the various waves of the pandemic. Researchers used a survey to assess how different characteristics affect mode choice pre-, during lockdown, and after lockdown restrictions were removed (Srikanth et al., 2023). The results show that pre-COVID-19, only 4.85 percent of respondents had the opportunity to work remotely. During lockdown restrictions, this number quickly climbed to 41.75 percent because of widespread adoption of work-from-home policies by various companies. After lifting all COVID-19 related restrictions, the proportion of remote workers decreased to 19.42 percent once companies resumed regular in-office operations.

Unfortunately, not all sociodemographic groups have the opportunity to work from home or have private cars to make their commute to work trips. Some groups rely heavily on transit and despite service disruptions during the pandemic, continued to rely on public transportation. One study in of transit service in Austin showed that areas of the city with older populations and higher percentages of Black and Hispanic populations had less severe declines in ridership (Jiao et al., 2023). On the other hand, areas with high unemployment saw very steep declines in ridership, highlighting the disparities in usage and dependence on public transit.

2.4. Mode Choice Shifts at Universities

Very few studies have been done on the shifting commute patterns at university campuses, despite that research has shown considerable changes in telecommuting and shifts away from public transportation (Schneider & Schinkowsky, 2021). The University of Wisconsin-Milwaukee campus conducted an online survey to the entire campus to determine the commute shifts that occurred between the Fall 2019 and Fall 2020 semesters and reactions to their mode shifts. The results showed the new telecommuters enjoyed not having to commute and that commuters with fewer economic resources were less likely to shift to telecommuting. A university in Istanbul also used an online survey to understand student's mode preferences and showed that students preferred private a car and a decrease in demand for shared modes such as buses and LRT (Bagdatli & Ipek, 2022). Lastly, this study also pointed out an increase in demand for active transport (e-scooters and hoverboards). Overall, there are many unanswered questions regarding the long-term impacts of mode choice at universities in a post-pandemic setting.

3. METHODS

3.1. Research Approach

This paper sought to explore The University of Texas at Austin respondent self-reported commuting (revealed preference method) after pandemic regulations had been lifted in the U.S. and UT Austin announced resumption of all in-person classes and campus operations:

- Step 1: Develop and Distribute the travel preference survey in Spring 2022
- Step 2: Re-Distribute the survey in Spring 2023
- Step 3: Compare and Analyze the data
- Step 4: Draw conclusions and Develop Recommendations

Qualtrics Survey Software was used to develop and distribute the survey to the whole UT community including all students, faculty, and staff. The two surveys aim to capture the evolving post-pandemic travel patterns to and from the UT campus/research centers after the campus operations have resumed in person.

3.2. Sampling

The survey respondents were informed that their participation in the study is voluntary and confidential through a carefully drafted informed consent. To increase the survey response rate, the survey duration was estimated to be three to five minutes and included in the informed consent.

Based on the number of respondents of each survey shown in Figure 1, the sampling fraction for each UT primary role was calculated as shown below (*Sample Size Calculator & Complete Guide in 2022 - Qualtrics*, n.d.). The total number of undergraduate students, graduate students, faculty, and staff are posted on the UT official website and provided by UT Human Resources Department. Table 1 shows a decrease in the sampling fractions of the 2023 survey compared to the 2022 survey specially in the undergraduate students and graduate students sampling fractions. This might be explained by the distribution of the 2023 survey during a busy time of the semester, the last week of the spring 2023 semester, and the lower number of reminder emails sent for the 2023 survey.

The undergraduate students sample size represents the undergraduate student population with a confidence level of 99% and a margin of error of 3%, and 4% for 2022 and 2023 respectively.

The graduate students sample size represents the graduate student population with a confidence level of 99% and a margin of error of 3%, and 5% for 2022 and 2023 respectively.

TABLE 1. Sampling Fractions for the 2022 and 2023 Survey Respondents

Sampling Fraction	2022 Survey	2023 Survey
Undergraduate Students	$\frac{2544}{40916} = 0.062 = 6.2\%$	$\frac{1205}{40916} = 0.029 = 2.9\%$
Graduate Students	$\frac{1916}{11075} = 0.173 = 17.3\%$	$\frac{727}{11075} = 0.065 = 6.6\%$
Staff	$\frac{3237}{13426} = 0.241 = 24.1\%$	$\frac{3336}{13426} = 0.248 = 24.8\%$
Faculty	$\frac{919}{3919} = 0.234 = 23.4\%$	$\frac{779}{3919} = 0.199 = 19.9\%$

The staff sample size represents the staff population with a confidence level of 99% and a margin of error of 2% for both 2022 and 2023.

The faculty sample size represents the faculty population with a confidence level of 99% and a margin of error of 4%, and 5% for 2022 and 2023 respectively.

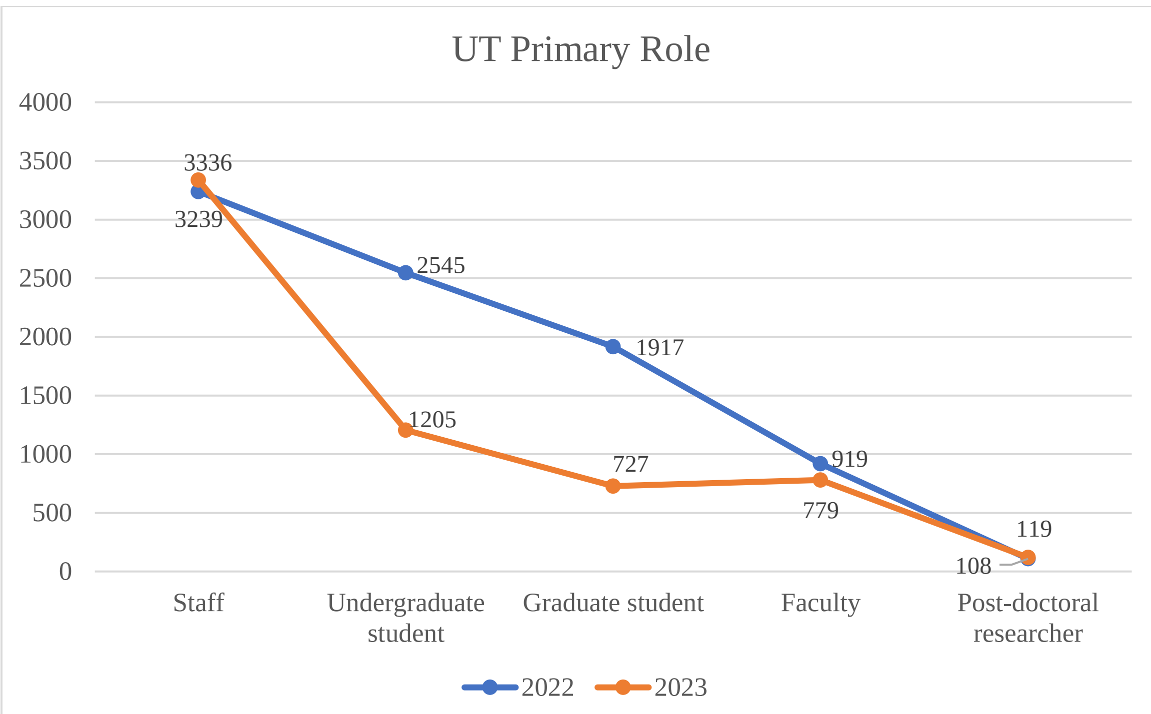


FIGURE 1. UT primary role counts of the 2022 and 2023 survey respondents

3.3. Survey

The 2022 survey was redistributed in 2023 with the same aim to understand the respondent's travel behavior and patterns through a series of carefully drafted questions. The questionnaire also gave the respondents a space to share their opinions/concerns/issues about their commute to campus. These findings and observations are shared in the results section of this paper. The survey explored the following areas in order: UT Primary role, commute frequency, knowledge about university transportation services, zip code, trip start closest intersection, trip purpose, commute time, primary mode of transportation to campus, time spent in the primary mode of transportation, secondary mode of transportation to campus, time spent in the secondary mode of transportation to campus, primary mode of transportation from campus, time spent in the primary mode of transportation from campus, secondary mode of transportation from campus and the time spent in the secondary mode of transportation (Bassil et al., 2023).

3.4. Analytical Approach

The analytical approach of the 2022 survey is used (Bassil et al., 2023). It consists of analyzing the responses of each UT primary role (undergraduate students, graduate students, faculty, staff, and postdoctoral researchers) as separate categories given their different characteristics and attributes. The collected results were converted into percentages for ease of comparing the different categories. Keep in mind that sampling error is always present due to non-feasibility of studying the whole population with the limited resources available. The 2022 survey results are compared to the 2023 survey results for each UT primary role.

4. RESULTS, DISCUSSION & FINDINGS

4.1. Commute Frequency to the UT Main Campus

FIGURE 2 and FIGURE 3 illustrate the commute frequency to the UT main campus each week during 2022 and 2023 respectively for each UT primary role. When comparing these two years no major changes or behavioral shifts are noticed in the commute frequency of each UT primary role from 2022 to 2023.

Our 2022 interesting observation about post-doctoral researchers still holds in 2023. In fact, post-doctoral researchers commute most frequently to campus with 51% commuting 5 days a week or more in 2022 and 53% commuting 5 days a week or more in 2023. Undergraduate students remain the second most frequent commuters with 43% commuting 5 days a week or more in 2022 and 40% commuting 5 days a week or more in 2023.

For the staff category, the percentage working remotely dropped from 11% in 2022 to 9% in 2023. But staff remains the category with the largest percentage of remote work. An interesting observation is that the 2023 percentages of staff commuting 5 days or more, 3-4 days, and 1-2 days per week are almost the same as the 2022 percentages.

The percentage of respondents commuting 1 to 2 days or 3 to 4 days per week to campus in 2022 are: 54 % of staff, 69% of faculty, 47% of post-doctoral researchers, 61% of graduate students and 33% of undergraduate students. These number are compared to the percentage of respondents commuting 1 to 2 days or 3 to 4 days per week to campus in 2023 that are: 56 % of staff, 64% of faculty, 42% of post-doctoral researchers, 54% of graduate students and 31% of undergraduate students. Which means that even in 2023, a significant percentage of all categories do not commute daily to campus, opting for 3 to 4 days per week or 1 to 2 days per week. These observations imply that the hybrid mode of work is still persistent after COVID-19 regulations have been lifted.

These numbers can imply that the hybrid mode of work is still persistent after COVID-19 regulations have been lifted.

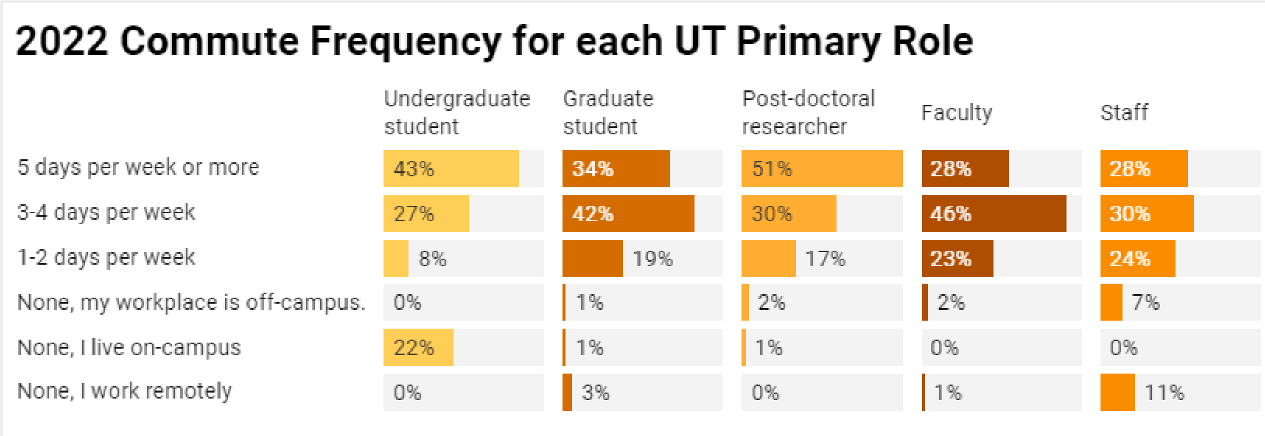


FIGURE 2. 2022 Commute frequency to the UT main campus for each UT primary role

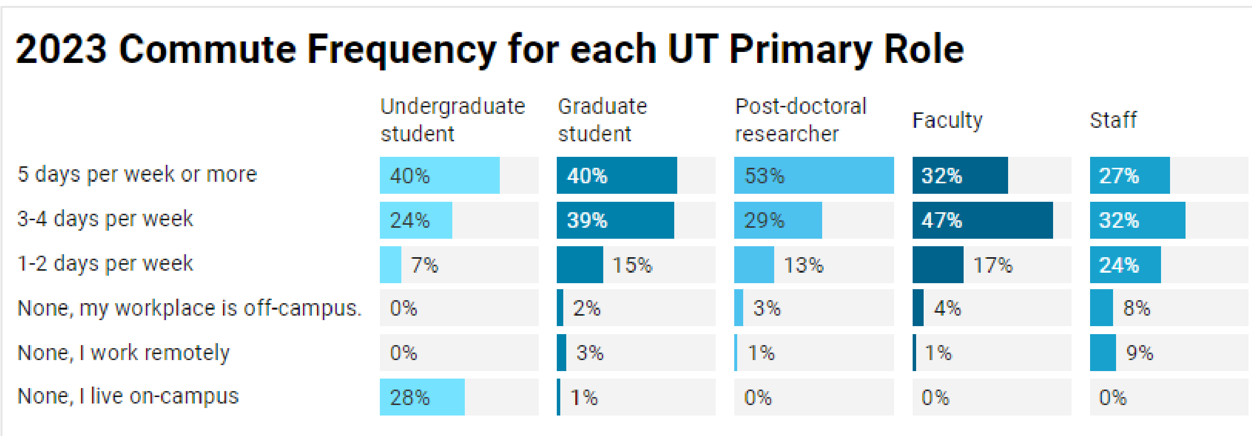


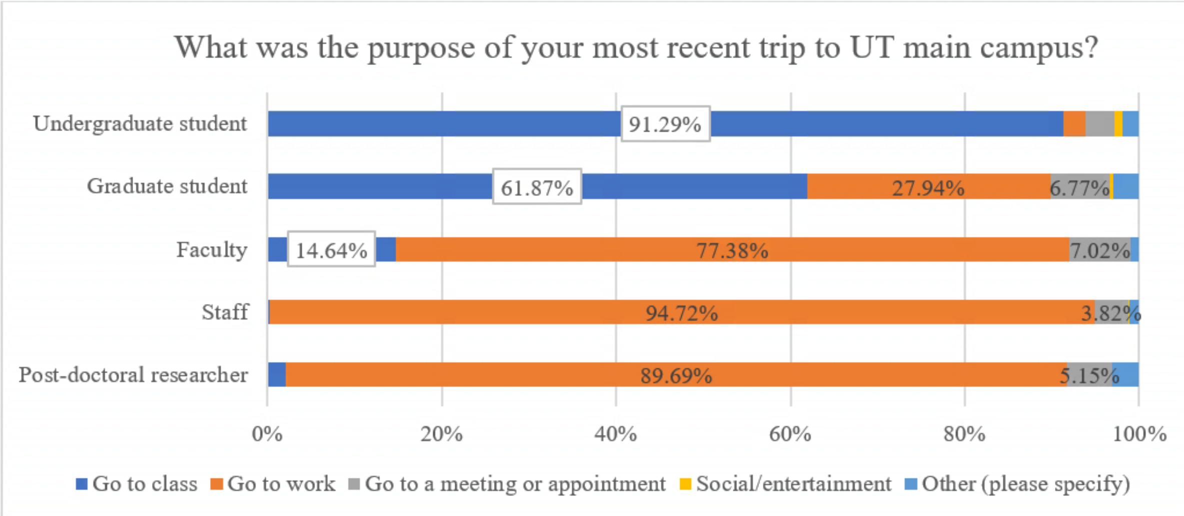
FIGURE 3. 2023 Commute frequency to the UT main campus for each UT primary role

4.2. UT Transportation Services

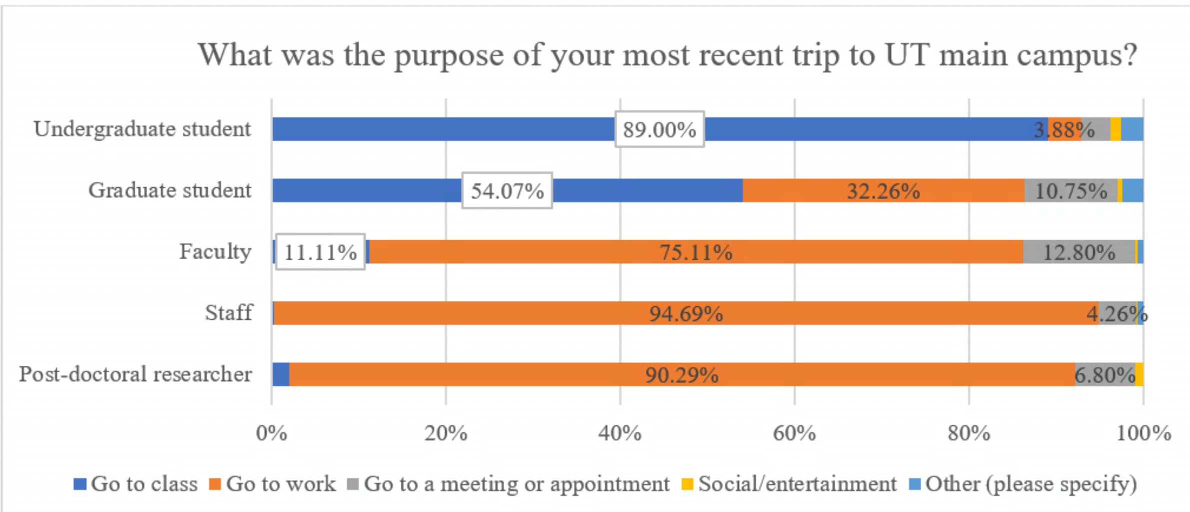
Regarding the awareness of the UT community about the transportation services available to them, the 2022 and 2023 survey revealed similar findings. In both surveys, the most popular services are found to be UT shuttles, electric scooters, and UT night rides. Meanwhile, the least popular services are electric vehicle (EV) charging and the carpool program. This observation shows that not enough awareness is raised about the carpooling program to incentivize the UT community to be greener and more sustainable.

4.3. Trip Purpose

To analyze the trip purpose, Figure 4 (a) and Figure 4 (b) are developed for the year 2022 and year 2023 respectively. As expected, Figure 4 (a) and Figure 4 (b) show that attending classes remains the main purpose of trips to the UT campus for undergraduates and graduates. And going to work remains the main purpose of trips to the UT campus for faculty, staff, and postdoctoral researchers.



(a) Trip purpose based on the Spring 2022 Survey



(b) Trip purpose based on the Spring 2023 Survey

FIGURE 4. Trip purpose and Time-of-day Commute to the UT main campus for each UT primary role

4.4. Primary Mode of Transportation to the UT Main Campus

The primary modes of transportation used in 2022 and 2023 by undergraduate students, graduate students, staff, and faculty are illustrated in Figure 5, Figure 6, Figure 7, and Figure 8 respectively. The primary mode of transportation constitutes one of the most important points explored in the surveys to analyze the post-COVID-19 shift in travel behavior.

Figure 5 compares the 2022 and 2023 primary modes of transportation used by undergraduate students. The percentage of undergraduate students walking increased from 39.1% in 2022 to 45.9% in 2023. It was expected that walking will remain the most common primary mode of transportation among undergraduate students, given that many students live close to UT in the West Campus area. However, the research team was anticipating a higher percentage of walk trips based on the results of preliminary in-class surveys showing that more than 70% of the students walked to campus. Despite the ability of UT students to ride public transportation for free using their UT identification card, the percentage of undergraduate students riding the bus decreased from 23.1% in 2022 to 18.1% in 2023. This observation refutes the hypothesis stating that undergraduate students declined to use the bus due to COVID-19.

Another observation is that the percentage of undergraduate students commuting by car remains at 27.8% in 2023 compared to 29% in 2022. These observations are counterintuitive and may suggest that both surveys are biased toward undergrad students owning and using cars as their primary mode of transportation. This might be caused by the sample size and survey respondent characteristics. The accuracy of the survey results regarding the primary mode of transportation are best evaluated by comparing the data collected each year to the previous years.

When looking at the response fraction (%) of undergraduate mode by year, there is a significant difference in mode choice, but not a significant difference in Survey 1 versus Survey 2. TABLE 2 shows the results from an analysis of variance (ANOVA) on response fraction for undergrads by mode and year.

TABLE 2. ANOVA Response Frequency Result

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Mode	6	0.3310	0.05517	87.37	$1.42e^{-05}$
Survey year	1	0.0000	0.00000	0.00	
Residuals	6	0.0038	0.00063		

The ANOVA does not show a significant difference in survey years when controlling for mode.

When looking at the number of responses for undergraduates mode by year, there is a significant difference in the mode choice and between Survey 1 versus Survey 2. TABLE 3 shows the results from an analysis of variance (ANOVA) on number of responses for undergraduates by mode and year.

TABLE 3. ANOVA Number of Responses Result

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Mode	6	480443	80074	9.700	0.00706
Survey year	1	50761	50761	6.149	0.04783
Residuals	6	49532	8255		

Here, the response differs by year when controlling for mode, indicating that in terms of numbers of undergraduates commuting in each mode differs by year.

For graduate students the percentage of each primary mode of transportation used in 2023 is almost the same as the 2022 percentage (2023 percentages are within 0.2% to 1.7% of the 2022 percentages). Car remains the most commonly used mode of transportation, followed by public transportation, followed by walking and biking. These observations show no major shifts in the mode of transportation used which means that the 2022 travel behavior still holds in 2023.

E-scooter usage remains insignificant given UT’s regulations regarding e-scooters that include restricting scooter parking in designated areas only, enforcing scooter operation to a low speed in the presence of pedestrians and even forbidding e-scooters in specific areas.

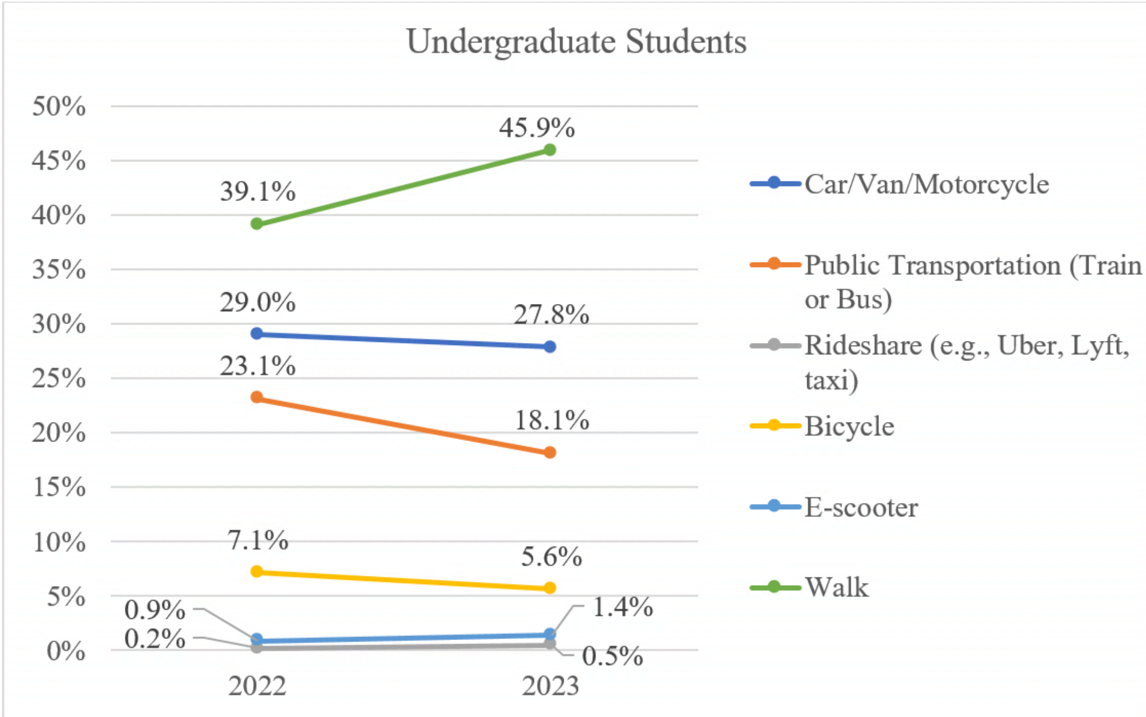


FIGURE 5. Undergraduate Students Primary mode of Transportation to campus in 2022 and 2023

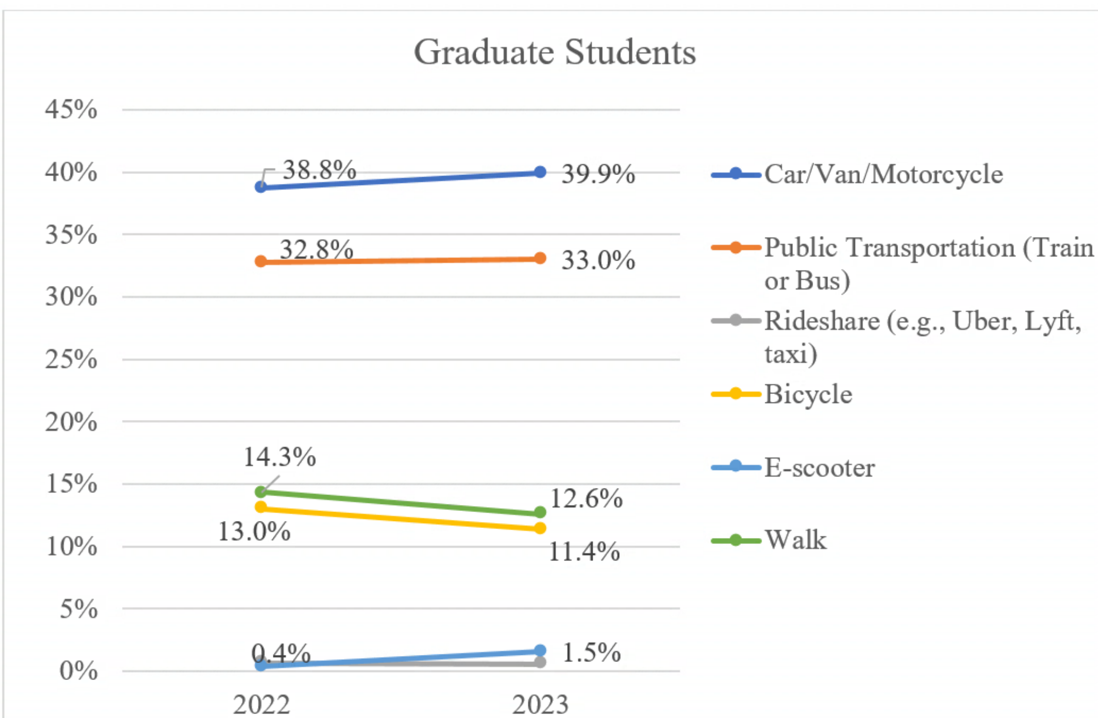


FIGURE 6. Graduate Students Primary mode of Transportation to campus in 2022 and 2023

In 2023 as in 2020, the faculty and staff rely mostly on car for their commute to campus as shown in Figure 7 and Figure 8. This observation is likely to remain true in the future because most faculty and staff reside further away from campus.

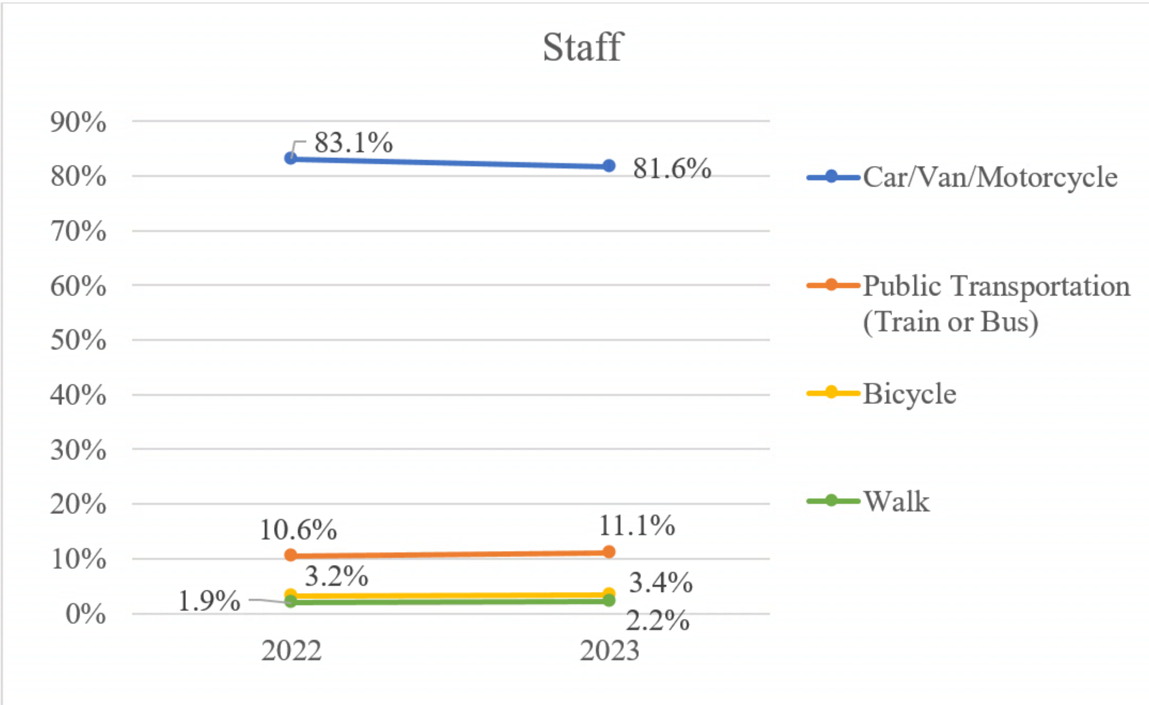


FIGURE 7. Staff Primary mode of Transportation to campus in 2022 and 2023

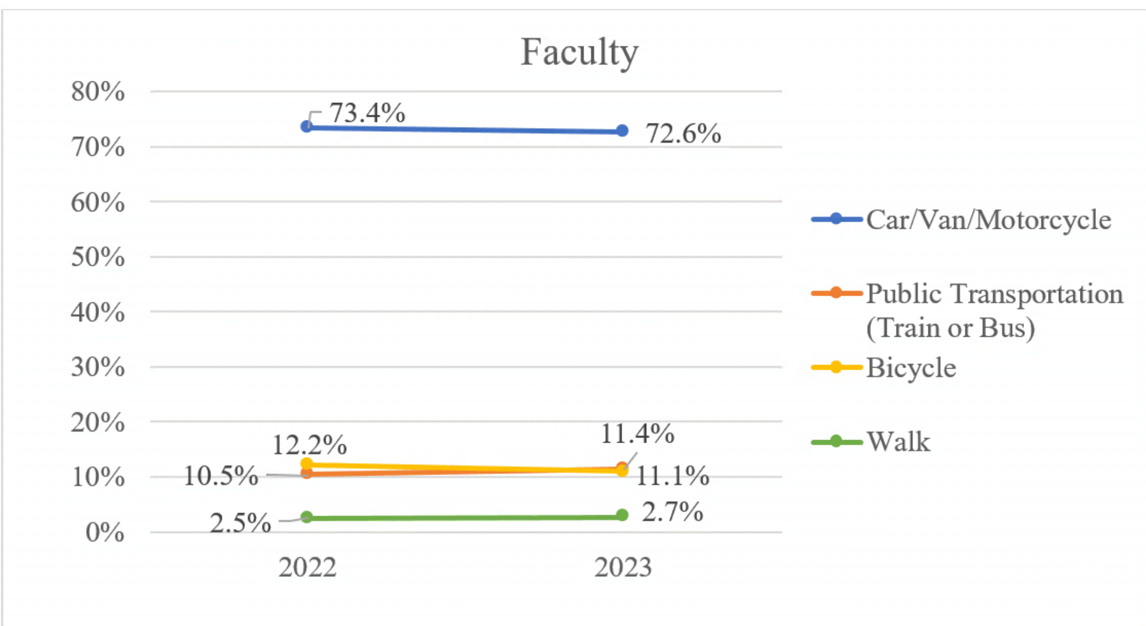


FIGURE 8. Faculty Primary mode of Transportation to campus in 2022 and 2023

The commute time of the staff who use their cars in 2022 and 2023 was further explored. In both years, 70% of staff spend more than 20 minutes driving to campus. Furthermore, 42% and 43 % of staff spend more than 30 minutes driving to campus in 2022 and 2023 respectively. The 2023 observations confirm our 2022 data and expectations and imply that the gathered data reflect the real-life commute patterns of the UT staff in 2022 and 2023.

4.5. Carpooling/ Vanpooling

In 2023 as in 2022, more than 90% of car drivers chose not to carpool/vanpool. The reasons behind this decision are also explored in 2023 in the follow-up questions. The three main reasons behind this decision in 2023 are found to be the same as those provided in 2022 which are: car is the fastest way to get to campus, the respondents' preference to drive their own vehicles and the lack of reasonable transit options. The lack of reasonable or reliable transit options, the lack of transit routes and the unavailability of transit options remains a concern for several potential transit riders. It worth noting that the number of respondents using their cars of out Covid-19 concern decreased in 2023 compared to 2022.

4.6. Primary Mode Travel Time

The follow-up questions on the primary mode of transportation explored the primary mode travel time. The 2023 findings agree with the 2022 findings. In fact, 83% and 79% of public transportation commuters walk from the trip starting point to the transit stop in 2022 and 2023 respectively. The behavior of public transportation riders is still the same in 2023 with the highest percentage of riders spending 10 to 20 minutes on public transportation (36.7% in 2022 and 34.2% in 2023).

While 40% of bikers spent 10 to 20 minutes biking to campus in 2022, 43% of bikers spent 10 to 20 minutes biking to campus in 2022. Among the respondents who chose to walk to campus, 57 % walked 10 to 20 minutes both in 2022 and 2023.

In summary, the 2023 survey results match the 2022 survey results reflecting the travel patterns and behaviors of the UT community. This set of surveys presents valuable information on the travel behavior and travel patterns of the UT community during the post-COVID-19 period, revealing the modes of transportation used by each UT primary role and raising awareness about UT transportation services available.

5. LIMITATIONS

Every study has its own limitations, and this study is not an exception. Given that this study is based on data collected from two surveys over two years, the accuracy of the results is limited by the quality of the data collected. And given that the surveys are anonymous and voluntary, sampling errors and non-response errors might be present. And given that the targeted respondents are UT affiliates, the findings are specific to UT Austin, an urban campus with many off-campus commuters. So additional studies are needed to explore the impacts of the pandemic on campus commuting in other contexts.

6. CONCLUSIONS

This paper seeks to address the question How are the post COVID-19 travel behavior evolving at UT Austin? by comparing two years of survey data (2022 and 2023). It builds upon the results of the 2022 survey designed to address and explore the UT community travel patterns during the Spring of 2022 (Bassil et al., 2023).

Based on the 2022 and 2023 survey data, the research team noticed the persistent hybrid mode of operation. In fact, only 40% of undergraduate students, 40% of graduate students 32% of faculty, and 27% of staff commuted 5 days a week to campus in 2023. The flexibility and convenience associated with the hybrid mode of work (which is a mix of work from home and in person) made it persist to the year 2023. This study also shows that staff remains the largest group driving to campus and commuting the longest distances. Given that staff respondents expressed their tendency to use the car mode because of the lack of transit options available to them, reliable public transportation should be provided if a shift in staff commute patterns is required.

CTo reveal future travel patterns and behavior, this survey can be repeated every spring semester. By that, the research team can evaluate their assumptions regarding the commuting behavior of UT affiliates.

7. ACKNOWLEDGMENTS

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8. AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Bassil, M., Baumanis, C., Ross, H., Machemehl, R.; data collection: Bassil, M. Ross, H., Machemehl, R.; analysis and interpretation of results: Bassil, M., Baumanis, C., Ross, H., Machemehl, R.; draft manuscript preparation: Bassil, M., Baumanis, C.; writing-reviewing and editing: Bassil, M., Baumanis, C., Ross, H., Machemehl, R., All authors reviewed the results and approved the final version of the manuscript.

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Factors Impacting Customers' Satisfaction with Parking: A Case Study

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ABSTRACT

Parking is a growing problem globally due to the growth of urbanization, and it is particularly problematic in densely populated areas, such as college campuses, where the demand for parking is high. This research investigates the complexities of parking management at the University of Texas at Arlington (UTA) and looks carefully at its implications for urban planning and sustainability. Qualitative interviews with 19 participants who were either students, faculty, or UTA provided insight into their experiences and satisfaction levels with the campus parking system and found that socioeconomic characteristics, travel behaviors, and specific parking challenges have a significant impact on an individual's parking experience. The interviewees revealed a profound reliance on private vehicles; a marked preference for close, convenient, on-campus parking; and a keen interest in technological advancements such as smart parking solutions and real-time availability systems, suggesting a campus-wide readiness to embrace innovative parking management strategies. As a result of the findings, the study proposes policy recommendations such as tiered parking permit pricing, strategic parking lot placement, flexible pricing strategies, and the promotion of alternative transportation methods to alleviate parking pressure and support sustainability goals. This paper contributes to the discourse on transportation challenges within the microcosm of a university campus, offering insights that are pertinent to the development of responsive, efficient, and sustainable parking management policies.

INTRODUCTION

Parking in urban areas is often constrained by a limited number of available spaces, tight spots for parking, high costs, and a rate of congestion that demands immediate attention (Einsiedler et al., 2017; Patel et al., 2023b). Vehicles searching for parking contribute to approximately 30% of city traffic, with drivers spending an average of six minutes to locate a parking slot (Klappenecker et al., 2014; Arnott et al., 2015; Etminani-Ghasrodashti et al., 2022; Khan et al., 2022b). Furthermore, the Insurance Institute for Highway Safety reports that more than 20% of vehicular accidents occur in commercial parking areas, a statistic that gains pertinence considering that the consumption rate of automobiles in United States doubled over the last decade, challenging the capacity of existing parking infrastructures (Yang et al., 2020; Channamallu et al., 2023; Subramanya et al., 2022).

The quest for parking is not just a personal problem but also a public concern, as the overflow of vehicles contributes to traffic congestion, emissions, and urban sprawl. It is estimated that cruising for parking accounts for a considerable proportion of traffic in metropolitan areas, exacerbating carbon footprints and hindering the sustainability goals of communities (Zheng et al., 2015; Kotb et al., 2017; Patel et al., 2022a). The environmental implications are profound, as studies suggest that the average search time for a parking spot results in an additional 345 grams of CO_2 emissions per vehicle, per search (Weinberger et al., 2010; Khan et al., 2022c).

The urban design and architecture of university campuses are often significantly influenced by the parking infrastructure, as large parking areas can dominate the landscape, detracting from the aesthetic and functional design (Rowe, 2017; Etminani-Ghasrodashti et al., 2023; Patel et al., 2023c). The challenge is to integrate parking solutions in a way that respects and enhances the campus environment, rather than imposing upon it. Addressing these challenges is not only a matter of improving the campus experience but also aligns with broader environmental and urban planning goals. Sustainable mobility solutions, including efficient parking management, are pivotal in the journey towards greener and more livable urban spaces (Litman, 2020; Khan et al., 2023a; Channamallu et al., 2023c). Efficient parking management is a key component of broader strategies aimed at promoting sustainable mobility in urban areas (Marsden, 2016; Patel et al., 2023a). By adopting innovative and sustainable parking solutions, universities can lead the way in demonstrating how urban areas can balance the need for parking with environmental and social responsibilities (Willson, 2018; Pamidimukkala et al., 2023; Khan et al., 2022a).

While existing studies provide general insights into parking challenges, this study seeks to contribute to the discourse on parking challenges by providing a deeper exploration of the specific factors influencing satisfaction levels. By capturing the diverse experiences and opinions of the campus community, the research aims to understand the challenges and offer suggestions for improvements. Through a qualitative analysis of these narratives, this study seeks to (1) shed light on specific challenges, (2) reveal the underlying patterns that define the campus parking experience and (3) identify opportunities for policy interventions that could lead to improved satisfaction and efficiency, thereby contributing to the discourse on urban sustainability and campus planning.

LITERATURE REVIEW

The field of parking management and user satisfaction is constantly evolving, shaped by technological progress and shifts in user preferences. This area, crucial to urban planning and transport, involves various factors including the diversity of user needs and the influence of new technologies on efficiency and sustainability. In urban university settings, parking challenges represent a complex matrix of logistical considerations that significantly influence the daily rhythms of campus life. These issues extend beyond mere inconvenience, seeping into the very fabric of the campus experience and shaping the daily routines of students, faculty, and staff. Despite the potential revenue from car parking services, they can create hurdles for infrastructural development (Aalsalem et al., 2015; Channamallu et al., 2023a). Managing the parking supply and demand is a persistent concern, and understanding the user experience, defined as one's perceptions and responses resulting from the use or anticipated use of a product, system, or service (Ketola & Roto, 2008; Patel et al., 2022b), is critical. Inadequate parking facilities can lead to extended commutes, a rise in tardiness, and increased stress levels among the campus populace, affecting academic and professional performance (Shoup, 2006; Khan et al., 2023b; Channamallu et al., 2023b).

Ibeas et al. (2014) explore the variability in parking choices among users, noting significant differences based on aspects like distance, cost, and convenience, particularly in university settings. This variability highlights the complexity of parking challenges and the necessity for customized solutions. Handy and Thigpen (2018) further discuss how commute quality affects satisfaction, emphasizing the influence of transportation mode and location on parking experiences. Morris and Guerra (2015) look into the psychological aspects of commuting, pointing out how parking experiences can affect individuals' well-being and mood, and underline the need for emotional and psychological factors in parking management. The literature also covers the balancing of parking demand and supply, especially in academic contexts, with Nadimi et al. (2021) investigating the determinants of parking lot selection. Rye and Koglin (2014) discuss the contribution of public and private sectors to parking infrastructure and the effects of parking supply and management tactics on cities.

The body of literature provides a detailed view of the multifaceted nature of parking management, covering user behaviors, technological innovations, and sustainable urban planning. Yet, there's a gap in research specifically addressing the unique challenges and prospects of parking management in urban university contexts, particularly in integrating these technologies and approaches to meet the specific demands of such settings. This study seeks to bridge this gap by delving into parking satisfaction and management within an urban university framework, contributing to the advancement of more effective and sustainable parking solutions.

METHODOLOGY

The methodology depicted in Figure 1 outlines a structured approach to qualitative research. In the first step, an extensive literature review was conducted to establish a theoretical foundation and to identify knowledge gaps in existing studies.

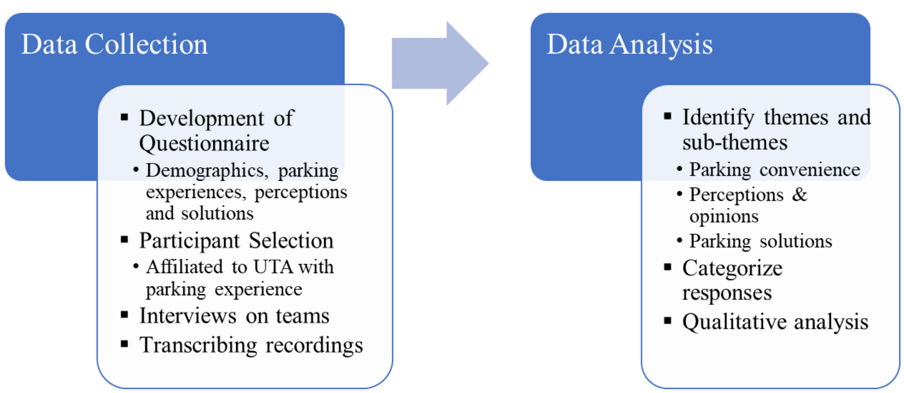

Figure 1. Research methodology

The foundational step was the development of an interview questionnaire that was designed to probe into the participants' experiences, perceptions, and suggestions concerning parking. In the next phase, the participant selection process aimed to encompass a diverse range of individuals with varying affiliations to the University of Texas at Arlington (UTA), thereby ensuring a breadth of perspectives in the study. Structured interviews were conducted with a total of 19 individuals who participated, averaging 25 minutes in duration, and the responses were meticulously recorded. The data processing stage followed, in which responses were transcribed, anonymized, and organized for analysis. The core of the methodology lies in the data analysis phase, in which the responses are examined to identify recurring themes and patterns, using a combination of qualitative and, occasionally, quantitative techniques. This process involved categorizing responses under identified themes and, if applicable, quantifying certain aspects to elucidate the data further. In the final step, the findings were interpreted from the data analysis, their implications were discussed, and conclusions were drawn.

Interview Questionnaire

The study's questionnaire covered diverse topics to thoroughly evaluate campus parking experiences. The demographic section assessed personal factors like age, education, and employment, alongside campus roles and commuting patterns, to understand their impact on parking needs. The section on parking experiences focused on routine behaviors, challenges in finding spaces, and permit usage, aiming to identify common parking issues and interactions with the permit system. The theme on parking perceptions examined views on facility conditions, cost sensitivity, location convenience, and information accessibility, intending to assess satisfaction with current parking solutions and ease of access to information. Lastly, the section on attitudes towards parking solutions explored the community's openness to parking technology, views on space allocation fairness, and ideas for enhancing parking services with sustainability in mind, aiming to measure the community's engagement with and support for sustainable parking initiatives and technologies.

Data Collection

Figure 2 presents a breakdown of the demographic characteristics of participants in the study. In the first chart, participants were grouped by the number of years they have used campus parking facilities, with categories ranging from less than one year to more than five years. The majority of them fell into the category of one to four years, representing both newer members of the university community and those who had been there a moderate amount of time. Those who had been at the university for more than five years were a smaller group but brought a long-term perspective to the study.

The second chart categorizes participants according to the highest educational degree they have obtained, ranging from individuals with only a high school diploma to those with advanced degrees, such as master's and Ph.Ds. This diversity in educational attainment not only suggests a range of parking needs and experiences among our sample, from undergraduate students to postgraduate researchers and faculty, but also implies that those with postgraduate degrees may possess unique insights due to potentially having parked on multiple campuses. The third chart focuses on the role of participants on campus. A substantial majority of them are students; the remainder are faculty and staff members, offering a professional perspective on campus parking. Lastly, the age range chart depicts a predominance of younger individuals, typically those who fall within the traditional college-age bracket, but also some in older age groups. This indicates that the study captures the parking experiences of traditional and non-traditional students, as well as younger faculty and staff. These demographic details provide a snapshot of the UTA community's diversity and set the stage for an analysis of parking experiences that vary widely based on personal and professional circumstances.

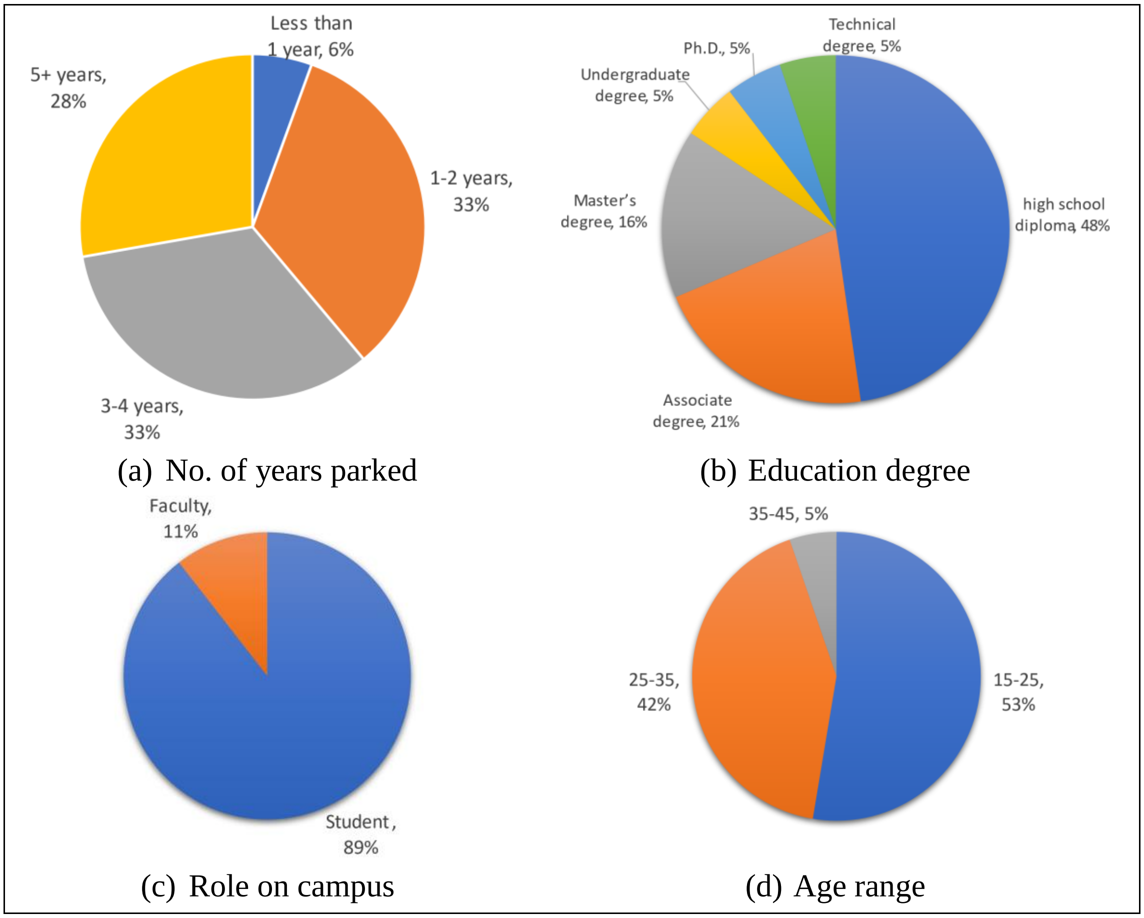

Figure 2. Participant demographics

RESULTS AND DISCUSSION

In the comprehensive analysis of campus parking dynamics, two interrelated themes shaping the daily lives of the campus community were identified and explored. First, the experience of campus commuters was delineated as their direct interactions with the parking system, such as the availability of spaces and ease of access. This was contrasted with their perception of the parking department services, which encompasses attitudes and opinions about the management, effectiveness, and responsiveness of the parking solutions provided. By separately examining these aspects — the tangible experiences and the subjective perceptions — the study aimed to construct a multifaceted understanding of how individuals interact with and feel about the parking system. Following this, potential solutions for improving parking, which included technological innovations and policy changes, and how these might address the specific needs and concerns highlighted by the campus community, were discussed.

Parking Experience

Personal travel behavior presents a cross-section of the daily logistical considerations individuals face in their commute to campus. A majority of the study participants rely on private vehicles as their primary mode of transportation, indicating a significant dependency on the campus parking infrastructure. Their preference for on-campus parking, as indicated by most participants, underscores the importance of convenience, availability, and price.

The preference for convenient parking is a dominant theme among the study participants, as highlighted by their statements. One participant emphasized the time-saving aspect, stating, “I always choose spots based on proximity to my building. It saves a lot of time.” This sentiment reflects a widespread preference for spots close to destinations, with proximity being a primary factor in choosing parking spots. However, this preference for convenience is juxtaposed with notable dissatisfaction regarding the availability of parking spaces. The effort and time invested in finding a parking spot are substantial, often leading to frustrations. As one participant described, “It's great when I find a spot near the class; it's rare but always a good start to the day.” The scarcity of conveniently located spots underscores the challenge of balancing demand with available resources.

While convenience and availability are critical, price also plays a significant role in personal travel behavior. Participants are acutely aware of the costs associated with parking, seeking options that offer the best value. As expressed by one individual, “Lower cost with close proximity to my department is key for me when choosing a parking spot.” This statement indicates that while proximity remains a top priority, the financial aspect of parking cannot be overlooked, with cost considerations significantly influencing decision-making.

In discussing the role of communication in addressing parking challenges, participants highlighted mixed experiences. While they receive general emails from the college , there is a desire for more targeted communication about available parking lots. One participant stated that he "receives general emails from the college” and another stated that he “would like more direct communication about available lots.” The participants' moderate level of satisfaction with the communication about parking highlights the need for more effective and direct information-sharing strategies.

Perception of Campus Parking System

This section delves deeper into the campus community's perceptions of the parking system, which are inherently shaped by their daily experiences, as previously discussed. While the tangible interactions with parking, such as convenience and availability, have been detailed, this analysis explores how these experiences culminate into broader perceptions and attitudes toward the parking department's services. The mixed perceptions and varying degrees of satisfaction, from low to high, reflect a complex interplay of factors, including the time spent searching for parking, cost implications, and the perceived fairness of parking regulations enforcement.

For instance, participants who found parking spots relatively easily or had parking lots conveniently located near their destinations tended to express higher satisfaction. In contrast, those who frequently encountered difficulties in finding spots, especially during peak hours, reported lower levels of satisfaction. The recurring issue of “scarcity of spots, especially during peak hours” near popular buildings indicates a multifaceted challenge. It points to the necessity of ensuring maximum parking capacity while also communicating with drivers in real-time about where to find available spaces. This approach recognizes that effective solutions should not only manage the existing spaces better but also enhance the communication and guidance provided to drivers, facilitating a smoother parking experience.

The cost of parking permits is an indicator of their satisfaction with the parking system. Our analysis revealed a predominantly negative sentiment among the campus community, with a significant majority expressing dissatisfaction. While a few individuals perceive the cost as reasonable, with comments like, “Considering the location, I think the parking rates are reasonable compared to other universities,” a larger number of participants voiced their discontent, describing the fees as “Expensive for students” and “Pretty expensive.” These negative reactions highlight a prevalent perception that the cost is disproportionate to the value received, especially considering the difficulties in finding spots and the financial constraints of the student population. This disparity in views, with only a very few showing a positive reaction and many voicing negative opinions, indicates that while there is some variation in how cost and value are correlated, the dominant trend leans towards a belief that the parking fees are excessive. This finding underscores the need for a deeper examination into the pricing structure and the provision of services to ensure that the parking system meets the needs and expectations of its users, particularly those who are most affected by the costs.

The enforcement of parking regulations also played a role in shaping perceptions. Some participants noted improvements in this area, with comments like, "I've noticed an improvement in parking enforcement lately, which makes things fairer for everyone," and "I've noticed more patrols lately, which keeps the parking fair." These observations suggest that enhanced enforcement efforts have been recognized and are appreciated by some of the campus community members.

Potential Parking Solutions

Several solutions and suggestions were proposed to enhance the parking experience in response to the varied experiences and needs of campus community members. These reflect a collective desire for more efficient, user-friendly, and equitable parking services. To address the availability of parking many participants experience, a common idea was to increase parking capacity through carefully planned enhancements in parking infrastructure, such as strategically located new parking facilities, rather than simply increasing the number of garages.

There was also a significant interest in improving communication to drivers to reduce the time searching for parking by adopting smart parking solutions, with participants expressing enthusiasm for technological advancements with comments like, "I'm really excited about the potential of smart parking solutions. It sounds like a game-changer," and "Any tech that can save me time finding a spot sounds good to me." Some, however, expressed reservations about user privacy, as one participant mentioned, "Depends on the extent of user tracking." Overall, the attitude towards smart parking solutions indicates a readiness to embrace technology for improved parking efficiency and user experience.

An example of smart parking solutions could be a real-time parking availability system, which garnered high interest. Participants valued the potential benefits of such technology, especially in addressing the challenge of finding available spots. Statements like "A real-time system would be amazing. It would reduce so much stress in finding a spot," and "Real-time updates would be a lifesaver during exam periods," highlight the anticipated positive impact of these systems. However, there was also caution regarding their reliability, as expressed by a participant: "I'm a bit skeptical about these systems. They need to be reliable to really work."

The idea of reserved parking based on payment received mixed reactions. While some saw it as potentially boosting efficiency, with remarks like, "Reserving parking for faculty during peak hours would be great. It would make things much more efficient," others raised concerns about exacerbating inequality in parking access, as noted in the comment, "Reserved parking sounds good, but I worry it might lead to more inequality in parking access." The diverse opinions and suggestions highlight the complexity of balancing different needs and perspectives in parking management, pointing towards a future where technology, inclusivity, and efficiency play key roles in shaping parking policies and systems.

POLICY REMMENDATIONS

Universities must proactively implement smart parking systems as a strategic priority to optimize the utilization of existing parking facilities, expedite the parking process for users, and significantly enhance the overall parking experience. Our comprehensive research unequivocally demonstrates that such systems not only streamline the management of parking resources but also play a crucial role in elevating user satisfaction. Adopting these advanced parking solutions is essential for universities seeking to address current challenges and improve campus parking dynamics effectively. By acting on this recommendation, university administrators will take a decisive step towards creating a more efficient, user-friendly, and satisfactory parking environment for their campus community.

The insights gained from this study will be helpful to university administrators who seek to understand the multifaceted aspects of parking management and its significant impact on the university community. The data suggests that parking policies should not be one-size-fits-all but rather tailored to accommodate the diverse needs of different age groups, roles, and socioeconomic backgrounds. The diverse tenure of participants at UTA, varying from less than a year to several years, coupled with their roles and employment status, highlight the need for parking policies that cater to a wide range of campus community members. For instance, more experienced university members might prioritize parking availability and location due to their established routines, while newer members may be more cost sensitive.

The near-universal reliance on private vehicles for commuting to campus suggests that the current transportation infrastructure and services may not sufficiently support or incentivize alternative modes of transportation. Policies that encourage diverse commuting options can lead to a more efficient use of campus space and a reduction in traffic congestion. These measures could improve the parking experience while also contributing to the university's sustainability goals by reducing the carbon footprint associated with the current high levels of vehicle dependency.

The convenience of parking lot locations and factors in choosing a parking spot, such as proximity to destination and cost, underscore the importance of strategic parking lot placement and pricing. While the instinct might be to build more garages in response to parking demand, our recommendations emphasize optimizing the use of existing parking capacity. This approach involves redirecting parking demand to underutilized lots through flexible pricing strategies that link convenience to price. By adjusting permit costs based on location desirability and proximity to core campus locations, the university can encourage a more even distribution of vehicles across available parking areas. This not only ensures a more efficient use of existing resources but also reduces the need for costly new constructions. Additionally, embracing smart parking solutions and real-time parking availability systems can further enhance this strategy by providing commuters with the information they need to make informed decisions about where to park, based on current availability and their personal valuation of convenience and cost. Together, these measures aim to create a more dynamic and responsive parking ecosystem that better serves the diverse needs of the university community while also aligning with broader sustainability goals.

The preferences expressed by the university participants are in alignment with larger trends in urban mobility and sustainability. For instance, the desire for convenience and accessibility mirrors the urban dweller's need for efficient transportation solutions. The frustration with parking scarcity and the high cost of parking permits highlights the challenges of managing limited urban space, a core concern in urban planning. Furthermore, the participants' openness to smart parking solutions and real-time availability systems reflects a wider societal shift towards embracing technology to enhance urban living. These findings underscore the importance of sustainability in urban transport planning, where parking management is increasingly recognized as a tool to reduce congestion; lower carbon emissions; and promote alternative modes of transport such as cycling, walking, or public transit.

CONCLUSION

Understanding user experiences is crucial in the context of the rising demand for customer satisfaction, as it informs the development of effective strategies to alleviate parking problems and enhance overall campus accessibility and functionality. This study delved into the complexities of parking services in a college campus setting to explore the varied perceptions and experiences of the users. Through a detailed investigation that involved structured interviews with 19 diverse participants, the research aimed to uncover the nuances of user experiences related to parking on the campus. This exploration sought to not only understand the immediate challenges and satisfaction levels associated with campus parking but also to identify potential areas for improvement and policy intervention.

The predominant reliance on private vehicles among the study participants underscores a significant dependence on the campus parking infrastructure. This preference for on-campus parking, largely driven by the need for proximity and convenience, especially for those with demanding schedules, is counterbalanced by the frustration over the availability of parking spaces and the time investment required to find these spots. These factors collectively point to an urgent need for a parking system that not only accommodates but also anticipates the diverse requirements of the university community. The study reveals varied satisfaction levels with UTA's parking system, influenced by search times, location convenience, and permit costs. A notable disconnect exists between parking costs and perceived value, indicating the potential for reevaluating parking management and pricing. The participants' keen interest in smart parking technologies and real-time availability systems reflects a trend towards tech-enhanced parking efficiency. The call for reserved parking spaces for those with disabilities or other specific needs highlights a commitment to inclusivity.

These findings suggest actionable policy recommendations. Short-term solutions include flexible pricing and smart technology integration for quick, cost-effective improvements in parking efficiency and user satisfaction. For more substantial, long-term changes, strategic parking placement and the development of new facilities should be considered, alongside expanding alternative transportation to alleviate demand. By distinguishing these recommendations, universities can prioritize actions that balance immediate impact with sustainable transformation, ultimately enhancing the campus parking experience.

In conclusion, the study sets a foundation for understanding satisfaction levels and potential improvements in the campus parking system, encouraging continuous evaluation and adaptation to meet the evolving needs of the university community. This study highlights some of the intricacies involved in managing university parking, emphasizing the need to balance diverse needs and expectations. It offers valuable insights for those in similar settings, underscoring the importance of effective parking solutions and communication strategies in academic environments.

The limitation of the current study is its concentration on a single university setting, which may not reflect the experiences of other institutions with different geographic and demographic contexts. Future research should aim to expand the scope of this study by incorporating a larger and more diverse participant pool to enhance the generalizability of the findings. Longitudinal studies could provide insights into how parking experiences and perceptions evolve over time, particularly with the implementation of new policies or infrastructural changes. Additionally, comparative studies with other universities could offer a broader perspective on effective parking solutions.

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Evaluating the Feasibility of Pedestrian and Bicycle Facilities in Frederick County Government

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ABSTRACT

Transportation agencies nationwide have been shifting toward strategic planning goals to reduce automobile dependence and promote diverse and sustainable multimodal systems. With the increased government funding for pedestrian and bicycle transportation, a resulting increase in shared-use pathways, pedestrian infrastructure, bicycle lanes, and sidewalks has been recognized across the United States. It is indeed important for state agencies, local municipalities, and governments to develop research studies to address the overall feasibility, design, and operational issues of such facilities. Integrating diversity in the transportation modes such as transit, pedestrian, bicycling, and ADA-accessible facilities has been one of the main focuses of Frederick County Government (FCG). The primary objective of this study is to analyze and investigate the feasibility of potential routes in the county for shared-use path corridors. This paper evaluates a case study of multiple alternatives for a shared-use facility along a generally north-south alignment between the city of Frederick and Urbana District Park. Two final alignment alternatives for the proposed shared-use path were shortlisted and evaluated using feasibility-level construction cost estimates based on a cost-per-mile estimate. Additional consideration was given to potential design minimization alternatives that could be considered as part of future design efforts to reduce the cost of construction. Transportation researchers and the American Society of Civil Engineers (ASCE) community are believed to be benefitting from this study.

INTRODUCTION

Pedestrian and bicycle facilities are considered key elements of a multimodal transportation system as part of an overall complete street network. Recently, there has been a significant increase in government funding, at the state and federal levels, to promote sustainable transportation systems and infrastructure. The most economical way to support these initiatives is by integrating these facilities in the early stages of land development plans and roadway design. FCG, Maryland, has adopted the Complete and Green Streets Policy (CGSP) which emphasizes the importance of improving the accessibility and mobility of pedestrians and bicyclists and reducing conflict with motorized traffic (FCG, 2020). The County transportation infrastructure is planned to be designed to provide a more environment-friendly network which in turn will reduce pollution and climate change concerns. The adoption of this policy is consistent with the Livable Frederick Master Plan which encourages non-motorized transportation and enhances active living (FCG, 2019).

The CGSP also identified the need for FCG to develop a design manual or guide to help implement these types of projects early in the development stage. FCG developed a Complete and Green Streets Plan (FCG, 2022) which provides a decision-making framework that can be used by planners, designers, and engineers to incorporate different roadway design components for a more inclusive and sustainable transportation network. As such, case studies should be developed to evaluate the return on investment of transportation infrastructure projects, including the challenges associated with users' behavior and local differences such as traffic culture and the surrounding environment (Arafat et al., 2020).

Transportation researchers worldwide have always been concerned with all aspects pertinent to the feasibility of pedestrian and bicycle infrastructure and their impacts on the transportation network. For instance, Kim et al., (2020) conducted a comprehensive review of relevant case studies in Korea related to the feasibility evaluation of non-motorized transportation projects. The researchers suggested cost estimation methods and divided the cost of these projects into three main categories that included construction cost, land compensation cost, and maintenance cost. The study reported that the cost estimation method, based on unit cost per facility, was the most common method used. In addition, it was recommended that a direct appraisal of the land be included in the cost estimation process or, alternatively, a land compensation cost be estimated by applying standard official land prices.

Previous studies highlighted some of the challenges associated with identifying non-motorized project costs. Pedestrian and bicycle projects often occur as part of larger multi-modal roadway projects, and bicycle-related costs are not tracked separately (Weigand et al., 2013). A published report by the Virginia Transportation Research Council identified several challenges faced by transportation agencies in measuring the feasibility of pedestrian and bicycle facilities. One of the main challenges is attributed to the lack of documentation on pedestrian and bicycle usage and demand (Ohlms et al., 2018). Additionally, it is hard to calculate performance measures for pedestrian and bicycle facilities when compared to vehicle-centric modes of travel. Therefore, conducting feasibility studies can be more challenging due to the limited data availability and limited research efforts in this area. It is increasingly important for local municipalities and governments to develop research studies to address the overall feasibility, design, and operational issues of such facilities. To fill in the academic literature gap, the primary objective of this study is to analyze and investigate the feasibility of potential routes in Frederick County, Maryland for a shared-use path corridor. This paper evaluates a case study of multiple alternatives for a shared-use facility that will provide connections to the existing trail network within Urbana District Park. Route recommendations generally follow the routes identified as part of the Frederick County Bikeways and Trails Plan (FCG, 2018). Feasibility level construction cost estimates for the alternatives are developed based on a cost-per-mile (CPM) estimate with major infrastructure including bridge structures, retaining walls, and environmental impacts.

LITERATURE REVIEW

Feasibility studies are considered one of the most important key elements in transportation planning projects. According to the United States Department of Transportation Systems Engineering Guide, a feasibility study needs to consider alternative solutions to satisfy the identified needs and select the most viable option (Hadi et al., 2019). Despite the importance of feasibility studies, there have been a limited number of case studies dedicated to the development of pedestrian and bicycle-feasible projects in the technical and economic framework.

Zhankaziev et. al, (2018) addressed the role of the feasibility study in the life cycle of transportation projects. The researchers reported three indicators that are commonly used during the evaluation of project implementation efficiency. These three methods include changes in the physical values of the functional performance indicators, criterion analysis of the project implementation efficiency, and the project cost estimate. The indicators were applied in the field of intelligent transportation systems and can be applied to non-motorized transportation projects.

Previous research efforts investigated the relationship between pedestrian volumes and traffic congestion. For instance, Sari et al., (2015) examined the feasibility of pedestrian facilities and the effectiveness of utilizing a pedestrian bridge at certain congested areas. The researchers defined the feasibility of a pedestrian facility by a performance indicator such as the Level of Service (LOS). Public involvement was conducted by utilizing a survey questionnaire covering various aspects of the project. The researchers also carried out a geometric feasibility using standard design specifications. The effectiveness of the pedestrian bridge was defined in the study as the ratio of the pedestrian bridge users to the total number of people crossing the street. The results showed that the level of service of all segments of the examined pedestrian facilities ranged from LOS A to LOS C, and the pedestrian bridge displayed LOS C. The geometric feasibility assessment results showed that the facilities were not considered feasible and the effectiveness of using the pedestrian bridge was found to be only 50.26%.

Non-motorized traffic safety and related crash data analysis can significantly impact the outcomes of feasibility studies. The construction of safe, well-connected pedestrian and bicycle facilities can protect and support the safety of daily commuters, as well as reduce automobile dependency and negative environmental impacts. Klobucar and Fricker (2007) emphasized the importance of providing pedestrian and bicycle facilities in areas with increased numbers of crashes, traffic congestion, poor air quality, and high fuel prices. The researchers proposed rational methods for evaluating the benefits of integrating bicycle-friendly facilities into highway project designs for the Indiana Department of Transportation. The study analyzed a database of bicycle-related crashes and developed a Bicycle Network Analysis Tool to assess the LOS offered to bicyclists in Indiana. The results showed that the developed tool can successfully assist in the selection of locations for bicycle facility improvements. The researchers concluded that the number of incidents between bicyclists and motor vehicles can be reduced by enforcing sidewalk ordinances and encouraging cyclists to ride on streets, bike lanes, and paths, where motorists are more likely to expect them. Feasibility studies on pedestrian and bicycle facilities require gathering and analyzing accurate data related to non-motorized crash rates, pedestrian volume counts, environmental resources, and points of interest. Chen et al., (2022) explored the feasibility of connecting pedestrian and bicycle routes with public sports facilities and green spaces in Nanjing, China. The researchers analyzed 25 major public sports facilities and green spaces and collected data related to cycling routes, areas of residential communities, local population information, outlines of parks, and the locations of entrances to those parks. The spatial intersections between park entrances and pedestrian routes were examined. The study results showed that the integration of bicycle lanes and public sports facilities has the potential to improve services to most residential areas and potential interactions between the facilities and existing parks. It was found that the layout of the facilities, the density of bicycle lanes, and the configuration of green spaces can significantly impact the service gaps and potential interactions.

Identifying pedestrian and bicyclist safety needs at signalized and unsignalized crossing locations is one of the important goals of non-motorized feasibility studies. Marisamynathan and Perumal, (2014) reported that a clear understanding of pedestrian crossing behavior is needed to provide the necessary facilities and to improve pedestrian safety at crossing locations. Abaza et al., (2018) analyzed six intersections at high pedestrian crash locations in Anchorage, Alaska to help understand the crossing compliance of pedestrians at crosswalks. The study showed that more pedestrian violations occurred at unsignalized crosswalks, as opposed to signalized locations, especially during the evening peak period. The rates of pedestrian crossing compliance were significantly reduced due to the presence of bus stops and the proximity of the bus stops to intersections. The data displayed the rate of crossing compliance increases with the increase in traffic volume, however spatial and overall compliance decreases as the pedestrian volume approaches 100 – 120 pedestrians per hour.

According to the review above, conducting feasibility studies for shared-use paths and the associated corridor alignments is extremely important and can be challenging due to the lack of documentation on pedestrian and bicycle usage and demand at the local government level. This paper evaluates multiple alternative alignments, for an approximately five-mile shared-use path connection between the City of Frederick (Maryland’s second largest municipality) and Urbana District Park, as a case study. The alignment is designed to primarily follow existing linear features such as roadways, railways, stream valleys, and utility corridors to create a continuous connection while minimizing land use and property impacts.

METHODOLOGY

The case study corridor is approximately five miles long and encompasses alternatives that vary from indirect natural scenic routes to direct transportation facilities along existing arterial roadways. Each alternative seeks to maximize access to Frederick County’s main attractions, with a focus on providing opportunities for safe and convenient non-motorized transportation alternatives between established commercial and residential areas. This section includes the methods utilized for data collection, an evaluation of existing conditions, an impact analysis for each of the alternative alignments, a constructability review, and closes with a feasibility level cost estimate.

Data Collection

The existing roadways within the case study area include arterial roads such as Urbana Pike (MD 355) and Old National Pike (MD 144), collector roads such as Reichs Ford Road, and local roads such as Reels Mill Road, Ball Road, and Araby Church Road. The existing public transportation system within the project study area is provided on MD 355 from the City of Frederick south to the Monocacy MARC Station, and on MD 144 to Spring Ridge, while paratransit needs are provided through the entirety of the study area. Data related to the environmental resources were obtained from topographic maps, Maryland Department of Natural Resources mapped wetlands, Maryland Department of the Environment mapped streams, Federal Emergency Management Agency floodplain mapping, FCG mapped forest resources and agricultural preservation.

There are multiple points of interest and major destinations within the case study area including Francis Scott Key Mall (FSK Mall), Frederick Fairgrounds, Frederick Municipal Airport, and Monocacy National Battlefield. Other parks in the study area include Urbana District Park at the southern project limits on MD 355, and Pinecliff Park near Reichs Ford Road, directly adjacent to the Monocacy River.

Design Criteria and Alternative Alignments

The design criteria for the shared-use path were created using the Frederick County Complete and Green Streets Plan and references AASHTO Bike Book, the AASHTO Policy on Geometric Design of Highways and Streets (Green Book), the Bicycle Policy and Design Guidelines (MDOT SHA Bike Policy), and Public Right-of-way Accessibility Guidelines (PROWAG). Table 1 shows the design criteria for the proposed case study off-road shared-use path between the City of Frederick and Urbana District Park.

Table 1. Design criteria for the off-road shared-use path.

Criteria	Guidance	Reference
Bicycle Design Speed	20 MPH max Recommended, 12 MPH max for urban areas, and 8 MPH max speed at intersections	MDOT SHA Bike Policy
Shared-use Path Width	12 ft to 14 ft preferred. If under 10 ft, a design waiver is needed from the State. (8 ft min for short segments)	
Min. Curve Radius	74 ft	AASHTO Bike Book
Stopping Sight Distance	200 ft	
Horizontal Sightline Offset	58 ft	
Shoulder Clearance Width	2 ft min. (6:1 slope)	
Safety Grading	Barrier / Fence required if buffer < 5’ or: 3:1 for 6’ vertical drop, 2:1 for 4’ vertical drop, and 1:1 for 1’ vertical drop	
Buffer Width (with and without Curbs)	5’ min, greater than 5’ preferred for high-speed roadways from the outside edge of the shoulder. If the buffer < 5’, a vertical barrier should be installed for separation from vehicle lanes	
Vertical Clearance	8 ft min (above Path) 10 ft preferred (above Path)	MSHA Bike Policy AASHTO Bike Book
Vertical Clearance	15 ft (above Roadway)	AASHTO Green Book
Maximum Grade	Not to exceed roadway grade (within ROW)	PROWAG
Cross Slope	2% max	
Pedestrian Access Route	Full width of shared-use path	
Pavement Design	Pervious/impervious depending on soil characteristics. 3” Hot Mix Asphalt (HMA) for Surface, 4” Graded Aggregate	AASHTO

A desktop review is performed to identify multiple potential alignments for the case study shared-use path. All alignments begin at the City of Frederick line and end at the Urbana District Park as shown in Figure 1. The typical section for all alignments is a 12-foot-wide shared-use path with a 5-foot grass buffer. The 12-foot width is the recommended width of MDOT SHA. It should be noted that this typical section was not feasible in some areas of the shared-use path alignments due to site constraints. In such cases, a reduced buffer or path width is proposed.

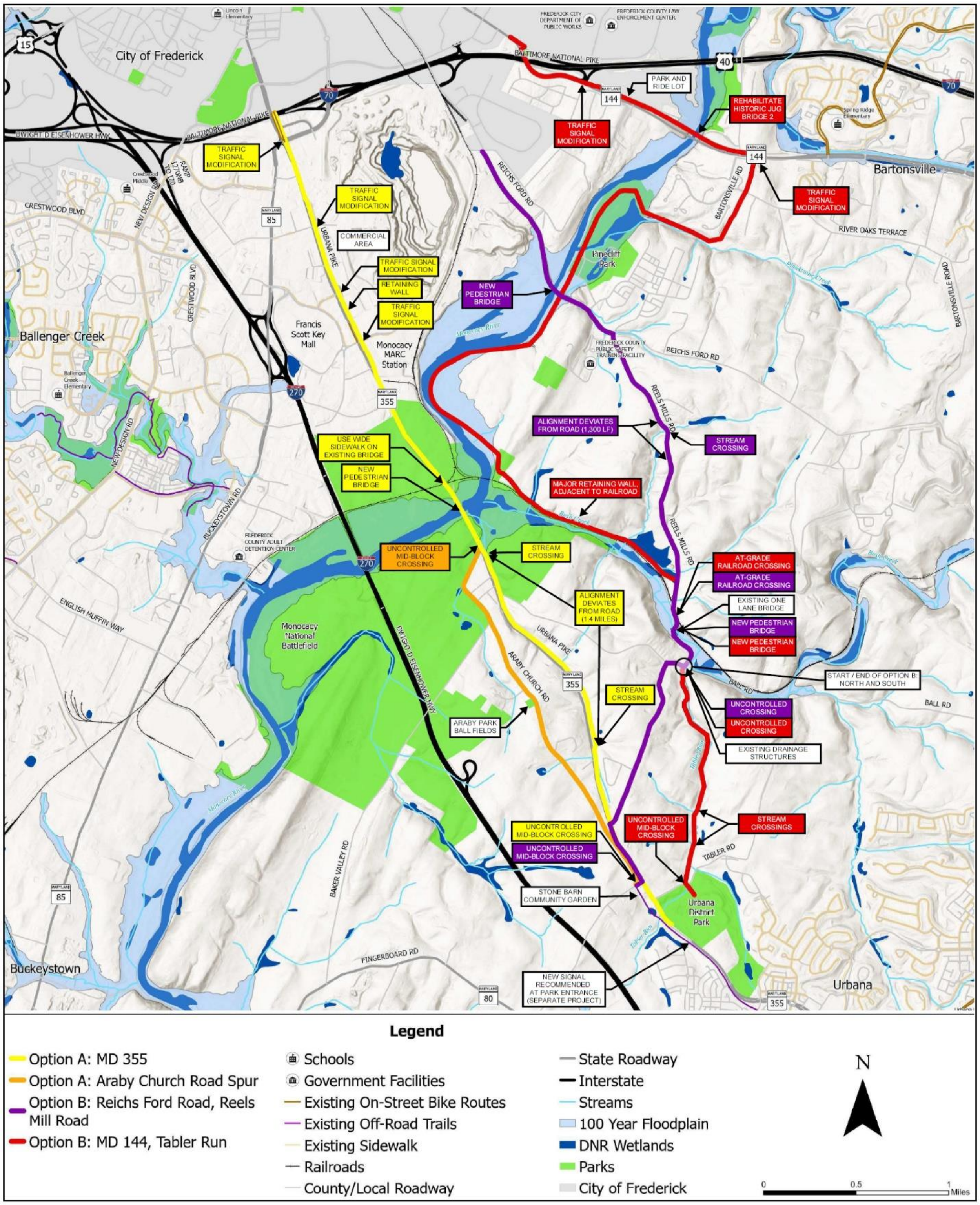

Figure 1: Alternative Alignments Map

Two options are examined to assist in the development of the shared-use path final alignment recommendations as follows:

- Option (A): Urbana Pike (MD 355) – Frederick to Urbana District Park
  - Sub-option (A): Araby Church Road Spur
- Option (B) North: Old National Pike (MD 355) and Reichs Ford Road
- Option (B) South: Reels Mill Road and Tabler Run

Option (A) begins at the City of Frederick on Urbana Pike (MD 355) and follows MD 355 southeast for approximately 5.0 miles. One of the main challenges associated with this alternative is that the existing roadway bridge crossing the Monocacy River does not have sufficient width to safely include a pedestrian or bicycle connection, so a new adjacent pedestrian bridge, approximately 300 feet long across the Monocacy River is included in the analysis. Figure 1 shows improvements that are required for this alternative including marked crosswalks and pedestrian signals to provide safe pedestrian crossings.

Option (B) alignment alternative is divided into north and south sections, each of which consists of two sub-options as shown in Figure 1. This alternative alignment provides a more scenic environment to users. Either of the north alignments can be paired with either of the south alignments. This alignment utilizes the historic Jug Bridge to cross the Monocacy River. Repairs and safety improvements on Jug Bridge 2 and Old MD 144 are required for the roadway surface and parapet walls. Due to limited right-of-way, the recommended typical section along Bartonsville Road and Tobery Road is reduced to an 8-foot-wide shared-use path with a five-foot buffer along the west side of the roadway. A new pedestrian bridge, approximately 85 feet in length, was identified in the analysis in order to cross Bush Creek, adjacent to the existing bridge. The criteria used in the evaluation of each shared alignment alternative include facility design, structures, environmental resources, and transportation improvements as shown in Table 2.

Table 2. Criteria for the Impact Evaluation

Facility Design	
Alignment Length	Overall length for each alternative alignment
Roadway Conditions	Assessment of the current roadway condition (Poor, Fair, Excellent)
Trail Access Points	Locations where the trail can be accessed with available parking
Slopes	Running grades of 15 – 25% along alignment, 25%+ for very steep slopes
Parcels Impacted	Number of individual parcels adjacent to the path alignment
Available Right of Way	Average distance between the edge of the roadway and the property line
Structures	
Existing Bridges and Structures	Total number of existing bridges and retaining walls along the path
New / Reconstructed Structures	Newly constructed structures and repaired structures
Environmental Resources	
Stream Impacts	Linear feet of direct and parallel stream impacts within path alignment
Other	Wetlands, Floodplains, Sensitive species, Historical areas
Transportation Improvements	
Driveways / Entrances	Property entrances or driveways crossed by the alignment
Alignment Crossings	Number of crossings that have a stop sign, traffic light, or no traffic control

Table 3 illustrates a comparison of the shared-use path alignment utilizing Option (A) MD 355 Frederick to Araby Church Road and sub-options Araby Church Road to Urbana District Park and Araby Church Road Spur.

Table 3. Option (A) Cross Evaluation

Item	**Option (A)** Frederick to Araby Church Rd	**Sub-option (A)** Araby Church Rd to Urbana District Park	**Sub-option (A)** Araby Church Rd Spur
Alignment Length	2.6 miles	2.4 miles	2.2 miles
Roadway Conditions	Fair	Fair	Fair
Trail Access Points	4	2	2
Steep Slopes (15-25%)	0	0	1
Very Steep Slopes (25%+)	0	0	0
Parcels Impacted	26	34	33
Available Right of Way	MD 355 east: 8-16 ft	MD 355 east: 16-18 ft	Araby Church Rd: 8 ft MD 355 west: 34 ft
Existing Bridges	2 bridges	0	0
New / Reconstructed Structures	1 new retaining wall, 1 new bridge	0	0
Stream Impacts	125 LF	250 LF	60 LF
Adjacent Streams	0 LF	8,375 LF	1,275 LF
Wetlands	0 acres	0 acres	0 acres
Floodplains	0.75 – 1 acre	0.25 – 0.5 acre	0 acres
Forests	0.5 – 1 acre	10 – 10.5 acres	2 – 2.5 acres
Sensitive Species	2.25 – 2.75 acres	12 – 12.5 acres	9 – 9.5 acres
Historical Areas	6 – 6.5 acres	0.5 – 1 acre	3 – 3.5 acres
Driveways / Entrances	16	7	25
Stop Controlled Crossings	0	3	3
Uncontrolled Crossings	0	1	1
Signalized Intersections	4	0	0
Railroad Crossings	0	0	0

*Note: The color of headings corresponds to the alternative alignments map color shown in Figure 1.

It should be noted that there is a steep slope directly adjacent to MD 355 requiring significant earthwork and retaining walls to construct the shared-use path directly adjacent to the roadway. It can be inferred from Table 3 that the combination of Frederick to Araby Church Road route with sub-option (A) Araby Church Road Spur alternative provides fewer environmental impacts. This alignment provides a more comfortable experience for users along the lesser traveled roadway. Therefore, this alternative is shortlisted and moved forward with further analysis and comparison with Option (B). Table 4 shows a comparison of the shared-use path alignment utilizing Options (B) North which include Old National Pike (MD 355) or Reichs Ford Road and Options (B) South which include Reels Mill Road or Tabler Run.

Table 4 provides support that the combination of Reichs Ford Road and Tabler Run alignments provides fewer impacts and avoids the need for large retaining walls located in close proximity to an active railroad. This route also provides a more direct connection between Frederick City and Urbana District Park and does not require the rehabilitation of historic Jug Bridge 2. The alignment along Tabler Run, south of Ball Road, provides a scenic route that is largely separated from existing narrow roadways and provides a direct connection to Urbana District Park. This combination of options does not require an uncontrolled crossing of Urbana Pike, a minor arterial, to connect to the Stone Barn Community Garden. Therefore, this alternative is shortlisted and moved forward with the final analysis and comparison with the shortlisted alternative from Table 3. It should be noted that there is a large drainage culvert and outfall on the northeast corner of the intersection of Ball Road and Reels Mill Road that conflicts with the path alignment for Option (B). Construction of the facility would require modification of this culvert and outfall, or reconfiguration of the intersection to shift towards the north to make space for the shared-use path.

Table 4. Option (B) North Cross Evaluation

Item	Option (B) North Reichs Ford Rd	Option (B) North MD 144	Option (B) South Reels Mill Rd	Option (B) South Tabler Run
Alignment Length	3.3 miles	6.6 miles	1.5 miles	1.4 miles
Roadway Conditions	Fair	Fair	Fair	Fair
Trail Access Points	2	3	1	1
Steep Slopes (15-25%)	1	4	1	4
Very Steep Slopes (25%+)	0	1	0	0
Parcels Impacted	25	39	19	4
Available Right of Way	Reichs Ford Rd: 26 ft Reels Mill Road: 4.5 – 5.5 ft	East Patrick St: 0.5 ft MD 144: 50+ ft Bartonsville Rd: 19ft Tobery Rd: 19ft Reels Mill Road: 5.5 ft	Ball Rd: 3 ft, MD 355: 16.5 ft Reels Mill Road: 9.5 ft	N/A
Existing Bridges	2 bridges	3 bridges	0	0
New / Reconstructed Structures	2 new bridges	2 new bridges 1 repaired bridge 1 retaining wall	0	0
Stream Impacts	530 LF	445 LF	0 LF	250 LF
Adjacent Streams	1,725 LF	2,700 LF	0 LF	6,550 LF
Wetlands	0.5 – 0.75 acres	4 – 4.25 acres	0 acre	0 acre
Floodplains	4.5 – 5 acres	17 – 17.5 acres	0 acre	1.5 – 2 acres
Forests	4 – 4.5 acres	18.5 – 19 acres	1.5 – 2 acres	3 – 3.5 acres
Sensitive Species	1 – 1.25 acres	2.75 – 3 acres	3 – 3.5 acres	0 acres
Historical Areas	0 acre	11 – 11.5 acres	0 acre	0 acre
Driveways / Entrances	11	6	15	0
Stop Controlled Cross	2	3	1	0
Uncontrolled Cross	0	3	2	2
Signalized Intersections	0	2	0	0
Railroad Crossings	1	1	0	0

*Note: The color of headings corresponds to the alternative alignments map color shown in Figure 1.

Cost Estimates

Feasibility-level cost estimates were developed for the two shortlisted shared-use path alternatives on a CPM basis using the SHA Cost Estimating Manual and a 25% inflation factor to reflect the 2023-year unit costs. Estimates include major items such as bridge structures, retaining walls, traffic signal modifications, utility pole relocations, and mitigation for environmental impacts (within a conservative assumed limit of disturbance). Additional cost categories are included as percentage contingencies for maintenance of traffic, drainage, landscaping, and utilities. A 40% contingency is included in the project cost to account for unknown costs through the design process, as established in the SHA Cost Estimating Manual. Estimates do not include the cost of acquiring additional right-of-way. Table 5 shows a cost estimate for Option A - MD 355 and Araby Church Road Spur alignment and Option B - Reichs Ford Road and Tabler Run.

Table 5. Feasibility Cost Estimate for shortlisted shared-use path alternatives

Item	Unit	Unit Cost	Option A		Option B	
			Quantity	Total Cost	Quantity	Total Cost
Shared-Use Path, 12' width	MI	$1,253,000	4.8	$6,014,400	4.7	$5,889,100
New Bridge Structure	SF	$325.78	4,650	$1,514,877	6,000 1,350	$1,954,680 $439,803
Retaining Wall	SF	$375.90	3,760	$1,413,384	0	-
Traffic Signal Modification /leg	EA	$81,445	4	$325,780	0	-
Pedestrian Lighting Pole	EA	$12,530	0	-	18	$225,540
Utility Pole Impact	EA	$6,000	100	$600,000	10	$60,000
Cantilever Sign Structure & Signs	EA	$125,300	1	$125,300	0	-
Wetland Mitigation	AC	$952,280	0	-	0.5	$476,140
Stream Mitigation	LS	$877,100	1	$877,100	1	$877,100
Tree Felling / Forest Impacts	AC	$3,759	3	$11,277	LS	$46,987
Subtotal 1			**$10,882,118**		**$9,969,350**	
Contingent Categories						
Category 1: Preliminary, MOT	30% of Subtotal 1		$3,264,635		$2,990,805	
Category 3: Drainage	15% of Subtotal 1		$1,632,318		$1,495,403	
Category 7: Landscaping	12% of Subtotal 1		$1,305,854		$1,196,322	
Category 8: Utilities	15% of Subtotal 1		$1,632,318		$1,495,403	
Subtotal 2			**$18,717,243**		**$17,147,283**	
Contingency	40% of Subtotal 2		$7,486,897		6,858,913	
Feasibility Level Cost (rounded value)			**$26,300,000**		**$24,100,000**	

For Option A, one major cost includes the construction of a retaining wall along MD 355. The estimated cost of this retaining wall is approximately $3 million, and the impacts could potentially be avoided by realigning the route through existing parking lots. This change would increase the length of the route and was not included as part of the analysis. For Option B, adjusting the location of the northern terminus of the alignment to end at Pinecliff Park could reduce the cost by approximately $7.1 million. This change would shorten the alignment and eliminate the need for an additional pedestrian bridge across the Monocacy River. However, this would not provide a connection to the City of Frederick, as it would remain approximately 1.0 miles from the City of Frederick boundary.

CONCLUSION AND RECOMMENDATION

This paper investigated the feasibility of potential routes in Frederick County, Maryland for the construction of a pedestrian and bicycle facility between the City of Frederick and Urbana

District Park. Two final alignments for the shared-use path were compared in terms of facility design, required structures, impacts on environmental resources, and transportation infrastructure. Feasibility level construction cost estimates for both alternatives were developed based on a CPM estimate. Evaluation of the anticipated impacts shows that Option (A) has fewer environmental impacts on streams, wetlands, floodplains, and forests compared to Option (B). Option (A) alignment takes a direct route which provides efficiency for commuters and greater utility for the community, as it provides connections to more points of interest including the Monocacy MARC Train Station, Francis Scott Key Mall, and a large shopping center. Option (B), consisting of a route along Reichs Ford Road and Tabler Run is considered a less direct route that provides a more scenic alternative. This alignment has fewer impacts on sensitive species, historical areas, and properties. However, it carries the potential for more complexities in the design and construction phases. This alignment identified potential challenges such as the impacts on the large culvert and drainage outfall near the intersection of Reels Mill Road and Ball Road. Option (B) navigates through properties that are not within or directly adjacent to the County right-of-way and will require additional property acquisition. Design optimization through future design stages is required to minimize the impacts of both options. Finally, the results showed that Option (A) along with Araby Church Road Spur is recommended as the most feasible route for the shared-use path.

DISCLOSURE STATEMENT

There is no financial interest or benefit arising from the direct applications of this research. The authors declare no conflict of interest. The opinions, findings, and conclusions expressed in this paper are those of the authors and not necessarily of any other organization.

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Proactive Seismic Rehabilitation Decision Making for a Road Network Considering Multiple Assets' Performance Uncertainties

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ABSTRACT

The functionality of a road network is disturbed by seismic events. The disturbance in the road network is associated with damage to the network's assets (e.g., pavement, bridge) and unexpected changes to the network's functionality. Proactive road network rehabilitation helps reduce damage to the network's assets and prevent unexpected changes in network functionality due to seismic events. However, all road network assets cannot be rehabilitated at once due to the limited availability of rehabilitation resources. This research aims to identify the optimal combination of a network's concrete assets that should be proactively rehabilitated to reduce the road network's functionality changes when limited resources are available for rehabilitation. The analysis was conducted in three stages: characterizing concrete assets' performance uncertainties, estimating the pre- and post-disaster road network's functionality using traffic simulation, and formulating and solving a stochastic combinatorial optimization problem to identify the optimal combination of a network's concrete assets. A road network located in California was selected for this study. Probabilistic seismic fragility functions were used to identify all critical road network concrete assets (e.g., pavement, bridge) and their associated failure probabilities subject to seismic events. Traffic simulation was performed to calculate the changes in functionality due to the damage to identified critical concrete assets. Simulation of Urban Mobility (SUMO), an open-source software, was used to conduct the traffic simulation. A simulated annealing-based optimization algorithm was used to solve the optimization problem and identify the optimal combination of road network assets. This study supports optimal resource allocation for road network seismic rehabilitation, which is essential for post-disaster transportation infrastructure safety and efficiency.

INTRODUCTION

Seismic events can have significant operational impacts on road networks, including travel time delays, speed reductions, and traffic congestion. These effects can be categorized into three types: (1) damage to road network assets leading to permanent traffic interruption until restoration, (2) partial damage limiting operation, and (3) interruption in traffic flow without any damage. For example, the Northridge earthquake in California (1994) significantly affected travel times due to the collapse of two bridges on an interstate highway (I-10) connecting Santa Monica and Los Angeles (Giuliano and Golob 1998). The average travel time from north Los Angeles to the workplace increased from 29.4 to 51.1 minutes, a 73.8% increase immediately after the disaster (Giuliano and Golob 1998).

Existing component-level seismic vulnerability analysis methods of road networks can be classified into four categories: expert-based (Werner et al. 2006; Winter et al. 2014), empirical

(Maruyuma et al. 2010; Kaynia et al. 2011; Oblak et al. 2019), analytical (Banerjee and Shinozuka 2007; Moschonas et al. 2009), and hybrid fragility functions (Kappos et al. 2006; Kappos Penagopoulos 2010). However, these models often concentrate on a single component, limiting their ability to comprehensively assess the correlation between a road network's asset damage and its functionality.

Network-level seismic vulnerability analysis methods of road networks can be categorized into those considering network topology and graph theory, and those considering traffic data and traffic simulation. Network topology and graph theory-based vulnerability assessment models can be further classified into several sub-categories: accessibility-based (e.g., El-Maisi et al. 2022; Novak and Sullivan 2014), game-theory-based (e.g., Bell et al., 2008;), importance-based (e.g., Knoop et al. 2012; El-Rashidy and Grant-Muller 2014), robustness-based (e.g., Snelder et al. 2012), and connectivity-based (e.g., Rupi et al. 2015). Seismic vulnerability assessment models focusing on traffic data and traffic simulation can be further classified into those that are hazard-based (Jayaram & Baker 2010), risk-centric (e.g., Bil et al. 2014), direct loss quantification (e.g., Kiremidjian et al. 2007), and performance indicator evaluation (e.g., Argyroudis et al. 2015; Faturechi & Miller-Hooks 2015).

Despite existing research on the network-level seismic vulnerability of road networks, state highway authorities often face a complex dilemma in prioritizing proactive seismic rehabilitation (Nicolosi et al. 2023). Transportation network performance is not evaluated on a single asset type like bridges or pavements alone, but on the network; hence, multi-asset management tools are needed to manage the infrastructure (Hudson et al. 2014). One of the key decisions made on the transportation network is how to where the critical network links are. Most proactive or post-earthquake vulnerability assessment tools for a road network to identify the critical assets of the network were developed based on the vulnerability or performance of a single asset (Karlaftis et al. 2007; Virtucio et al. 2023; Kilantis and Sextos 2019; Rasulo et al. 2021). A tool is needed to consider the performance of multiple assets and identify the critical assets of a road network vulnerable to seismic events. This study addresses this gap using a stochastic combinatorial optimization method integrated with a probabilistic network-level seismic vulnerability analysis approach to identify the most critical road network concrete assets considering multiple assets' performance uncertainties.

METHODOLOGY

The methodology of identifying the critical concrete assets within a road network for proactive rehabilitation, particularly when the budget is limited, involves two stages. First, a stochastic combinatorial optimization problem is formulated to identify a rehabilitation strategy that minimizes the loss of serviceability in the road network following a seismic event. Subsequently, the formulated optimization problem was solved using a simulated annealing-based optimization algorithm.

Formulation of Optimization Problem

The overall objective is to minimize the loss of transportation network serviceability after a seismic event. This loss is characterized by integrating travel time and distance resulting from the closure of a specific asset following seismic activity. The developed optimization problem is summarized in Table 1.

Table 1: Summary of Optimization Problem

Objective Function	Minimize the expected value of SM, $min_{r \in R} E(SM_r)$
Constraints	$\sum_{k=1}^{N_k} S_k * L_k < L_{max}$
Variable	R is the set of all the rehabilitation policies (r). SM_r in the Serviceability Measure for Rehabilitation Policy (r) L_{max} is the maximum possible rehabilitation length N_k total number of links in the road network L_k represents the length of link k

The rehabilitation policy (r) is formulated by considering two potential outcomes: "rehabilitation" or "no rehabilitation." To illustrate, a road network with three concrete assets or three links was assumed. Concrete assets were defined as links of a road network for this study. The rehabilitation policy can be expressed as {S1, S2, S3}, where S_k=1 indicates that link k in the road network is rehabilitated, and S_k=0 signifies that the link is not rehabilitated. Without any feasibility constraints, R ∈ $X^{2^{N_k * N_k}}$ constitutes the entire combinatorial decision space for a network with. However, the size of R is bounded by the constraint that any rehabilitation policy (r∈R) cannot allow the rehabilitation of links whose cumulative length exceeds L_{max}.

The value of $E(SM_r)$ for each rehabilitation policy r was calculated based on the following equation:

$$E(SM_r) = \frac{\sum_{n=1}^{N} [\Delta T_r^n * C_d + \Delta L_r^n * C_{op}])}{N * Z} \tag{1}$$

ΔT_r^n = increase in travel time during nth Monte Carlo run in a network whose rehabilitation policy is represented by r

ΔL_r^n = increase in travel length during rth damage simulation in a network whose rehabilitation policy is represented by r

C_d = Cost associated with travel time

C_{op} = Per mileage cost associated with operation and maintenance of a vehicle

N = Number of Monte Carlo Runs

Z = Number of intensity measure field

For simplification of calculation, Eq. (2) was used.

$$\Delta T_r^n * C_d + \Delta L_r^n * C_{op} = SM \tag{2}$$

For this study, the operational and maintenance cost per mile for a passenger vehicle was assumed to be 67 cents per mile (Baral and Shahandashti 2022; Bureau of Transportation Statistics 2021). Additionally, the cost attributed to travel delays was assumed 30.12 dollars per hour (Baral and Shahandashti 2022).

Solution of Optimization Problem

The combinatorial optimization problem is challenging to solve with conventional algorithms due to the non-convex, non-continuous nature of the objective function and the absence of a closed-loop representation of the objective function. A simulated annealing algorithm was designed to solve the optimization problem defined in Table 1 for identifying the optimal combination of links to be rehabilitated to minimize the loss of serviceability during network disruption caused by seismic events.

The simulated annealing process was initialized by randomly selecting a rehabilitation policy (r). Two cases are considered: $\sum_{k=1}^{N_k} S_k * L_k < L_{max}$ and $\sum_{k=1}^{N_k} S_k * L_k > L_{max}$. In both cases, a greedy heuristic approach was employed to avoid infeasible or inexpensive policies.

If the current rehabilitation policy (r) fell into Case 1, the policy was updated by adding an unrehabilitated link until further additions exceed $\sum_{k=1}^{N_k} S_k * L_k > L_{max}$. If r belongs to Case 2, it is updated by removing the shortest rehabilitated link until $\sum_{k=1}^{N_k} S_k * L_k > L_{max}$ holds true. A simulated annealing optimization algorithm was initialized with an initial temperature of 100 and a cooling rate of 2 at each decrement. Ten iterations are performed before each temperature decrement. These parameters were determined through sensitivity analysis. The simulated-annealing approach used by Shahandashti and Pudasaini (2019) was adopted in this study to solve the optimization problem.

Evaluation of Objective Function.

The evaluation of the objective function was initiated with the identification of a scenario earthquake, determined through deaggregation analysis (USGS 2018). A scenario earthquake was selected due to its ability to incorporate spatial correlation between seismic intensities (Adachi 2007; Zanini et al. 2016, Zanini et al. 2017).

Once the earthquake scenario was selected, we employed the ground motion prediction equation (GMPE) to generate a spatially correlated field of intensity measures (Abrahamson and Silva 2007; Zanini et al. 2016; Zanini et al. 2017).

$$\ln IM = \ln(\overline{IM}) + \sigma_{ij}\xi_{ij} + \tau_j\eta_j \tag{3}$$

where,

$\overline{IM}$= Median Intensity Measure
σ_{ij} = Intraevent Standard Deviation
ξ_{ij} = Normalized Intraevent Residuals
τ_j = Interevent Standard Deviation
η_j = Normalized Interevent Residuals

In this study, peak ground velocity (PGV) was chosen as the seismic intensity parameter. It was assumed the site was not susceptible to earthquake-induced geotechnical instability, and peak ground displacement was considered zero. The average value of PGV was computed using the Scenario Shake Map Calculator of OpenSHA version 1.4.0 (Field et al., 2005). The PGV value for each link was then determined following the methodology proposed by Shahandashti and Pudasaini (2019). A total of 20 random PGV fields were generated for this study (*Z=20*).

For each PGV field, the fragility equation given in Eq. (4) was utilized to calculate the probability of failure for each road (Basöz and Mander 1999; Argyroudis et al. 2013).

$$F\,(IM,\,\mu,\,\sigma) = \Phi\left(\frac{\ln(IM)-\mu}{\sigma}\right) \tag{4}$$

where, $\Phi(.)$ is the probability density function of a standard normal distribution with parameters μ and σ. Table 1 was used for the values of μ and σ.

Table 2: Parameters of fragility equation

Types of Concrete Assets	Slight Damage		Moderate Damage		Severe Damage		Reference
	μ_1	σ_1	μ_2	σ_2	μ_3	σ_3	
Two Lane Concrete Road	6	0.7	12	0.7	24	0.7	National Institute of Building Sciences 2004
Multi-Lane Concrete Road	12	0.7	24	0.7	60	0.7	National Institute of Building Sciences 2004
Concrete Bridges	3.9	0.2	3.9	0.2	13.8	0.2	Basoz and Mander 1999

For each PGV field, *N* number of Monte Carlo simulations were conducted. The value of *N* was selected based on a convergence study. For each Monte Carlo simulation, a uniformly distributed random number (r_{zk}) between 0 and 1 was generated to evaluate the damage state. The damage state was assigned for each link using Table 2.

Table 3: Condition for each damaged state

Damage State	**Condition**
No Damage	$r_{zk} \epsilon [F(IM, \mu_1, \sigma_1), 1]$
Slight Damage	$r_{zk} \epsilon [F(IM, \mu_2, \sigma_2), F(IM, \mu_1, \sigma_1)]$
Moderate Damage	$r_{nj} \epsilon [F(IM, \mu_3, \sigma_3), F(IM, \mu_2, \sigma_2)]$
Severe Damage	$r_{nj} \epsilon [0, F(IM, \mu_3, \sigma_3)]$

The road network was modified by reducing the capacity of each road based on the damage state. For multi-lane concrete roads, the value of reduction of capacity is 0% for no damage, 25% for slight damage, 50% for moderate damage, and 100% for severe damage. For two-lane concrete roads, the value of reduction of capacity is 0% for no damage, 55% for slight and moderate damage, and 100% for severe damage (Allen et al. 2021). Figure 1 describes the process of calculating the value of $E(SM_r)$ for each rehabilitation policy.

APPLICATION AND RESULTS

The proposed approach was applied to a small network in Inglewood City, California. Figure 2 shows the network selected for this study. For this study, two types of concrete assets were considered: bridges and pavement roads. The red mark denotes bridges of the network, while the black mark denotes pavement roads.

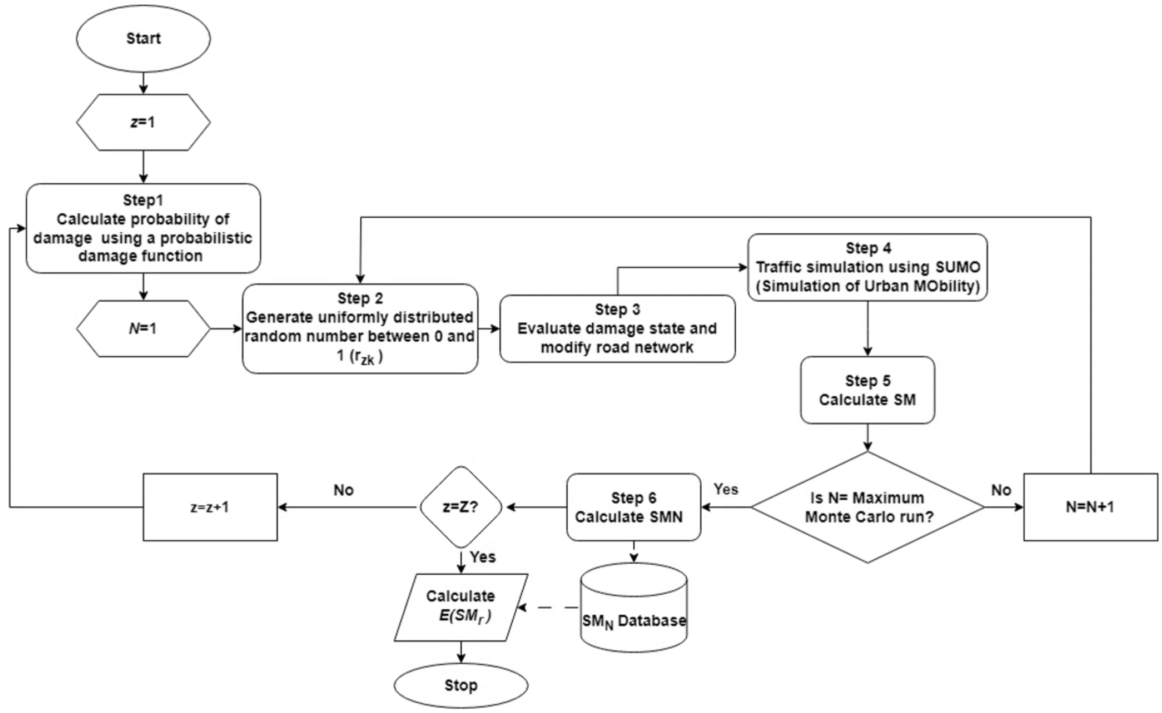


Figure 1. Steps of evaluating the objective function.

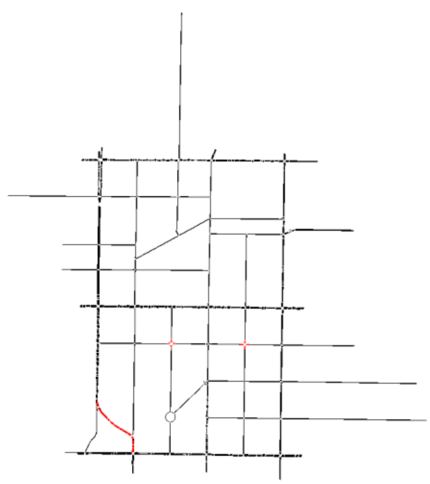


Figure 2. Layout of the selected road network.

A deaggregation analysis was conducted to identify the scenario earthquake (1.0-second spectral acceleration and 2,475 years return period). From the deaggregation results, an earthquake originating at the Newport-Inglewood fault, with a magnitude of 6.63, emerged with the highest contribution ratio (27.78%). This earthquake was selected as the scenario earthquake. A peak ground velocity map was generated due to the scenario earthquake (Field et al., 2005). The resulting peak ground velocity map is shown in Figure 3.

To integrate interevent residuals and intraevent residuals, 20 sets of intraevent and interevent residuals were generated. These intraevent and interevent vectors were then added to the value from the peak ground velocity map to create 20 random PGV fields. For each PGV field, the average PGV was calculated for each link. These average PGVs for all links were used to determine the value of the probability of damage and the damage state of each link.

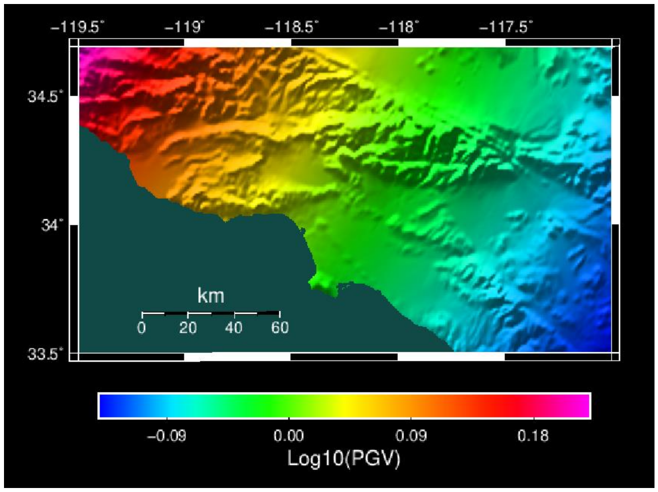


Figure 3. Peak ground velocity map (without interevent and interevent residuals).

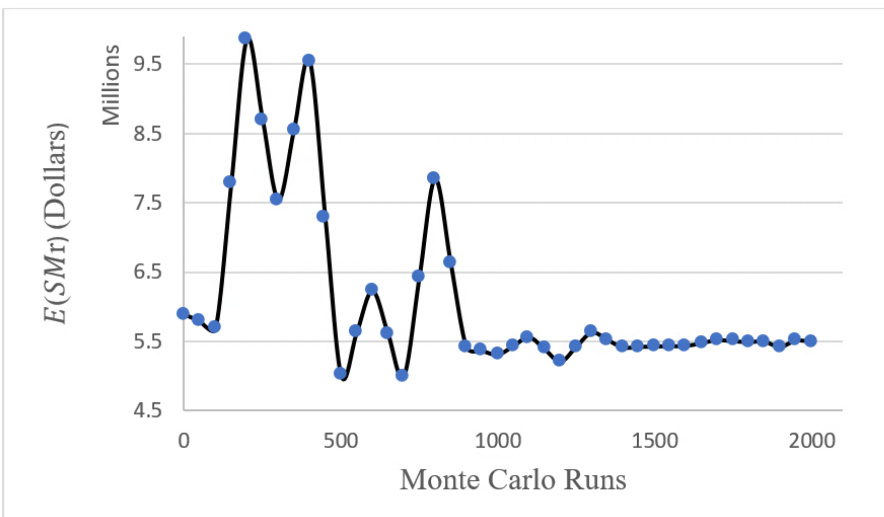


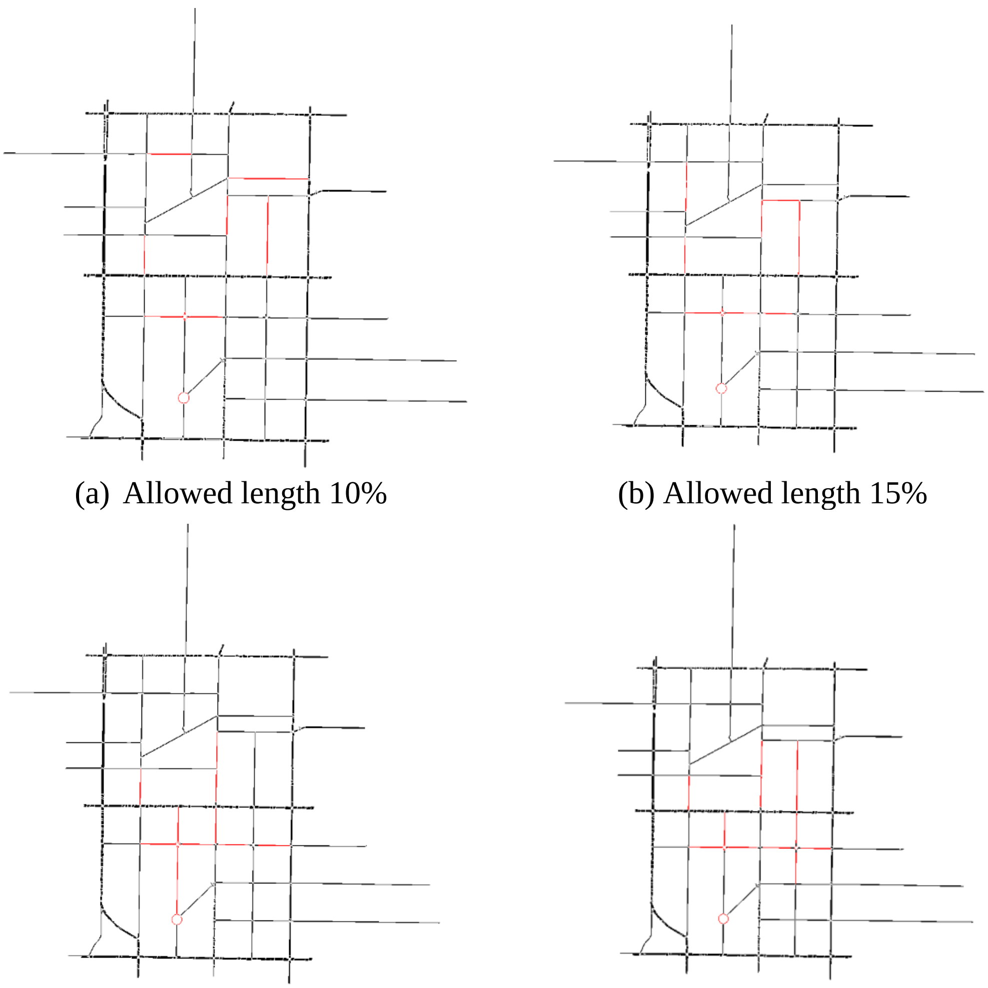
Figure 4. Convergence study result.

Traffic simulation was conducted using an open-source traffic simulation package named SUMO (Simulation of Urban Mobility) (Lopez et al., 2018). The study area map was extracted using OpenStreetMap (OSM). To make it compatible with SUMO for traffic simulation, the map was converted using NETCONVERT. This editing process was carried out using NETEDIT, a visual network editor. A random route file was generated with the origin and destination of each vehicle using SUMO. The road network was modified based on the damaged state and current rehabilitation policy. The vehicles were modified to use the shortest possible route using the re-router tool of SUMO. The simulation time used for this study was 6 hours as it was assumed that the links would have normal operating conditions after 6 hours. The increase in travel time and travel distance was recorded for each vehicle and each Monte Carlo run. The value of $E(SM_r)$ for the current rehabilitation policy was calculated based on the process described in Figure 2.

A convergence study (Figure 4) was used to determine an appropriate number of Monte Carlo runs. The selected network with a no-rehabilitation scenario was used as it exhibits the maximum uncertainty compared to any rehabilitation scenarios. The convergence study revealed that 1,500 Monte Carlo runs were adequate (Figure 4).

Table 4: Summary results for different rehabilitation length constraints.

Allowed for Rehabilitation (%)	Actual Amount of Rehabilitation (%)	Minimum $E(SM_r)$ (\$)
10%	9.96%	$4,495,983.00
15%	14.91%	$4,017,234.00
20%	19.77%	$3,646,214.00
25%	24.63%	$2,221,145.00



(a) Allowed length 10%

(b) Allowed length 15%

(c) Allowed length 20%

(d) Allowed length 25%

Figure 5. Critical roads identified by the devised approach.

Employing this methodology described in Figure 1, rehabilitation policies were identified for various rehabilitation length constraints. Four length constraints were considered in this study (10% of the total length, 15% of the total length, 20% of the total length, and 25% of the total length). The results for these policies are detailed in Table 3, with critical links identified corresponding to each policy highlighted by thick lines in Figure 5. The critical links are marked with red lines. Concrete bridges are more vulnerable to seismic events than pavement roads if they are in seismic zones. The pavement roads connected to bridges are more vulnerable than other roads. Single-lane roads are more vulnerable than multi-lane roads.

This study is a limited study considering a length-based approach, considering only damage due to peak ground velocity (PGV). This study can be further extended by integrating repair cost and benefits in the approach (Zahed et al. 2018); considering investment valuation under uncertainty (Ahmadi and Shahandashti 2017); considering a risk-averse methodology (Shavreen et al. 2022); integrating PGD; considering other metaheuristics (i.e., Genetic algorithm and Hybrid metaheuristics) to enhance computational efficiency (Pudasaini and Shahandashti 2018); considering non-concrete assets (e.g., geotechnical assets); integration with non-transportation lifeline sustainabilities (e.g., pipelines) (Roy et al 2021).

CONCLUSION

An approach to proactively identify a rehabilitation strategy for concrete assets, aimed at minimizing serviceability loss after a seismic event for road networks, was developed by integrating a simulated-annealing algorithm with a network-level traffic simulation considering the seismic performance of multiple assets. The proposed approach was designed to identify critical combinations of links that should be rehabilitated proactively, considering constraints on the rehabilitation budget faced by transportation agencies. The application of this approach was demonstrated using a road network in California. Two types of concrete assets were selected for this study. Critical links were identified for different allowable rehabilitation length scenarios with minimum serviceability loss for each scenario.

This study can be further extended by combining the types of soil, integrating other types of concrete assets, considering different components of the concrete assets, considering the actual traffic count data, integrating the effects of the built environment (e.g., buildings), integrating repair cost and benefits in the approach; considering investment valuation under uncertainty; considering a risk-averse methodology; integrating PGD; consider other metaheuristics (i.e., Genetic algorithm and Hybrid metaheuristics) to enhance computational efficiency; integration with GIS; considering non-concrete assets (e.g., geotechnical assets); integration with non-transportation lifeline sustainabilities (e.g., pipelines), and integrating the impacts of human decision-making characteristics. This study can be modified into a resource-allocation-based simulation algorithm by considering the cost of rehabilitation for each concrete asset.

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Balancing Housing Affordability and Transportation Efficiency in the Inland Empire

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ABSTRACT

Housing affordability and transportation efficiency refer to a household's ability to spend less than 45% of their gross income on housing and transportation costs. Past research indicates that low-income households generally allocate a significantly higher portion of their income to housing and transportation costs. In areas of Southern California like the Inland Empire (a common term given to the two-county area including Riverside and San Bernardino counties), relatively low housing costs (compared to neighboring coastal counties) place financial strain on households, particularly those in underserved communities, defined by FEMA as socioeconomically disadvantaged people, people of color, ethnic and national origin minorities, people with limited English proficiency, and others, who face increased transportation costs due to car-dependent environments. The research investigates how housing costs, affordability, transportation efficiency, and accessibility affect disadvantaged communities in the Inland region, particularly on the challenges faced by underserved populations. The research findings indicate that disadvantaged populations in the region encounter disproportionate obstacles within housing and transportation policies, with geographical disparities exacerbating these challenges. This includes housing development occurring away from job centers, which not only burdens residents financially but also limit their access to essential opportunities, thereby perpetuating cycles of poverty. It's worth noting that similar challenges can affect higher-income individuals and families, albeit to a lesser extent. These findings underscore the critical need for more conclusive actions to address these disparities and create more equitable housing and transportation solutions for all residents.

1 INTRODUCTION

The Inland Empire, consisting of Riverside and San Bernardino counties, is currently home to about 4.6 million people as of 2022. Over the past decade, the region has undergone a significant demographic transformation, shifting from a predominantly White population to one where 54% identify as Hispanic/Latino. This demographic shift has brought about challenges for the growing region. As coastal regions become less affordable due largely to skyrocketing housing prices, an increasing number of individuals and families from disadvantaged backgrounds are turning their attention towards the Inland Empire in search of more affordable housing options. The Inland Region faces limitations in high-quality job opportunities and suffers from low educational attainment rates compared to adjacent coastal counties Thousands of Inland Region residents living outside urban centers and job hubs face long commutes to and from work. These longer commutes and higher transportation costs further exacerbate the economic challenges they already face. This dynamic not only perpetuates income disparities but also deepens the divide in both housing and transportation costs within the Inland Empire, disproportionately impacting its disadvantaged populations.

In this paper, we developed a "disadvantaged communities index" to better understand which populations experience disparities in accessing resources and opportunities. This index considers a range of socioeconomic indicators, including median household income, the percentage of the population identifying as White, and levels of education. The analysis focuses on the nuanced aspects of housing affordability and transportation costs, often referred to as location-efficient neighborhoods (Makarewicz, 2020). According to the California Department of Housing and Community Development, housing affordability is defined as not exceeding 30% of gross household income. Transportation efficiency, as outlined by Newmar & Has (2015), involves neighborhoods with the lowest transportation costs achieved through shorter travel distances and the existence of alternative transportation modes.

In the Inland Region, optimizing the placement of services and amenities is crucial for enhancing the quality of life for disadvantaged communities through location efficiency. This is facilitated by a variety of alternative transportation options, including Omnitrans, RTA, and Metrolink, which are particularly beneficial for individuals without private vehicles.

2 LITERATURE REVIEW

2.1 Urban to Suburban Shift

As housing prices continue to soar in Southern California generally, we observe a significant shift from urban to suburban areas. Between 2018 and 2022, Los Angeles and Orange County experienced an outbound migration of approximately 400,000 residents. In contrast, the Inland Empire saw a gain of around 36,000 new residents, marking the third-highest population increase in the nation. According to the U.S. Census Bureau (2022), 3.3% of residents are migrating into the Inland Region from different counties compared to its neighboring Metropolitan Statistical Areas (MSAs).

Our findings indicate that the availability and affordability of housing are likely factors motivating individuals to move to the Inland Empire. Analyzing the housing market at the metropolitan statistical area (MSA) level reveals that the median housing cost in the I.E. stands at $534,900, with 47% of homes priced below $500,000. In contrast, the median housing costs in Los Angeles and San Diego are significantly higher, at $847,400 and $846,600 respectively, with only 30% to 32% of homes priced below $500,000. While Inland Region housing costs are generally significantly lower compared to the neighboring coastal counties it is crucial to recognize that focusing solely on housing costs can lead to detrimental outcomes.

2.2 Trade-offs for affordable housing

Geographic location significantly influences access to vital destinations such as workplaces, schools, and stores, and can impact transportation costs. Those moving to the Inland Empire in search of affordable housing face notable trade-offs due to the relative paucity of high-quality job opportunities locally, which results in long commutes for thousands of Inland workers to jobs located far from their place of residence often requiring job searches in neighboring metropolitan areas. The I.E. notably offers the lowest-paying jobs in Southern California, particularly in fields like Office & Admin Support and Food Prep & Serving, where wages typically range from $16 to $22 per hour (U.S. Bureau of Labor Statistics, 2022).

However, according to the Affordable Housing Needs Report for Riverside and San Bernardino Counties, residents need a wage of $34 per hour—approximately 2.3 times the state minimum wage—to afford housing costs (Mazella, 2022, as cited by Rio, 2023). This highlights a significant gap between income levels and housing affordability, compounded by the rising cost of living. These disparities not only affect immediate economic well-being but also shape the broader social landscape and long-term economic prospects of the region, particularly impacting disadvantaged communities as will be discussed.

Moreover, the Housing and Transportation Affordability Index (2022) suggests that transportation costs should not exceed 15% of household income, and when combined with housing costs, the two together should not exceed 45%. Inland residents allocate 26% of their income to transportation costs alone, surpassing rates observed in San Diego (20%) and Los Angeles (20%). These higher transportation costs are primarily attributed to longer commutes from those who live in the Inland region and travel long distances to job centers, often in Orange, Los Angeles, and San Diego counties.

Data from the U.S. Census (2022) shows that about 73% of Inland Region residents commute alone, with an average commute time of 32 minutes— higher than Los Angeles' average commute time of 28 minutes and San Diego's 24 minutes. Longer commute times not only result in increased transportation costs but also have been consistently linked to a decrease in quality of life. Research by Han, Libin, Peng, chong, and Xu, Zhenyu (2022) underscores this, highlighting the detrimental effects of commuting on overall well-being. Additionally, studies such as those by Heiko Ruger et al. (2017) and Kiron Chatterjee et al. (2020) have delved into the mechanisms underlying this relationship, suggesting that perceived stress may mediate the negative impact of commuting on health-related quality of life. This emphasizes the intricate relationship between housing affordability and transportation efficacy, which can disproportionately burden disadvantaged communities.

When considering both housing and transportation costs, the Inland Region residents spend 58% of their income on housing and transportation, further highlighting the trade-offs between proximity to work and housing affordability, which can disproportionately impact disadvantaged communities. This compromise for affordable housing often entails enduring extended commutes, leading to increased transportation expenses and overshadowing initial housing savings, primarily due to limited housing options near workplaces (Litman, 2021; Miller, 2004; California’s High Housing Costs: Causes and Consequences, 2015). These findings underscore the unintended consequences of solely prioritizing housing costs, particularly for disadvantaged communities.

3 METHODOLOGY FOR CREATING THE DISADVANTAGED INDEX

3.1 Data source

The data utilized in this study for housing burden and demographic information were sourced from CalEnviroScreen 4.0, which specifically incorporates the use of the Caltrans Equity Index (EQI). Developed by the California Department of Transportation (Caltrans 2023) in response to acknowledging disparities in benefits and negative impacts associated with the state’s transportation system, the EQI is designed to address inequalities in transportation decision-making, policy, and planning, particularly in underserved populations. This tool undergoes continuous development with input from public and internal discussions covering indicators, thresholds, and geographics. In addition, this study benefits from the current beta version, emphasizing the unique focus on transportation-related equity issues in the assessment of housing burden and demographic data.

The data about transportation accessibility was acquired from the California Department of Transportation EQI. It provides a comprehensive methodology designed to identify California communities disproportionately burdened by multiple sources of pollution. It also offers an interactive online tool for filtering and visualizing data.

3.2 Creation of the Disadvantaged Index

The Disadvantaged Index was constructed to reflect various socio-economic and demographic factors that contribute to the vulnerability of a population. The index was formulated by combining several normalized variables using Z-scores. from the CalEnviroScreen 4.0 dataset. These included median household income, percentage of the population identified as white, and education levels. To account for challenges faced by non-English speaking populations, linguistic isolation was subtracted. Similarly, to capture economic stressors, the poverty rate and unemployment rate were also subtracted. The resulting index is a composite score where a higher value indicates a greater level of disadvantage.

3.3 Creation of the Housing Burden Index

The Housing Burden Index was directly adopted from the CalEnviroScreen 4.0 dataset, where it is defined as the percentage of a household's income spent on housing costs. This single-variable index is normalized using Z-scores. reflects the economic pressure on households related to housing expenses, with higher values indicating greater financial strain.

3.4 Transportation Accessibility Index

Transportation accessibility data from the Caltrans EQI were normalized using min-max scaling to create the Transportation Accessibility Index. This scaling transformed the data to a fixed range of 0 to 1, allowing for a comparative analysis across different regions. The index aggregates normalized values for auto and multimodal access to work and nonwork activities.

3.5 Multiple Linear Regression Analysis

A multiple linear regression analysis was employed to elucidate the relationships between the indices. The Disadvantaged Index was used as the dependent variable, while the Housing Burden and Transportation Accessibility Indices served as independent variables. Prior to the regression analysis, all variables were checked for multicollinearity and standardized when necessary to facilitate interpretation. The regression output included coefficients for each predictor, the model's R-squared and Adjusted R-squared values, F-statistics, p-values, and the Residual Standard Error, which provided insight into the model's explanatory power and the significance of each index in predicting disadvantage within populations.

$$Disadvantaged\ Index = B_o + B_2 X\ Housing\ Burden\ Index + B_2 X\ Transportation\ Accessibility\ Index + E$$

B_o: Intercept, B_1: Coefficients for Housing Burden Index, B_2: Coefficients for Transportation Accessibility Index

Index, E: Error team

4 RESULTS

4.1 Disadvantaged Index

In Figure 1, we examine the Disadvantage Index Map. This visualization aims to illustrate the distribution of underserved populations in the Inland Empire. The resulting disadvantaged index Figure 1 categorizes the data into three levels—low, moderate, and high. ArcGIS Pro was utilized to visualize disadvantaged communities at the census tract level.

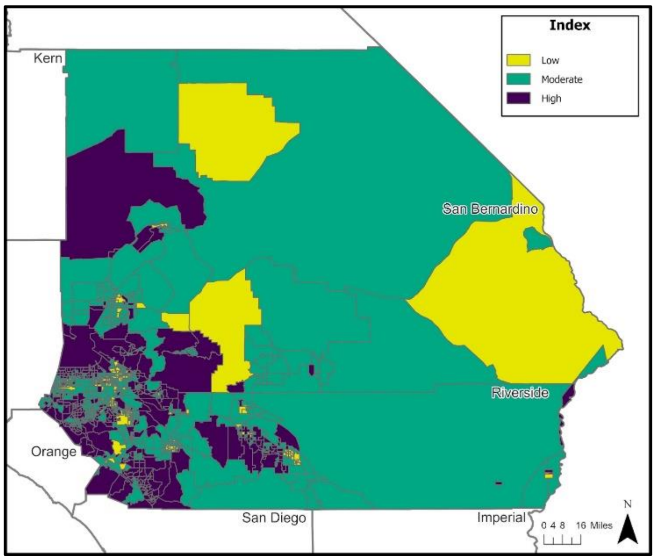

Figure 1: Socioeconomic Disparities in I.E.: Disadvantage Index Figure

In Figure 1, the Disadvantage Index Figure 1 explores socioeconomic disparities in the I.E. Purple signifies a higher concentration of disadvantaged communities, green represents moderate disadvantage, and yellow indicates the lowest disadvantaged population.

4.2 Housing Burden Index

In the Housing Burden Index Figure 2, the housing burden index ranges from the yellow area indicating the least burden, progressing to darker colors as the housing burden index increases. Green areas represent a moderate burden, while purple darker-shaded census tracts reflect the highest housing burden index.

4.3 Transportation Accessibility Index

Figure 3 examined in this study pertains to the transportation accessibility score. Similar to the previously discussed datasets, these figures were transformed into an index for enhanced clarity and comparative analysis. Just like the previous two maps, we utilized the ArcGIS Pro program to visualize Transportation Accessibility at the census tract level.

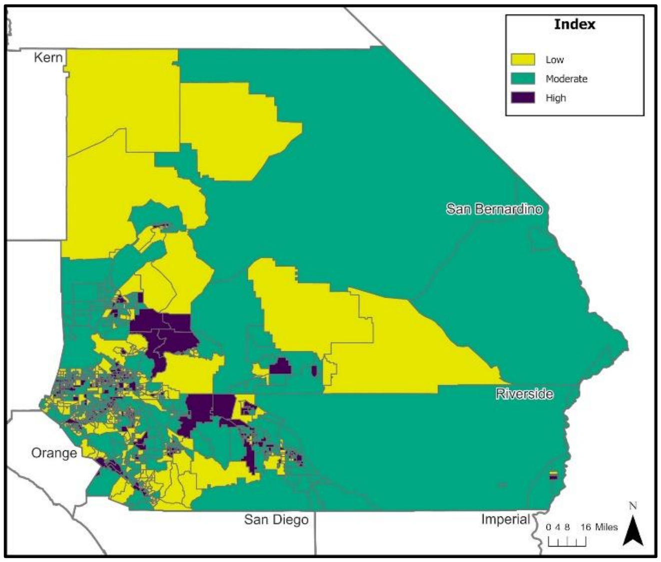

Figure 2: Housing Burden Index Visualization

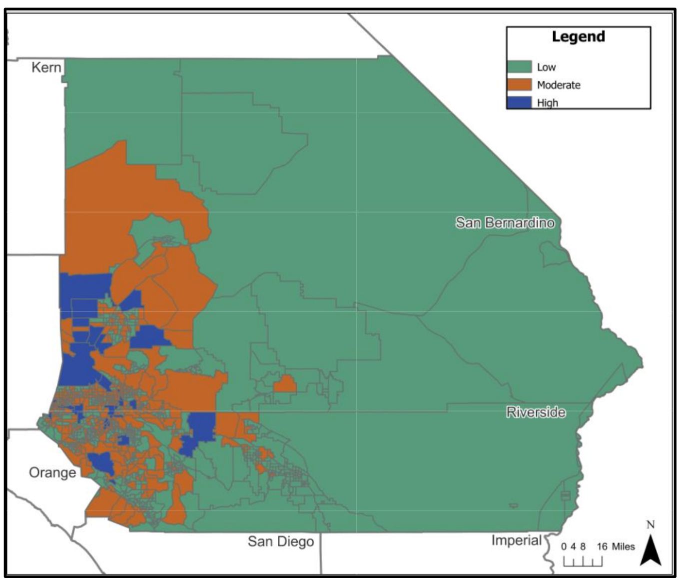

Figure 3: Transportation Accessibility Scores

In this Figure 3, let's explore the transportation accessibility score. As the Disadvantage Index increases, the Housing Burden and Transportation Accessibility Indices are also observed to rise.

4.4 Regression Results

Table 1 represents descriptive statistics for three different indices: Index 1 (Disadvantaged - DAI), Index 2 (Housing Burden Index - HBI), and Index 3 (Transportation Accessibility Index - TAI). Each index has been measured across a sample of 984 observations. These stats provide insights into the central tendency, variability, and distribution of each index within the dataset.

Table 1: Social Indicators Table: Disadvantaged, Housing Burden, and Transportation Accessibility Indices Statistics

Statistics	Index 1 (Disadvantaged)	Index 2 (Housing Burden)	Index 3 (Transportation Accessibility)
Count	984	984	984
Mean	2.31×10^{-16}	1.30×10^{-16}	-0.454
Standard Deviation	2.679	1.001	0.327
Minimum	-13.802	-1.782	-0.007
25%	-1.419	-0.688	0.242
50% (Median)	0.142	0.000	0.380
75%	1.785	0.653	0.583
Maximum	6.943	3.677	3.427
Tolerance	—	0.994	0.994

The dataset of 984 observations reveals that the Disadvantaged Index centers around zero with a broad spread, ranging from -13.802 to 6.943, and a median of 0.142. The Housing Burden Index, also centered around zero, shows less variability (standard deviation of 1.001) with a range from -1.782 to 3.677, a median of 0.000. Meanwhile, the Transportation Accessibility Index, with a mean of -0.454 and tighter spread (standard deviation of 0.327), ranges from -0.007 to 3.427, with a median of 0.380. The Tolerance values for Housing Burden and Transportation Accessibility Indices are 0.994, indicating a specified acceptable range.

Model Fit

Table 2 presents the model fit statistics for three different regressions involving the Disadvantage Index, Housing Burden Index, and Transportation Accessibility Index. The Model fit is evaluated through several metrics.

Table 2: Regression Model Fit Statistics

Model Fit	R^2	Adjusted R^2	F-Statistic	p-value	Residual Standard Error	df	N
Regression	0.734	0.732	245.67	<0.001	2.189	2	984

The model fit is the Disadvantage Index, Housing Burden Index, and Transportation Accessibility Index. As the Disadvantage Index increases, the Housing Burden and Transportation Accessibility Indices are also observed to rise. The R^2 value signifies that for every one-point increase in the Disadvantage Index, 73% of the data related to the Housing Burden and Transportation Accessibility Indices will correspondingly increase or decrease. The p-value is also important in determining the statistical significance of these R2 values; a p-value of <0.001, implies that the regression analysis R2 is indeed statistically significant.

Equation

$$DAI = -0.159 + 1.551\, HBI - 0.351\, TAI$$

Coefficient for HBI (1.551): This value indicates that as the Housing Burden Index increases by one unit, the Disadvantaged Area Index is expected to decrease by 1.551 units, assuming the Transportation Accessibility Index (TAI) is held constant. This suggests a positive relationship between the housing burden and the level of disadvantage —indicating that as the housing burden increases, it might actually increase the level of disadvantage in an area.

Coefficient for TAI (-0.351): This value indicates that as the Transportation Accessibility Index increases by one unit, the Disadvantaged Area Index is expected to decrease by 0.351 units, assuming the Housing Burden Index (HBI) is held constant. This suggests a negative relationship between transportation accessibility and the level of disadvantage — implying that better accessibility is associated with less disadvantage.

5 ANALYSIS AND DISCUSSION

5.1 Regression analysis

Table 3 provides a regression analysis that evaluates the impact of predictors on the dependent variable. The intercept, starting at -0.159 (std. error= 0.120), is statistically significant ($p<0.001$). The predictor HBI shows a positive effect, with an estimate of 1.551 (Std.error=0.070) and a substantial standardized beta of 0.579 ($P<0.001$). On the other hand, TAI has a negative estimate of -0.351 (std.error=0.014) and a standardized beta of -0.043, both statistically significant ($p<0.001$). The confidence intervals for all estimates are provided, and T-statistics reinforce the significance of these findings.

Table 3: Regression Coefficients

Predictors	Estimates	std. Error	Standardized Beta	std. standardized Beta	CI Lower Bound	CI Upper Bound	T-Statistic	p-value
(Intercept)	-0.159	0.120	NaN	0.120	-0.394	0.076	-11.332	<0.001
HBI	1.551	0.070	0.579	0.070	-1.689	-1.414	22.166	<0.001
TAI	-0.351	0.014	-0.043	0.214	-0.069	0.772	-11.639	<0.001

After confirming the statistical significance of the model fit, we proceed to examine the estimates. These estimates play a crucial role in formulating the equation to determine coefficients. The Beta values are as follows: Beta Zero is -0.159, Beta One is 1.551, and Beta Two is -0.351.

6 CONCLUSION

Underserved populations in the I.E. face disproportionate challenges in housing and transportation policies, with geographic disparities exacerbating these issues. Housing development away from job centers not only strains residents financially but also hinders access to crucial opportunities, perpetuating cycles of poverty. Contrary to the belief that well-intentioned development in the Inland Empire will inherently alleviate housing burdens, there is a risk that such efforts may inadvertently exacerbate existing inequalities. This underscores the unintended consequences of policies that overlook the connections between affordable housing and transportation accessibility in evolving developments.

To address this, a nuanced approach is essential, considering immediate housing needs and broader economic and social dynamics. Policymakers must prioritize affordable housing alongside transportation development, recognizing their intricate connection. Community engagement should be central to decision-making, ensuring the voices of affected populations shape policies. A comprehensive strategy must include safeguards against gentrification, and implementation measures to protect existing residents while fostering inclusive development. Adopting a holistic and inclusive approach is crucial for the Inland Empire to navigate housing and transportation challenges, striving for a more equitable and sustainable future.

7 RECOMMENDATIONS

As a recommendation, we believe that policymakers should collaborate on a comprehensive and inclusive approach, recognizing the dynamic connection between housing and transportation, particularly for disadvantaged communities that are considered marginalized. Prioritizing affordability and involving communities in the decision-making processes can contribute to creating a more equitable and sustainable future. Emphasizing long-term considerations, particularly the benefits of home ownership, and ongoing research will enhance the understanding and resolution of housing and transportation disparities within the Inland Empire.

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Real-Time Rainfall and Infiltration Rates in a Pervious Concrete Test Bed

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ABSTRACT

This research examined the infiltration rates on the surface of a pervious concrete (PC) test slab in Beaumont, Texas, and the infiltration rate into the soil below the underground aggregate storage bed. The site has very slow infiltrating clayey soils, and the trials are intended to provide information on the efficacy of using green stormwater infrastructure (GSI) in similar areas. The slab and associated storage bed measured 10 ft by 20 ft, with a total depth of 22 in. An analysis of the void ratio of the aggregate bed provided a relationship between the water depth in the aggregate bed with the soil infiltration rate. Furthermore, the relationship between the water depth in the bed was studied for a combined PC and rain garden (RG) system. The surface PC infiltration rate measurement was carried out using a single ring infiltrometer and for the newly placed slab was on average 1,450 in./h. The soil infiltration rate was measured with a real-time water level sensor with an associated rain gauge. The soil infiltration rate was estimated to be 0.01 in./h. With the combined PC/RG system the rate of the draindown of the water level in the pervious concrete storage bed at times doubled for larger storms, indicating that the rain garden may have aided in its effectiveness, possibly by evaporation or other processes.

INTRODUCTION

The use of pervious concrete (PC) pavement for stormwater management is gaining popularity due to its ability to allow water to pass through into stormwater systems or underlying soil (Costa et al. 2018). The major differences between PC and traditional Portland cement concrete pavement are the use of narrowly graded aggregate and the usage of less water in the mix resulting in interconnected voids. By allowing stormwater to seep into the sub-base through these gaps in the pervious concrete, the quantity of related runoff may be reduced. These gaps allow for additional rainwater storage below the pavement and in the soil, which may lower the peak runoff rate from built regions and lessen the downstream environmental effects. A typical pervious concrete slab is anticipated to have a vertical porosity distribution with the highest porosity region towards the bottom and the lowest porosity zone at the top (Haselbach and Freeman 2006).

A rain garden refers to a vegetated shallow depression designed to gather rainwater runoff originating from various surfaces, such as roofs and parking lots. It is sometimes also referred to as a bioretention cell. It aesthetically integrates with its surroundings and may even serve as a garden space. Its primary purpose lies in retaining and treating the stormwater it captures. Within the rain garden, a portion of the water will be utilized by plants or evaporated into the atmosphere. Simultaneously, some of this water will gradually percolate into the soil, thereby replenishing aquifers and contributing to groundwater recharge.

PC and RG systems can be connected using pipes. Depending on the rainfall rates and the various elevations of the PC and RG system components, water might flow from the PC system into the RG system at times or flow in the reverse direction at other times. This study focused on a conjunctive PC/RG system installed 2023 in Beaumont, Texas. The intent was to have a conjunctive green stormwater infrastructure (GSI) demonstration that allowed for water to flow from the pervious concrete system into a slightly lower rain garden bed to restrict water from flowing up through the pavement to the surface under most conditions, especially if relief into a stormwater system or waterbody is not available. In addition, both systems might provide additional water quality benefits.

The test beds in Beaumont, Texas are situated at latitude 30.0802° N and longitude 94.1266° W. The city is flanked on its east side by the Neches River and is situated on coastal lowlands approximately 30 miles inland from the Gulf of Mexico. Due to its closeness to the shore, Beaumont has a humid subtropical climate with an average annual precipitation of 60.42 inches and a mean temperature of 68.5 °F. (US Climate Data 2023). Multiple neighboring communities, a modest rural sector, and a strong petrochemical refining industry are features of the metropolis of Beaumont. The site is located at the facilities yard of Lamar University as shown in Figure 1.

Figure 1: Location of conjunctive PC/RG green stormwater test site in Beaumont, Texas.

This area of southeast Texas is low-lying in elevation and has poorly draining soils. It is also frequented by heavy rainfall and tropical storms. This paper focuses on the infiltration capabilities of the pervious concrete system for systems installed under similar conditions.

METHODS

Prior to construction a soil boring was taken at the site. Then two 10 feet by 20 feet adjacent pits were dug to construct a pervious concrete and a rain garden system. For the pervious concrete system, a 1.5-foot-thick layer of larger narrowly graded #57 (1 inch to 1.5 inch) stone was laid at the bottom, providing for an underground stormwater storage bed. To allow for sampling of the water in the underground aggregate storage bed a vertical 4-inch diameter perforated pipe was installed to serve as an observation well. In addition, a horizontal 4-inch diameter pipe was installed approximately 7 inches above the bottom of the aggregate storage bed (approximately 15 inches from the top of the later installed PC layer) to connect it to an outfall in the neighboring rain garden.

On April 11th, 2023, pervious concrete was mixed in a mixer truck and tested on-site prior to pouring. The first test involved forming a ball of concrete by hand and observing if it was too wet or dry. The ball held its shape, indicating that the concrete was not too dry. A bucket test was performed as per ASTM C1688/C1688M-14a (ASTM 2014) to test the density of the freshly mixed pervious concrete. Then a 4-inch-thick pervious concrete layer was placed over the aggregate storage bed and the surface was compacted using a roller. Finally, a plastic sheet was used to cover the concrete to create humidity and aid in curing. It remained for at least seven days.

Figure 2 shows the pervious concrete slab with the plastic sheeting on top. The void spaces between the aggregate particles in the aggregate storage bed allow water to be stored up to 7-inch level and then above the 7-inch level the water is interconnected with the rain garden.

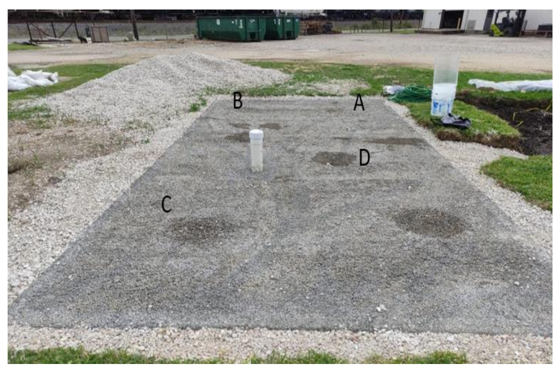

Figure 2: Pervious concrete slab placed April 11, 2023, with plastic and observation well pipe (left) and (right) the location of the surface infiltration tests on May 8, 2023.

After the plastic was removed from the PC layer, surface infiltration tests were performed. The test was conducted in accordance with the ASTM C1701 standard, which uses 1 gallon water for prewetting and 5 gallons for infiltration testing. Putty creates a seal between the single-ring infiltrometer and the pervious concrete (ASTM 2017). To gather rainfall and water storage level data on the pervious concrete system a real time rain gauge and water level sensor system were installed with the water level sensor at the bottom of the observation well and the rain gauge and node for the water level sensor on a pole next to the system as shown in Figure 3.

If the system did not have the underdrain connected to the rain garden or another outfall, it could completely fill up to the top surface for larger storms. In fact, this would also occur for extreme rainfall events that flood the surrounding areas. Based on direct rainfall on the pervious concrete surface alone, without contributions from runoff from other areas (runon), the system capacity would be estimated as follows. If 4 inches of pervious concrete has a porosity of 15% and 18 inches of storage aggregate bed has a void ratio of 40%, the nominal storage capacity would be 7.8 inches of rain when PC is not connected to the RG system (Tennis et al. 2004).

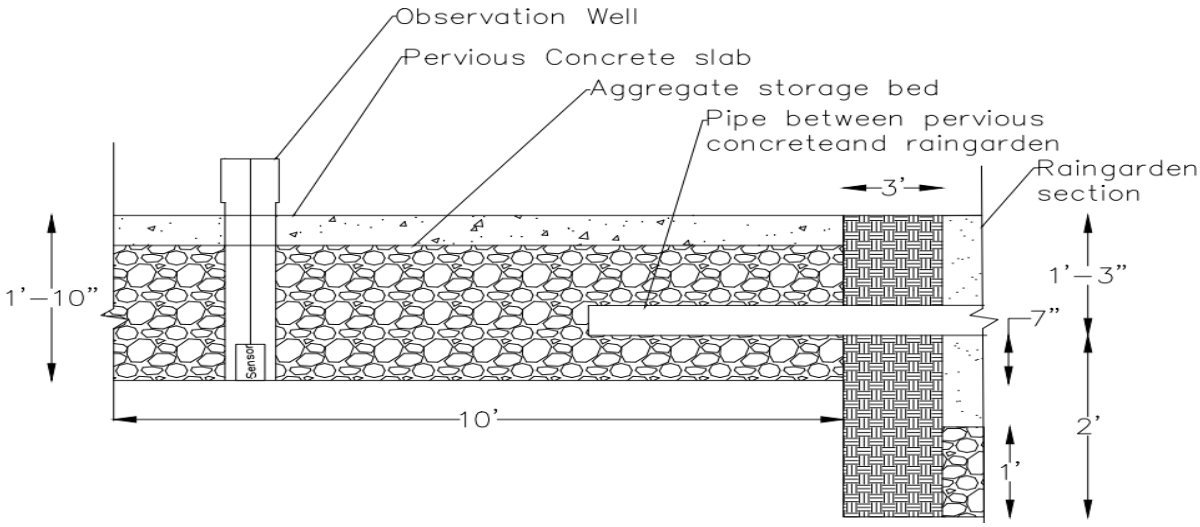

Figure 3: Partial elevation view of GSI test beds in Beaumont, Texas.

In the rain garden pit, a 1-foot 57 stone aggregate layer was placed, and soil was added on top. This soil was chosen to include 50% compost, 25% top soil and 25% sand to support the growth of plants in the RG as recommended by Texas A&M AgriLife Extension (Mechell and Lesikar 2008). The soil was added on top of various depths to make a concave storage feature that reached the neighboring grass grade on the edges but with a central aggregate storage region. The central aggregate storage region was elevated to a position slightly higher than the adjacent soil level to inhibit the soil from entering the aggregate surface. Plants were introduced into the rain garden, and mulching was subsequently applied to facilitate plant growth in September 2023. Figure 4 depicts the full conjunctive systems.

Figure 4: Plants on rain garden alongside pervious concrete slab (September 08, 2023).

When the water level in the PC aggregate storage bed is above 7 inches water may flow between the systems in either direction depending on head differentials. The RG and PC systems were interconnected in June 2023 and were subsequently separated by blocking the pipe that connected them for the month of July 2023 to test the infiltration rate in the PC system alone and to confirm that the PC aggregate bed infiltration rate is the same for the integrated system when the water depth is below 7 inches. For the separated PC and RG systems, realtime data for the entire month of July was recorded. The connecting pipe was then cleared and reconnected to the system on August 1, 2023. Figure 5 is an example of realtime data for the systems measured by a sensor placed at the bottom of the observation well and by the rain gauge. In Figure 5, 10-minute sensor data give information on rainfall, rainfall intensity, and the depth of water in observation well.

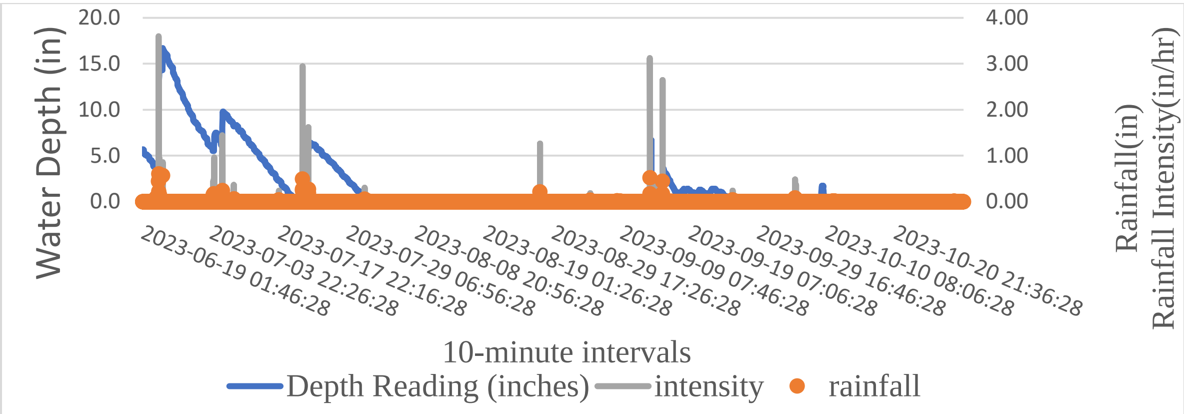

Figure 5: Example of 10-minute rainfall, rainfall intensity and water depth data.

The rate at which the water level is lowering in the pervious concrete underground aggregate bed can be referred to as the draindown rate (D) in units of length over time. However, it does not represent the infiltration rate into the soil below as the bed is full of aggregate and therefore volumetrically has less water per change in depth than a detention pond or other infiltration bed. To determine the void spaces in the aggregate bed, two buckets were filled with extra aggregate used in the underground storage beds and sufficient water added to fill to the top. The volume of the water added provided an estimate of the void space for this aggregate bed. The void ratio was approximately 0.4. Similarly, the average aerial infiltration rate (F) in units of length over time into the soil below the underground aggregate beds under the pervious concrete can be estimated as 0.4 times the draindown rate (D) for a standalone system as in Equation 1. If the rain garden is connected to the pervious concrete underground storage bed, then flows in either direction between the two underground storage beds and evaporation from the rain garden may be important and the draindown rate may not always be directly used in Equation 1 to estimate F in the pervious concrete bed. For the month of July 2023, the connecting pipe between the two different GSI systems was blocked so that the pervious concrete system was independent of the rain garden and Equation 1 could be used to estimate F. In addition, since the invert of the connecting pipe system is approximately 7 inches above the bottom of the pervious concrete underground storage bed, when the water level is less than 7 inches, the infiltration F can also be estimated by Equation 1.

$$F = 0.4D \tag{1}$$

As previously mentioned, there is a pressure sensor at the bottom of observation well which measures the depth of water above it and it is connected to a realtime rain gauge. Figure 6 depicts water depth and rainfall with respect to time as converted from this realtime system. The downslope of the water depth line between two consecutive rainfall events may provide an average draindown rate. For instance, the water depth reading on July 7, 2023, was 9.8 inches and 13 days later is zero inches. These dates reflect a time when the pervious concrete system was disconnected from the rain garden. The total time is 312 hours, and the slope is 0.03 in/hr. The infiltration rate into the subgrade using Equation 1 gives 0.01 in/hr.

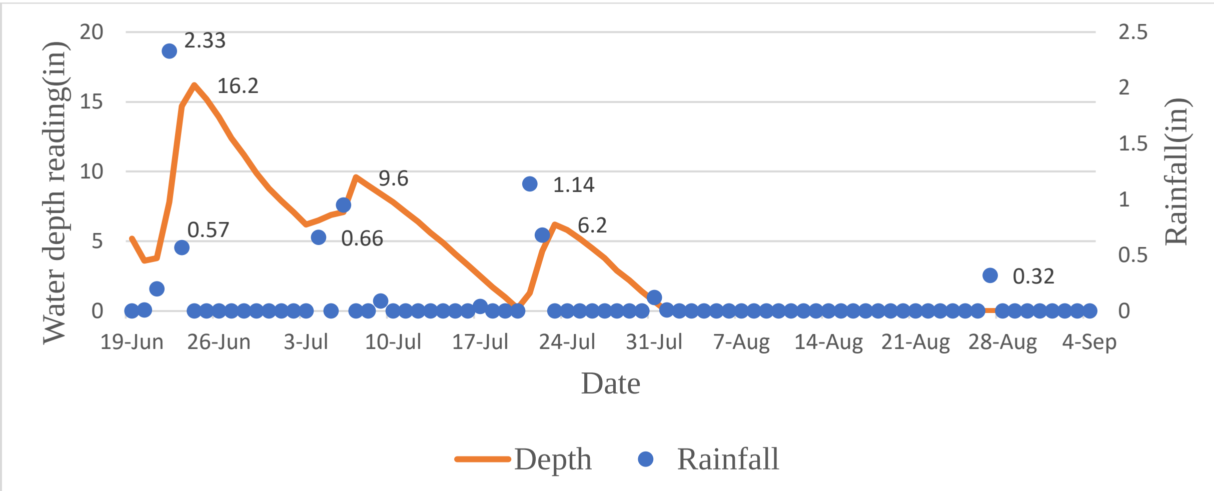

Figure 6: Example plots of realtime depth data (left) and rainfall data converted to a daily basis over longer time periods (right).

Some water that falls on a PC slab never goes into the bottom of the underground aggregate storage bed. To estimate the amount of rain that stays in the pervious concrete layer and possibly is absorbed to some of the rock near the top of the underground bed, a laboratory experiment involved measuring the water absorption capacity of a 7-inch-tall pervious concrete cylinder, which was found to be 0.36 inches. Figure 5 provides an approximate validation for this finding, as it shows no change in the water depth when the rainfall level reached 0.32 inches. This observation suggests that the water was either absorbed by the concrete or had evaporated.

Figure 7 presents a timeline of the study period. Note that the area experienced a severe drought in August and that the rain garden did not get planted till early September, at which time watering was required to establish the plants. This study ended at the end of October 2023.

Both the pervious concrete pad and the rain garden experience some runon from neighboring areas. Figure 8 was taken from ArcGIS Pro by delineating the 1 by 1 digital elevation model (DEM) file taken from USGS. and downloading the DEMs to give an approximate area of runon for the pervious concrete (ArcGIS 2023, USGS 2023). It resulted in a 660 sq. ft runon area. Runon is dependent on the intensity and duration of rain and the antecedent rainfall. Therefore, the volume of water in the pervious concrete aggregate storage bed is dependent on direct rainfall and the interconnections with the raingarden, as well as these contributing areas. As can be seen, the contributing area is not large and may be estimated as insignificant for very small rainfall events.

There is also a method to estimate the runon area using the rational runoff method and balancing it with the additional water accumulation in the pervious concrete aggregate storage bed. Equation 2 is used to estimate the volume that then might be contributed from runon “VRO” (Haselbach 2010). In Equation 2, Q is the runoff from the contributing area “ARO”, I is the rainfall rate and C is the rational runoff coefficient. The rainfall intensity is storm and time dependent. However, in this PC system, when not connected to the rain garden, the daily total rain may be used to estimate the volume stored in the system that day as the infiltration rate into the ground below the PC system is very slow. Therefore, Equation 2 can be modified to a water volume balance instead of a rate balance as in Equation 3 where Rt is the total daily rain.

$$Q = CIA_{RO} \tag{2}$$

$$V_{RO} = CR_t A_{RO} \tag{3}$$

By deducting the amount of water absorption, which is about 0.36 inches, in the pervious concrete system prior to accumulation at the bottom of the system from the total daily amount of rain "Rt", the effective direct rain "Re" into the aggregate storage bed may be calculated. Multiplying the area of the PC slab by the effective direct rain may yield the volume of direct rain "VRD". The calculation of the water volume in the aggregate bed "VB" involves multiplying the area of the PC slab by the water height "Ht" in the aggregate storage bed after that single event daily rain and the percentage of the aggregate bed void ratio "0.4". With these assumptions the volume of the runon can also be calculated by Equation 4. Equating the volume of runon in Equation iii to Equation 4 and rearranging results in Equation 5 to estimate the runon area. For this location the runoff coefficient C is estimated as 0.2 for heavy soil on a 5% grassy slope as measured on the field (Thompson 2019).

$$V_{RO} = V_B - V_{RD} \tag{4}$$

$$A_{RO} = \frac{(V_B - V_{RD})}{CR_t} \tag{5}$$

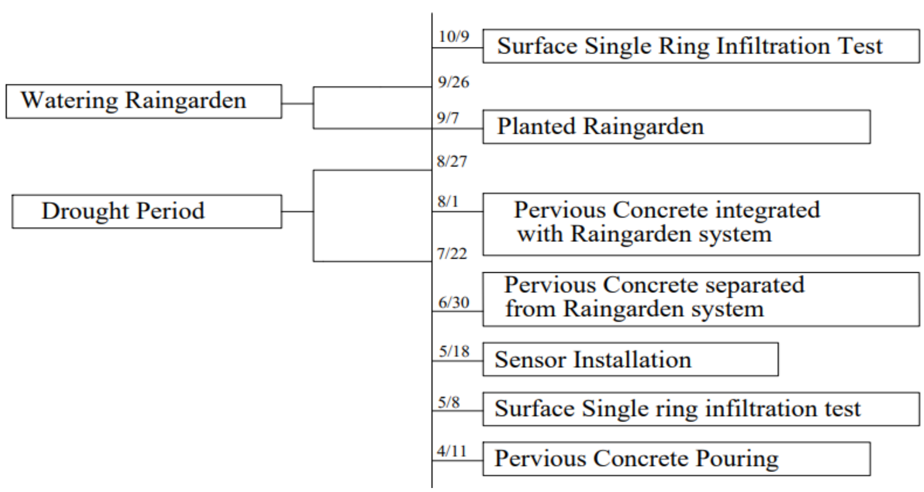

Figure 7. Project timeline chart 2023.

RESULTS

Using Equation 5, the estimates of the runon area providing additional water into the pervious concrete system for various single events without contributions from the rain garden are displayed in Table 1. If less than two years, then there will probably be more storage proportionally in the runon area, and if higher than 10 years than there is expected to be more runoff from that area since the storage is already assumed to be partially filled. Therefore, smaller events such as July 4, 2023 in Table 1 would estimate a smaller runon area. When return period “T” is greater than 2 year and less than 10 years, a return period adjustment factor of 1.0 is typically employed. For T greater than 10 year return period adjustment is greater than 1 (Dhakal et al. 2013). In this study, the runoff coefficient adjustment factor was set to 1, and a return period of less than ten years was assumed.

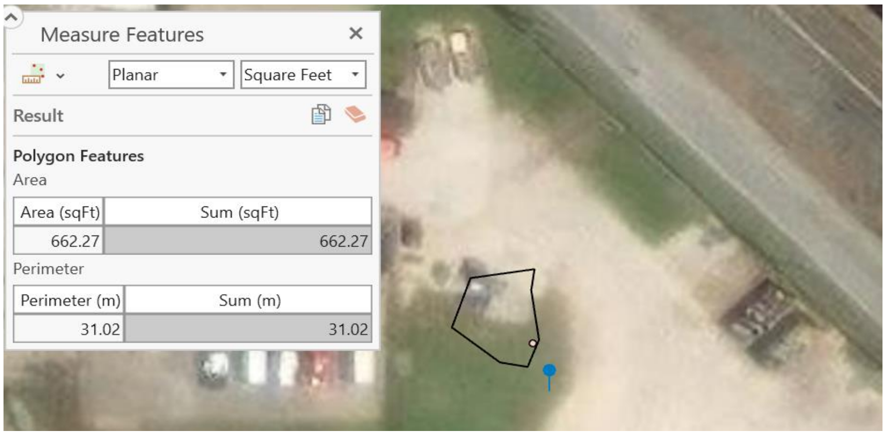

Figure 8. Approximate runon area (USGS 2023, ArcGIS 2022).

Table 1: Estimation of Runon Area

Time	R_t (ft)	R_e (ft)	H_t (ft)	V_B (ft^3)	V_{RD} (ft^3)	A_{RO} (ft^2)	A_{RO}(average)
21st July	0.095	0.065	0.35	28	13	790	620
4th July	0.055	0.025	0.125	10	5	450	

Soils at the Lavaca site are classified as an Anthroportic Ustorthent in the Artesol classification system, which describes a soil that is composed, at least in the epipedon, of human-altered, human-transported (HAHT) materials. The soil column was directly sampled with a Geoprobe direct-push type unit, and assessed in the laboratory for particle size distribution, Munsell color, and other taxonomic features. From the surface to 20cm, the ^Cu horizon was a poorly structured, lighter colored (2.5Y 4/2) sandy loam (AASHTO approximate A-1) with 50% rock and fragments as yard gravel. From 20-165 cm depth, we identified an urbanized ^A horizon that transitions at 110cm to a ^Cg1 horizon, each with a clay texture. Below 165cm depth, successive Cg (2-5) horizons were composed of dark (5Y 5/1) clay textured soils (AASHTO approximate A-7) to the 3.4m depth of assessment (AASHTO 2021). The clay mineralogy is such that the soil exhibits shrink-swell behavior, which is usually associated with Vertisols.

The pervious concrete surface infiltration test was performed on May 8, 2023. The weather was cloudy with an ambient temperature of 25°C. Four different spots were randomly selected on the pervious concrete slab three at corners and one in the middle. These are shown in Figure 2. After prewetting with one gallon of water, two consecutive infiltration tests of 5 gallons of water each were carried out at each location. The results of the surface infiltration test are in

Table 2. The testing was repeated on October 9, 2023, to see the differences as airborne, or surface water particles regularly clog pervious concrete surfaces. These results are also presented in Table 2. They show a small decrease in average surface infiltration over the 5-month period, which would be expected as atmospheric dust and other debris, including soils in the runon would slightly clog the pervious concrete over time.

The infiltration rate at location B was found to be larger than before, maybe because of experimental or handling error, whereas the infiltration rate at site A decreased the greatest, by 180 in/hr, possibly because of its closeness to the surrounding soil. After five months, the PC system performs well overall in terms of how far it infiltrates a topic that can be explored more in the years to come.

Table 2: Results of the Surface Infiltration Testing on the Pervious Concrete Surface

Spot	Prewet (PW) or Test #	Volume water (in^3)	Area (sq.in.)	May Time (s)	Oct. Time (s)	May Infiltration rate (in/hr)	October Infiltration Rate (in/hr)	Average infiltration rate (in/hr)
A	PW	230	107	5	5.4	1460	1432	
	1	1155	107	19	20.92	1990	1849	May 2060
	2	1155	107	18	20.22	2130	1913	October 1880
B	PW	231	107	5	5.54	1360	1396	
	1	1155	107	26	25.5	1465	1517	May 1500
	2	1155	107	25	25.8	1540	1499	October 1510
C	PW	231	107	5	5.86	1390	1320	
	1	1155	107	25	25.57	1500	1513	May 1540
	2	1155	107	24	25.53	1585	1515	October 1520
D	PW	231	107	9	7.68	790	1007	
	1	1155	107	49	47.8	780	809	May 800
	2	1155	107	46	50	830	779	October 790

The observation of daily rainfall and water depth in the PC system is studied from June to October, as illustrated in Figures 11 and 12. In Figure 9, daily rainfall data, derived by summing the original 15-minute rainfall data for a 24-hour period, is presented. Notably, June exhibits the highest recorded rainfall, while August experiences minimal rainfall, rendering it nearly dry throughout the month. Figure 10 displays daily water depth data, represented by the last 15-minute measurement over a 24-hour period. Corresponding to the rainfall pattern, the water depth in the observation well peaks in June, reaching a maximum of 16.6 inches on June 23. Conversely, August and the first half of September register zero inches of water depth, aligning with the absence of rainfall during this period. These findings underscore a direct correlation between rainfall and water depth in the observation well, providing valuable insights into the seasonal dynamics of the PC system.

On June 22, 2023, there was a significant rainfall event with 2.33 inches of rain. This resulted in a sharp increase in water depth in the pervious concrete system, reaching 16.6 inches that day. This event demonstrates the system's ability to effectively collect and store a substantial amount of rainwater. It might also emphasize how crucial it is to have adequate drainage into the rain garden to keep the pervious concrete system from flooding. Table 3 uses sensor data collected every 15 minutes to determine the water depth for each consecutive time. Draindown rate into soil with time and water level variations is computed by dividing the duration variation by the water level variation. Additionally, the calculation of soil rate involves multiplying the 40% void ratio by the draindown rate.

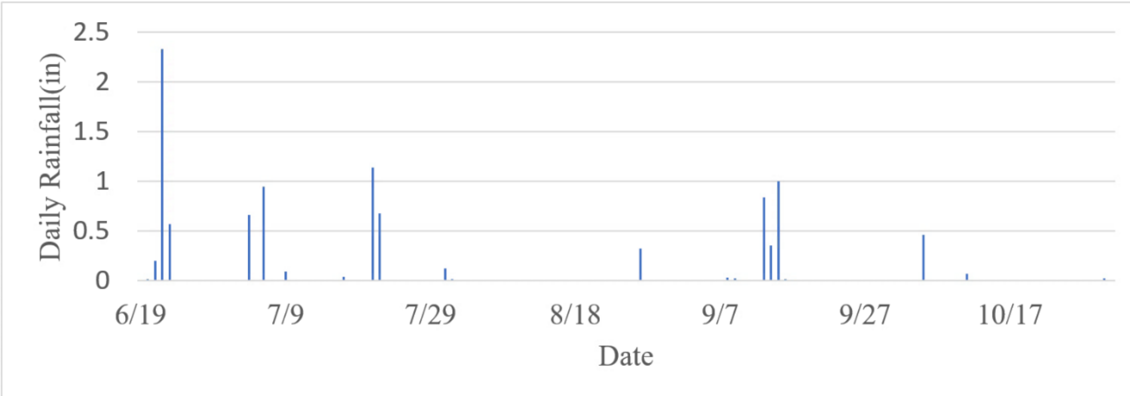

Figure 9. Daily rainfall from June to October 2023.

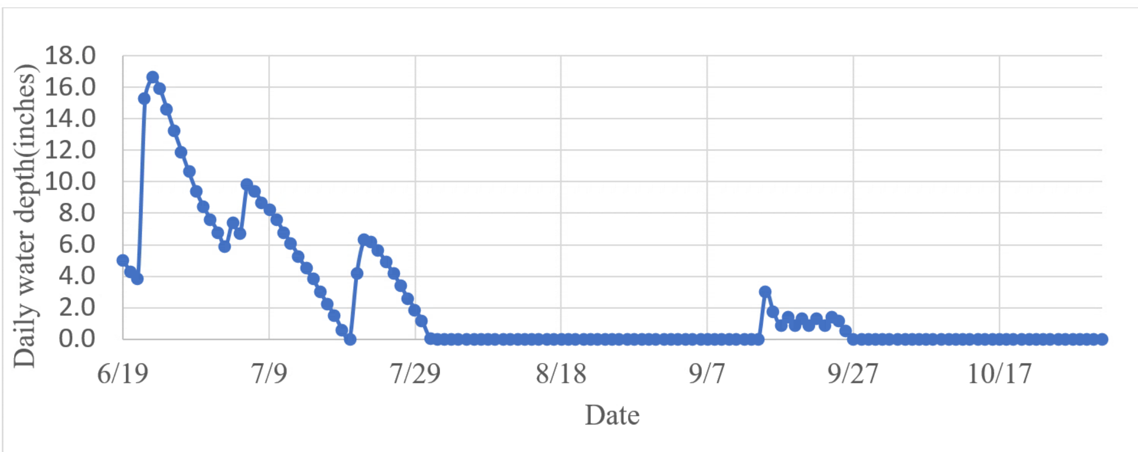

Figure 10. Depth of water in the pervious concrete observation well in 2023.

DISCUSSION AND CONCLUSIONS

The pervious concrete surface infiltration rate in May 2023 was found to be 1500 in/hr on average. A surface infiltration test was conducted in October 2023 to assess the PC's efficacy as well as to see whether runoff was causing any blockage. October saw no appreciable change in the infiltration rate. Location A had the largest decline, 180 in/hr, which may have been caused by its proximity to the nearby soil, which could have allowed runoff and soil particles to enter the PC slab. However, in general there was little clogging over these months, possibly due to the small runon area, no major flooding events, no vehicular traffic, and no nearby trees or other vegetation that might clog the system. However, it is important to occasionally monitor the surface performance and ascertain whether the system requires maintenance, especially if there might be contributions from vehicles, runon, or vegetation.

Table 3: Soil Infiltration Rate for 40% Voids in Storage Aggregate Bed

Year 2023	Depth of water from bottom (inches)	Difference in time (hr)	Difference in water level (inch)	Draindown Rate (Dr) (in/hr)	Soil rate (in/hr)	Remarks
24 June 0:06	16.7	144	7.3	0.05	0.02	Combined PC & RG
30 June 0:06	9.4					
6 July 22:06	9.8	60	1.5	0.025	0.01	Separate PC & RG
9 July 11:46	8.3					
19 June 1:46	5.7	67	2	0.03	0.012	Combined PC & RG
21 June 21:06	3.7					
11 July 14:26	7	214	6.9	0.032	0.013	Separate PC & RG
20 July 12:46	0.1					
9 Oct 14:06	1.7	11	1.6	0.15	0.06	Separate PC & RG
10 Oct 1:06	0.1					

The soil infiltration rate in October 2023 was found to be much higher for a small amount of rain, about 5 times higher, than in June and July. This could be attributed to the drought period in August and September leaving the soil extremely dry and therefore available for more water absorption (12newsnow 2023). There were frequent rain events in June and July, so the soils below ground had significant water content, usually more than the norm for this region. This might provide more insight into seasonal infiltration into soil as shown in Table 3 due to extreme weather. Since the drought conditions were severe and this event in October was small, this rate is considered to be an anomaly. Based on the other data evaluated, without influence from the neighboring rain garden, it is estimated at this time that the soil infiltration rate is very slow around 0.011 in/hr. Future data will determine if this rate changes with time as small particles enter the underground storage bed and/or settling occurs.

With 18 inches of storage aggregate and a 4-inch PC slab on top, the PC system has a total depth of 22 inches. Figure 10 illustrates how the water's depth increases rapidly from 3.8 inches on June 21 to 16.6 inches on June 23. The PC system may flood if the water level increased above 22 inches, which was not too far from 16.6 inches. This highlights the benefit that combining with a rain garden or another discharge system for efficiency. The time lag between rainfall events and the consequent rise in water depth suggests that precipitation may be temporarily retained in the rain garden system and released gradually back into the pervious storage as shown in Figure 10.

The runoff area calculated using DEM file for Beaumont, Texas closely aligns with the volumetric estimation as shown in Table 1, only differing by 50 sq.ft. In this case, with only a 5% difference in runoff area, the volumetric estimation method seems reliable.

Darcy’s law can be used in the future to see if head levels significantly impact the soil infiltration rate but Darcy’s law was not used herein for simplicity (Chandrappa and Biligiri 2016). The main reason for using the simple draindown method and not employing Darcy’s law was for simplicity of data analysis, and with the consistency shown in Table 3, this simpler method appears to be adequate for these size systems. Draindown rate measurements directly capture how water behaves in real-world conditions within the aggregate bed and provide valuable information on the system capacity. When monitored over long periods of time, they might provide insight into system life limitations.

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Modeling Electric Vehicle Charging Load Using Origin-Destination Data

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ABSTRACT

The accelerating adoption of electric vehicles (EVs) poses challenges to the power grid, necessitating precise representation of mobility patterns for effective infrastructure upgrades. Traditional simulation-based charging demand estimation faces limitations in generating trip chains reflective of actual travel patterns without complex network modeling. Hence, an innovative agent-based trip chain generation model is introduced to overcome these challenges. Drawing from the National Household Travel Survey (NHTS) and the NextGen NHTS origin-destination add-on data for Clarke County, Georgia, this study proposes a simulation method capturing both temporal and spatial mobility patterns without relying on extensive network topology data. The resulting trip chains predict EV charging load at the Census Block Group level, validated with a 1.03 correlation to actual trip counts, affirming their reflective accuracy. Two charging scenarios, residential-only and charging-everywhere, reveal distinct demand profiles. The charging-everywhere scenario aligns closely with the trip profile, while the residential-only scenario exhibits an afternoon peak slightly surpassing the former. This study contributes a data-driven charging demand estimation methodology, offering critical insights for grid resiliency planning amid the evolving landscape of EV adoption.

INTRODUCTION

To address the dual imperatives of curbing pollution in the transportation sector and combatting climate change, cities are increasingly embracing policies geared towards fostering low-carbon transportation systems. A notable strategy gaining widespread attention involves the electrification of both public and private transportation modes. Coupled with a clean electricity generation mix, this approach holds the potential to significantly enhance air quality and contribute to a decarbonized future, all while bolstering energy security (Ku, Kammen, and Castellanos 2021; Muratori and Mai 2020).

The surge in the adoption of electric vehicles (EVs), although pivotal in the pursuit of sustainable transportation, presents a formidable challenge to the power grid. An essential aspect of upgrading existing infrastructure in the realm of electrification involves obtaining an accurate representation of the mobility patterns of EVs (Pareschi et al. 2020). In particular, precise energy load prediction assumes paramount importance for evaluating grid resiliency. These models also play a key role in determining necessary capacity upgrades or alternative strategies, such as vehicle-to-grid strategies and utilization optimization of charging stations (Moradipari, Tucker, and Alizadeh 2021; Yu et al. 2016).

Current methodologies for modeling EV charging load generally fall into two categories: data-driven and simulation-based approaches (Kang and Zhang 2018; Shahriar et al. 2020). However, data-driven methods encounter limitations due to the scarcity of available charging session data. On the other hand, simulation-based models often rely on trip-chain generation models, which typically necessitate detailed road topology and traffic flow data. Acquiring such data can be challenging, time-consuming, or outright unfeasible. Studies that lack access to these details face difficulties aligning their findings with actual travel demand (Xiang et al. 2019).

This paper aims to estimate the regional spatiotemporal EV charging load by analyzing revealed travel patterns and trip characteristics. Accurate charging load estimation hinges on comprehending trip chains and inferring the associated charging and refueling behaviors. However, this task presents significant challenges due to the limitations of existing datasets. For instance, the National Household Travel Survey (NHTS) provides trip chain information from a subset of survey samples, not the entire population. Similarly, mobility data products such as Origin-Destination (OD) data offers reliable travel demand insights but lacks detailed trip information. To address these challenges, our study introduces a novel spatiotemporal trip chain generation method that leverages both NHTS and OD data. This approach allows us to break down each journey into a series of trip chains with one or multiple destinations, facilitating a deeper understanding of traveler charging behaviors. Additionally, this paper presents a method for estimating electricity load for EVs at the Census Block Group level, offering a significant contribution to the field.

LITERATURE REVIEW

Numerous studies have utilized simulation-based techniques to forecast electric vehicle (EV) charging demand (Gong, Cao, and Zhao 2017; Y. S. Liu, Tayarani, and Gao 2022; Walz et al. 2020). One study employed a Markov chain model to simulate vehicle trip chains within a city, predicting charging demand specifically at public parking lot charging infrastructures (Shepero and Munkhammar 2018). However, their methodology involved random selection of locations in trip chains based on reasonable driving distances, potentially introducing a deviation from actual charging demands at specific locations. Several previous studies predominantly utilized survey data, such as travel surveys or time use surveys, to investigate charging behaviors, often in non-realistic scenarios or hypothetical maps (Y. Liu et al. 2022; Muratori 2018; Zhang et al. 2020). However, these studies sometimes fell short in accurately reflecting the actual geospatial movement and charging behavior of individuals. This limitation potentially diminishes their practical value in formulating real-world charging strategies.

In contrast, certain studies have embraced data-driven approaches by leveraging data such as EV charging session data, mobile phone activities, and ride-hailing trip data (Kara et al. 2015; Walz et al. 2020; Xing et al. 2019; Zhao et al. 2021). The common models employed in the literature include artificial neural network (ANN), support vector machine (SVM), and Auto Regressive Integrated Moving Average (ARIMA), demonstrating the potential of data-driven methodologies. One comprehensive study took a machine learning approach, training models with a dataset encompassing charging processes from a diverse EV fleet of 1001 vehicles with 18 unique models, collected at workplaces between 2016 and 2018 (Frendo et al. 2020).

However, a persistent challenge in these data-driven approaches lies in the limited availability of reliable EV charging session data. This scarcity is attributed to the nascent stage of electric vehicle supply equipment deployment, resulting in charging points that do not consistently provide relevant data for accurate EV load modeling. A comprehensive review highlighted the scarcity of public datasets in the United States, with only two available datasets from Boulder and Palo Alto public charging stations (Amara-Ouali et al. 2021). Additionally, the reliance on public charging locations in existing datasets poses challenges in estimating charging demand for entire cities, particularly in residential locations. Notably, data from utility companies, the primary source for residential data, is often challenging to obtain. These factors collectively underscore existing challenges in accurately modeling and predicting EV charging demand on a broader scale.

Research gap summary and paper objective

The literature review reveals two prominent research gaps. Firstly, there is not adequate research exploring simulation methods capable of generating trip chains with geospatial information, a critical element for predicting EV charging demand on a relatively large scale, such as in a city or county. Secondly, the constraints of existing public charging infrastructure data impede its efficacy in forecasting residential charging demand. The pivotal question of how to harness alternative transportation datasets to comprehend charging demand across various locations remains unresolved.

To tackle these challenges, we propose an agent-based trip chain generation model to better predict EV charging demand. Unlike conventional approaches reliant on extensive network topology data, our model could still capture actual travel demand without such dependencies. The model leverages travel survey data to glean temporal trip information, such as departure times, and origin-destination data to acquire spatial trip information. Through this hybrid approach, we generate trip chains that better reflect real-world travel behavior, which therefore informs better estimation of charging demands.

In essence, this study contributes to advancing simulation-based EV charging demand estimation methodologies by introducing a novel approach that strategically integrates diverse mobility data. This innovation paves the way for more robust and scalable EV charging demand estimations in the future.

METHODOLOGY

Data sets

National Household Travel Survey (NHTS)

The NHTS is a national travel survey of U.S. households, and it is sponsored by Federal Highway Administration (Federal Highway Administration 2017). This survey collects daily travel information linked to individual personal and household characteristics, as well as vehicle attributes. The gathered data encompasses crucial details such as trip frequency, travel distance and time, mode of transportation, and trip purpose.

In this study, we leverage the NHTS data specific to Georgia for the year 2017. This dataset comprises a comprehensive sampling of 52,694 trips made by 13,526 individuals during that year.

NextGen NHTS Origin-Destination Data (OD)

Complementing the core NHTS, the NextGen NHTS incorporates an Origin-Destination (OD) data program. This program generates multimodal passenger and truck travel OD tables at both national and local levels, utilizing passively collected data sources. The publicly available OD data includes daily OD trips between Metropolitan Statistical Areas (MSA) across the U.S.

In our study, we specifically utilize the NextGen NHTS OD add-on data for Georgia. This dataset provides hourly OD trips at the Census Block Group level.

Trip chain generation

In the trip chain generation process, we leverage NHTS and OD data to extract individual trip parameters. The process, illustrated in Figure 1, unfolds in two distinct phases: the temporal chain and the spatial chain.

Temporal Chain

The temporal chain encapsulates the temporal information of daily trips for each vehicle, with parameters drawn from the NHTS data. These parameters, including trip purpose and driving distance, are intricately interconnected. For instance, the departure time is contingent on the trip's position within the day's sequence. To address this complexity, we employed conditional probability distributions to sample individual trip parameters for each segment of a trip chain.

Spatial Chain

In the second phase, the spatial chain is generated based on the departure time obtained from the temporal chain. Relying solely on NHTS data has limitations in fully capturing the nuances of actual travel demand patterns. To overcome this, we integrate OD data to construct a zone-to-zone transition matrix. This matrix represents the probability of transitioning from an origin Block Group to a destination Block Group. The spatial information of the vehicle is then sampled using the transition matrix. This matrix serves as a guide to identify destinations for each segment of daily trip chains, presenting a more precise reflection of real-world travel patterns.

This dual-phase approach could ensure a comprehensive and accurate representation of travel demand patterns. The subsequent sections detail the sampling process.

1) Number of Vehicle Trips of the Day n

The initial parameter, denoted as n, represents the number of trips a vehicle undertakes during the day. This parameter is drawn from the NHTS and is assumed to follow a normal distribution, $n \sim N(\mu_n, \sigma_n)$ where μ and σ represents the mean and standard deviation, respectively, calculated directly from the NHTS data.

2) Departure Time of Each Trip Segment $d_{i,n}$

The start time of the i^{th} trip segment within the trip chain is assumed to be dependent on the number of trips during the day. It follows a normal distribution, $d_{i,n} \sim N(\mu_d(i,n), \sigma_d(i,n))$, with a departure time resolution of 30 minutes, allowing for departures at, for instance, 8:00 AM or 8:30 AM.

3) Trip Purpose of Each Trip Segment $p_{i,n}$

The trip purpose of the i^{th} trip segment is assumed to be conditional on both the departure time and the number of trips during the day. Three trip purposes—home, work, and other—are defined, following a generalized Bernoulli distribution. The probability distribution of trip purposes, denoted as $p_{i,n}$, is modeled categorically with parameters $\theta_{i,n}$, representing the probabilities of each discrete category for the given departure time $d_{i,n}$ and number of trips n. Symbolically, $p_{i,n} \sim Cat(\theta_{i,n})$.

4) Possible Block Groups, Driving Distance, Driving Time, and End Block Group

The transition matrix from the starting Block Group of the i^{th} trip segment to the next Block Group is calculated based on the number of trips during the departure time hour $d_{i,n}$, represented as $r = P(X_{i+1}|X_i, d_{i,n})$. Subsequently, the next Block Group is determined, and the driving distance is inferred based on the average route distance between the two Block Groups. Assuming a vehicle speed of 40 miles per hour, the travel time is then determined.

In summary, our approach integrates NHTS data for trip chain generation and OD data for spatial chain generation, collectively composing trip chains that authentically reflect real-world movement patterns. However, a pivotal consideration is determining the number of vehicles to simulate for each Block Group. For simplicity, we assume that the total number of vehicle trips originating from a Block Group k, denoted as nv_k as pop_k where pop_k represents the populations of Block Group k, obtained from the American Community Survey (5-year average from 2017 to 2021).

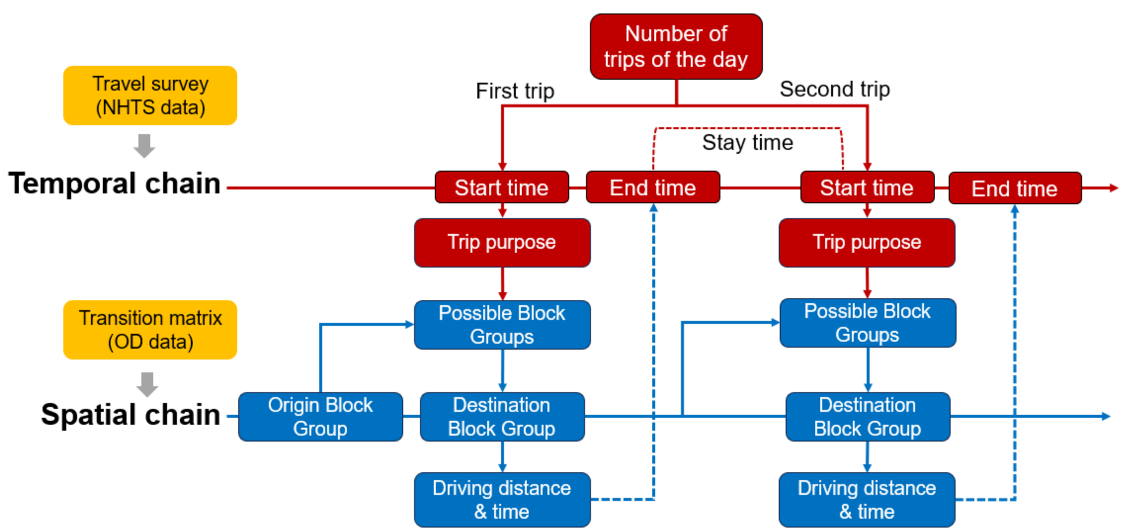


Figure 1. Trip chain generation process

Validation of the trip chain involves comparing three aspects: the total number of OD trips, the total number of OD trips by hour, and the total number of vehicle trips generated from a Block Group.

Charging modeling

For each trip segment of a vehicle with a starting time t, the charging rule is shown Table 1. In estimating charging demand, we simplify the process through several assumptions. Firstly, each vehicle is presumed to have a full battery capacity at the commencement of their first trip of the day. Secondly, the charging decision is made when the battery falls below its capacity as the vehicle arrives at a Block Group, irrespective of the duration of their stay. Charging is considered complete once the battery reaches 100% at the conclusion of the stay in that Block Group. Consequently, for each Block Group k, the energy consumption is calculated as $E_t^k = E_{t-1}^k + C^k \times \Delta t^n$, where the charging power of the charging station is denoted as C^k with a unit of kilowatts per hour. Thirdly, we assume that all simulated EVs are the same type which have an average battery capacity equivalent to that of a Battery Electric Vehicle (BEV) or Plug-in Hybrid Electric Vehicle (PHEV), set at 30 kWh. Fourth, vehicles will not deviate from their daily trip for general purposes or alter their route to utilize specific charging infrastructure; they will simply charge at their destination.

Table 1. Charging rule

E_t^n	Condition
E_0 (100%)	The first trip of the day ($t=0$)
$E_{t-1}^n - \lambda \times D_{t-1}^n$	Driving (λ represents the electricity consumed per mile driven with unit kilowatts per mile. D_t represents driving distance)
$E_{t-1}^n + C^k \times \Delta t^n$	Charging at Block Group k (Δt is the minimum of the stay time and the time needed for the battery to reach full capacity)
E_{t-1}^n	Not charging or driving

CASE STUDY AND RESULTS

Case study description

Our study focused on Clarke County, Georgia, encompassing 87 Census Block Groups. The generation of trip chains involves utilizing two primary data sources: NHTS for temporal chain creation and the transition matrix from OD for spatial chain development. To ensure the reliability of our approach, we initially compared the consistency between these two data sources.

The distribution of trips by departure time is illustrated in Figure 2. A comparison between the trip patterns from OD data and NHTS data reveals distinctions. Notably, NHTS exhibits a higher proportion of trips during the morning peak at 7 AM and the afternoon peak between 3-5 PM. Conversely, OD data indicates a greater share of trips during midday from 11 AM to 2 PM, as well as during the late-night to early morning hours, spanning from 10 PM to 6 AM. Given that OD data does not directly contribute to the temporal chain generation, the observed disparities in temporal patterns between simulated trips and OD data could be anticipated.

The parameters of charging demand estimation are summarized in Table 2. Two charging scenarios were devised based on the simulated trip chain. The first scenario exclusively considers EV charging at residential locations, aligning with trips whose purpose is returning home. This scenario mirrors situations where individuals predominantly charge at home, typically without many long-distance trips during the day.

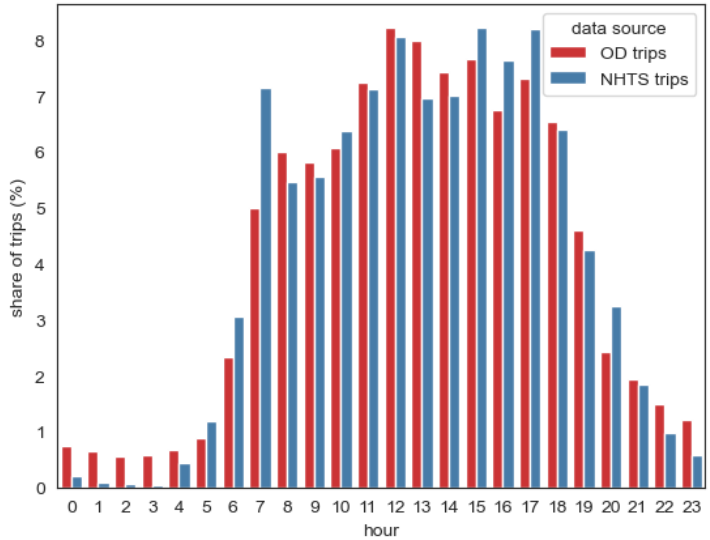


Figure 2. Departure time distribution of OD and NHTS

In the second scenario, it was assumed that EVs can charge at any location. This reflects a scenario where the development of public charging infrastructure enables people to charge wherever they park, such as in workplace or restaurant parking lots. Based on existing literature, the charging power is set at 6.7 kilowatts per hour, and battery usage is estimated at 0.36 kilowatts per mile driven (Falvo et al. 2014; Zhang, Brown, and Samuelsen 2011).

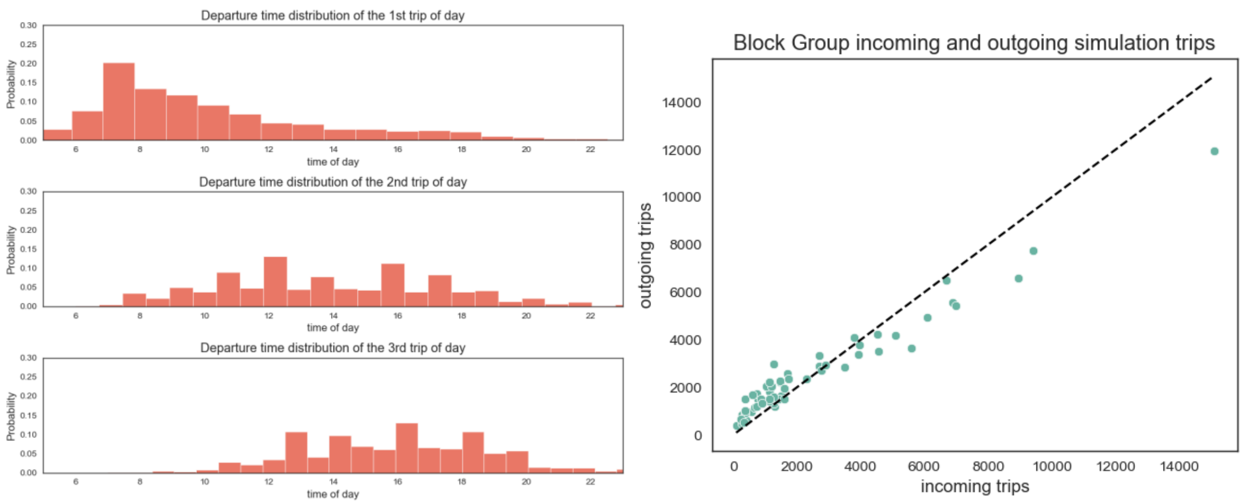
Table 2. EV charging estimation parameters

Parameter	Simulated values
Penetration rate (%)	10, 25, 50, 75, 100
Charging power C^k (kW/h)	6.7
Battery use λ (kW/mi)	0.35
Scenario	Residential only, charging everywhere

Trip chain validation

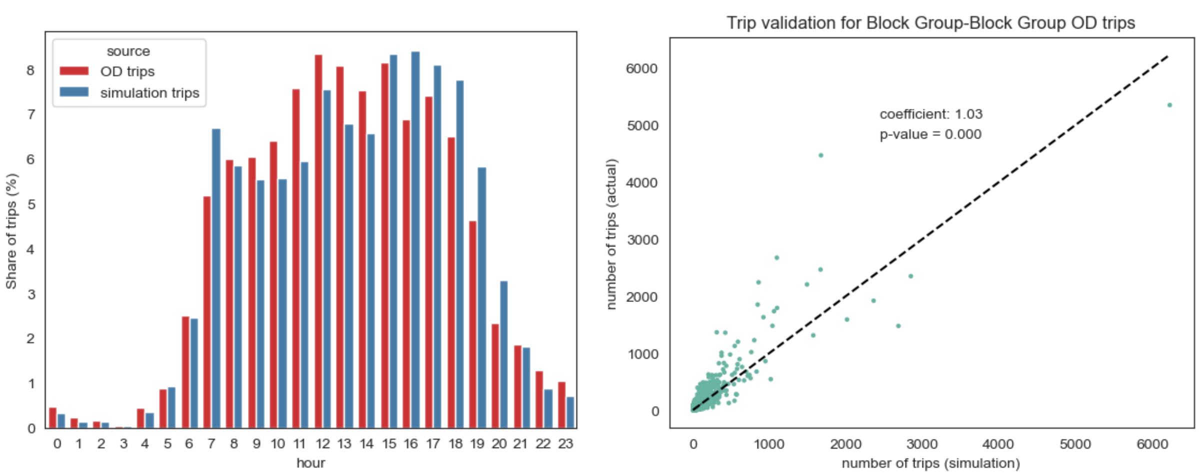
A total of 83,317 vehicles were simulated, and initial validity checks were performed. The departure time profiles for the first, second, and third trips of the day were examined. Most first trips occur between 7-8 AM, with the second trip exhibiting additional peaks around noon and the afternoon, displaying a more dispersed pattern compared to the first trip. The third trip follows a peak mainly centered in the later afternoon. This temporal trend aligns with common behavior, where individuals typically commute to work in the morning, may take short trips during the day, and return home in the afternoon. Further analysis of total incoming and outgoing trips by Block Group reveals close counts, validating the simulation's reliability. The comparable numbers suggest the simulated trips align reasonably with expected patterns.

A total of 207,707 trips were simulated using the proposed method, compared to 232,920 trips from the OD data. The average percentage difference between simulation and OD trips stands at 10.8%. Further analysis of temporal patterns reveals more detailed variations. Figure 4 (a) shows that simulation trips show a marginally higher share during early morning at 7 AM and in the afternoon between 4-6 PM, while midday between 11 AM-2 PM exhibits a slightly lower share. This discrepancy is attributed to inconsistencies in departure time patterns between NHTS and OD data, as depicted in Figure 2. The average percentage difference in the share of trips by time of day between OD trips and simulation trips is 18.2%. Trip count comparison, illustrated in Figure 4 (b), demonstrates a relatively good fit with a linear regression coefficient of 1.03 (p-value<0.001), affirming that simulated trip chains effectively mirror the actual OD pattern.



(a) Departure time profile of the simulation trips (b) Incoming and outgoing trips

Figure 3. Validity check results

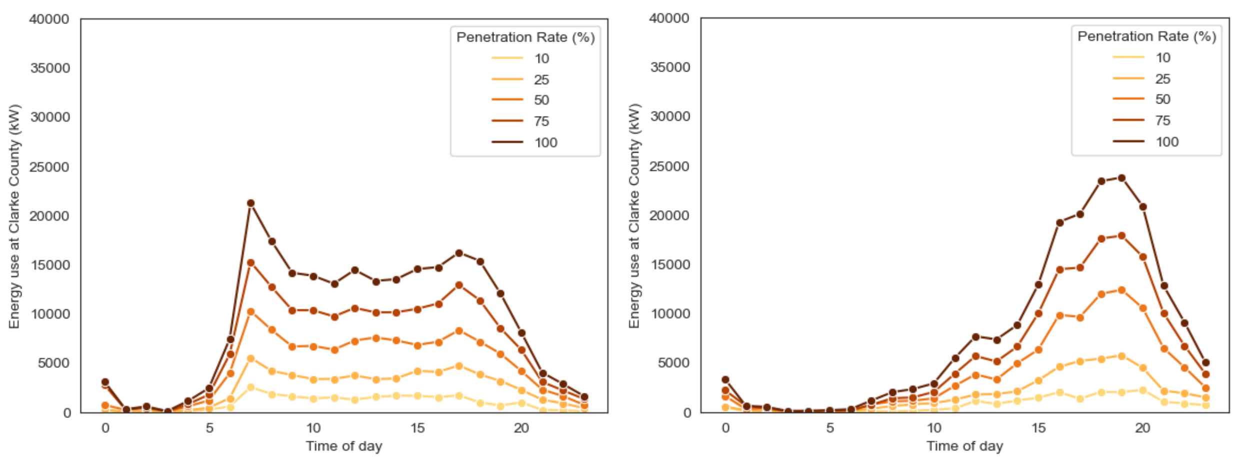


(a) Hourly trip comparison (b) OD trip count comparison

Figure 4. Trip count validation

Charging energy use

Figure 5 illustrates the temporal energy consumption in two scenarios. Both scenarios exhibit a peak demand of approximately 25 megawatts, yet the peak times differ. In the "charging everywhere" scenario, energy usage mirrors the trip pattern, with a morning peak at 7 AM (21.2 megawatts) and an afternoon peak at 5 PM (16.2 megawatts). This aligns with the expectation that individuals charge their cars upon arriving at and departing from work, with additional charging for various trips during the day. Higher EV penetration intensifies daytime energy consumption. In the "residential only" scenario, constrained to home charging, a singular afternoon peak emerges at 7 PM, reaching the highest electricity consumption of 23.8 megawatts. A comparative analysis reveals that peak energy use aligns with common commute patterns. The observation shows that when charging is predominantly centered, such as at home after work, energy consumption could surpass the scenario where vehicles can charge anywhere they park. These scenarios offer insights into how increasing EV ownership correlates to rising energy consumption and suggest the potential benefits of coordinated charging practices to mitigate electricity demand.



(a) Charge everywhere (b) Charge only at residential locations

Figure 5. Energy use of the two scenarios

Given the challenge of acquiring actual electricity usage data from utility companies, this study opted not to validate against real-world data. Instead, we validated our findings by comparing them with patterns identified in existing literature. A study simulating 44,000 Electric Vehicles (EVs) in Uppsala, Sweden also explored scenarios akin to our "charging everywhere" and "residential only" scenarios, revealing similar trends (Shepero and Munkhammar 2018). Future research could involve a comprehensive literature review, incorporating more scenarios with diverse factors, such as varying charging power and utilizing actual charging infrastructure locations for higher spatial resolution, such as building-level data.

CONCLUSIONS

This study proposed a trip chain generation method for estimating charging demand, utilizing travel survey and OD data. By extracting both temporal and spatial movement patterns from these mobility data sources, we constructed trip chains that correspond to the geospatial locations of trip start and end points at the Census Block Group level. Our contribution lies in presenting a trip chain generation method that captures mobility patterns without relying on intricate network topology. This approach can address the limitations of prior simulation methods, which struggled to reflect realistic geospatial patterns, facilitating more practical planning for charging strategies, such as infrastructure deployment and pricing. The two proposed charging scenarios offer insights into varying EV penetration rates and charging locations, providing valuable considerations for a future with increased EV ownership and expanded charging infrastructure. This study lays the groundwork for future research, paving the way for higher spatiotemporal resolution in trip chain generation and more realistic charging decision simulations.

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Tolling toward Congestion: The Jam-and-Harvest Effect and Its Equity Concerns

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ABSTRACT

Dynamic tolling stands as a pivotal tool in contemporary highway management, aiming to balance traffic flow and generate sustainable revenue. Yet, a somewhat paradoxical outcome, the jam-and-harvest (JAH) phenomenon, has emerged. This research scrutinizes the jam-and-harvest (JAH) effect in dynamic tolling, revealing its potential to exacerbate congestion on free lanes as traffic diverts from managed lanes. This simulation-based study highlights the revenue increase for operators during peak traffic times but also underscores a significant equity issue: lower socio-economic groups, with a lower value of time (VOT), face harsher delays in congested unmanaged lanes. Based on the findings, this paper comes up with policy suggestions to address the inequalities caused by JAH, advocating for more accessible public transport and regulated toll caps to ensure fairer access to roadways.

INTRODUCTION

As urban places expand, and road networks become increasingly congested, innovative traffic flow management methods have become more and more crucial for congestion mitigation and mobility fluency. As a result, High Occupancy/Toll Vehicle (HOT) lanes are introduced to the metropolitan freeway systems, allowing High Occupancy Vehicles (HOV) who has high number of passengers to bypass traffic in general purpose lane (GP) (Figueiras et al. 2019; Lombardi et al. 2023; Nohekhan et al. 2021). In order to avoid congestion in the HOT lane and further damage HOV flow's priority, dynamic tolling was suggested as an innovative approach to regulate traffic flow and fund transportation infrastructure(Lou et al. 2011). Yet, a paradox outcome, the Jam-and-Harvest (JAH) phenomenon, has emerged. JAH phenomenon is initially founded when maximize the operational revenue for the dynamic tolling schemes(Adurthi et al. 2022; Gocmen et al. 2015). By adjusting toll rate upwards, a sizeable portion of the vehicles are diverted towards the general purpose lane (GP). This diversion aggregates pronounced congestion for unmanaged lanes. As traffic peak nears, the managed lanes, now vacant, contrast to the clogged unmanaged lanes, become increasingly attractive, resulting revenue surge for the operators.

Our research is timely and significant, especially in the context of rising urbanization and increasing attention on equitable transportation development. By revealing the mask of JAH effect, this paper innovatively using simulation-based traffic flow simulation to evaluate the JAH phenomenon and its socio-economic influence. The implementation of dynamic tolling on people groups with different value of time (VOT) is simulated, thereby fostering a more sustainable and equitable transportation planning.

LITERATURE REVIEW

To lend empirical evidence to dynamic tolling scheme, much research employs the stochastic simulation techniques. A simulation study of Singaporean road pricing system demonstrates the effectiveness of dynamic tolling in reducing congestion during peak hours by changing the supply-demand curve (Koh and Chin 2022). another case study at Ben Gurion Airport (BG), Israel reveals that interaction between the toll rate and traffic conditions play important roles on traffic optimization(Gutman 2016). As long as the Jam-and-Harvest effect, a paradox from dynamic tolling, will unintentionally happens, if the operator maximizes their profit by leveraging myopic policies that only consider current conditions by preparing for future demand. However, the JAH may cause longer Total System Travel Time (TSTT) and extra travel delay to the commuters(Gocmen et al. 2015). Following this, research on dynamic pricing strategies for managed lanes with multiple entry and exit points, focusing on maximizing revenue and minimizing total system travel time (TSTT). Using Markov decision process, the findings indicate that revenue-maximizing policies tend to follow JAH phenomenon and this behavior is not observed when minimizing TSTT(Pandey and Boyles 2018).

In terms of the equity concerns in dynamic tolling, there always equity issues associated with congestion prices. Some research reviews evidence from both real-world implementations and models of congestion pricing systems, and it reveal that congestion pricing has unequitable influence on different social groups(Ecola and Light 2009; Panou 2020). A study on equitable dynamic pricing for express lanes explore the equity impacts for different groups. Its findings include the observation that higher tolls and increased demand can exacerbate delay differentials between groups of different value of time (VOT). And equitable discount is suggested to eliminate the equity gap. However, the equitable discount may cause significant revenue loss and increased delay(Pandey 2020).

PROBLEM DEFINITION

To evaluate and justify the JAH phenomenon and its impact, we conduct a simulation study based on the data of Southern California's State Route 91 (SR91). SR91 is a crucial transportation corridor that represent typical highway setting up as its location shown in Figure 1. And its management is further complicated by its pioneering role in deploying one of the first express lane system in United States, which integrate dynamic tolling. This tolling strategy is designed to control the demand for the express lane, maintaining free flow conditions even during the peak periods. Basic traffic pattern, such as weekly vehicle-miles traveled (VMT), traffic volume and toll rate are shown in Figure 2. Based on the current setting, we further test different tolling schemes during the simulation. One is the schedule tolling, where the toll price is set in advance based on the traffic demand prediction. Another toll policy is to raise the toll before the peak manually and keep high toll rate during the entire peaking period.

METHODOLOGY

The primary numerical approach to investigate the JAH phenomenon is stochastic simulation, a powerful technique that are capable of modeling complex systems under randomness and uncertainty. Stochastic simulation incorporate variability through random sampling from probability distribution, allowing for capture of essential fluctuations happened in real-world traffic. Leveraging these techniques, this paper simulates multi-scenarios toll schemes, representing different policies and we compare the total revenue and total system travel time (TSTT).

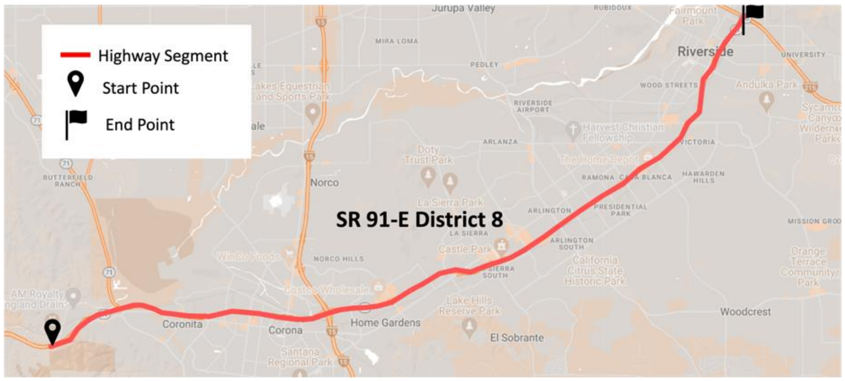


Figure 1. SR91-E District 8 location map

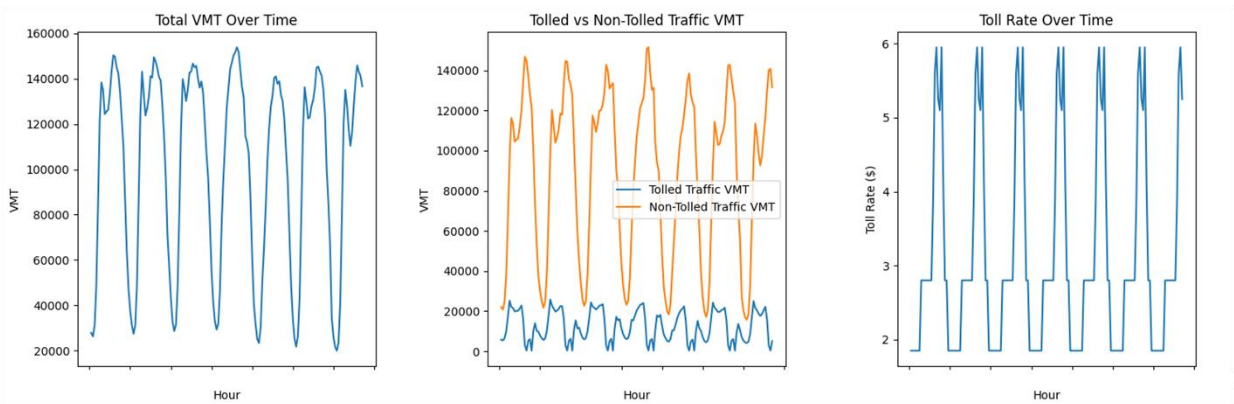


Figure 2. total VMT over time (left), managed lane and unmanaged lane traffic VMT (middle) & toll rate over time (right)

MODEL ASSUMPTIONS

Assumption 1: The simulation model assumes a linear relationship between toll rate and traffic demand on the managed lanes, where toll rate increase results in linear traffic reduction.

Assumption 2: A base percentage of traveler is assumed to use toll lane even at the lowest toll rate.

Assumption 3: Different VOT groups are assumed to have different sensitivities to toll rates, affecting their choice between tolled and non-tolled lanes.

MODEL CONSTRUCTION FOR TRAFFIC DYNAMICS

The simulation model for traffic dynamics was constructed to elaborate the behavior of a typical urban toll road system with both managed and unmanaged lanes. The model incorporates the following critical components:

Traffic demand generator: In our simulation settings, the arrival rate of vehicles varies with time, and we use a non-homogeneous Poisson process with a time-dependent parameter as input for each time step.

Toll decision process: For each individual, we formulate the driver's choice behavior by discrete choice theory, in which the traveler's choice between toll lane and unmanaged lane is modeled as utility-max problem shown in Figure 3. It involves in travel time difference between toll lane and unmanaged lane, toll rate difference and traveler's value of time.

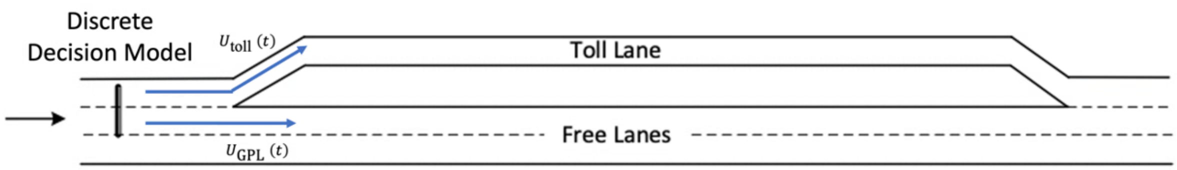


Figure 3. discrete decision mode

Traffic diversion percentage adjustment: When toll rate varies over time, there will be a diversion percentage adjustment based on utility, which how the utility of different routes affects the proportion of travelers' choice between toll lane and free lane. A logit function is introduced in equation 5.

The simulation algorithm is formulated by following equations:

$$P(N(t+\Delta t)-N(t)=k)=\frac{e^{-\lambda(t)\Delta t}(\lambda(t)\Delta t)^k}{k!} \tag{1}$$

$$U_{\text{toll}}(t)=\alpha\cdot T_{\text{free}}(t)-\beta\cdot C_{\text{toll}}(t)+\gamma\cdot \text{VOT}\cdot\left(T_{\text{free}}(t)-T_{\text{toll}}(t)\right)+\epsilon \tag{2}$$

$$C_t=C_{\text{base}}+\kappa\cdot\left(\rho(t)-\rho_{\text{opt}}\right) \tag{3}$$

$$Q(t)=V(t)\times\rho(t) \tag{4}$$

$$P_{\text{diversion}}(VOT)=\frac{e^{U_{\text{toll}}(\text{VOT})}}{e^{U_{\text{toll}}^{(VOT)}}+e^{U_{\text{non-toll}}(VOT)}} \tag{5}$$

$$R=\sum_{i=1}^{N} C_i \tag{6}$$

$$TSTT=\sum_{i=1}^{N} T_i \tag{7}$$

Here, $N(t)$ is the number of vehicles arriving up to time t; $\lambda(t)$ is time-dependent arrival rate of vehicles; Δt is small time interval for the calculation; k is actual number of arrivals observed in time Δt. $U_{\text{toll}}(t)$ is utility of taking the tolled route at time t; $T_{\text{free}}(t)$ is travel time on a free road at time t; $C_{\text{toll}}(t)$ is the cost of the toll at time t; VOT is the value of Time for the driver;

$T_{\text{toll}}(t)$ is travel time on the tolled road at time t; α, β, γ are parameters weighing the importance of free travel time, toll cost, and time savings; ϵ is random component of utility; C_t is toll rate at time t; $C_{\text{base:}}$ is the base toll rate; κ is sensitivity of the toll rate to changes in traffic density; $\rho(t)$ is traffic density at time t; ρ_{opt} is optimal traffic density for maximum flow; $Q(t)$ is traffic flow rate at time t; $V(t)$ is average speed of the vehicles at time t; $P_{\text{diversion}}$ is probability of a driver choosing the tolled route; ΔU is difference in utility between the tolled and free routes; R is total revenue from the toll; N is number of tolled vehicles; C_i is toll rate for the i-th vehicle; T_i is travel time for the i-th vehicle;

RESULTS

The simulation results provide comprehensive insights into the dynamics of the JAH phenomenon. Through the iterative operation of stochastic simulation, we observed congestion differences between toll lanes and unmanaged lanes. The following are the significant results we have simulated, supported by different toll policies based on toll schedule aimed at maximizing operator revenue and its influence on commuters' choices.

Congestion disparity happens during JAH phenomenon. In the simulation, we observed congestion in unmanaged lanes when toll rates were escalated during prior-peak hours (11:00 to 12:00). The toll lanes, operating under dynamic pricing aimed at maximizing revenue, experienced a reduction in traffic volume by an average of 17% during these hours. In contrast, unmanaged lanes were saw an increase in traffic volume by as much as 22%, leading to significant congestion as shown in Table 1 and Figure 4. This was particularly evident during the transition from off-peak to peak hours when the toll lanes had not yet adjusted to lower rates, and the unmanaged lanes were already saturated with diverted traffic.

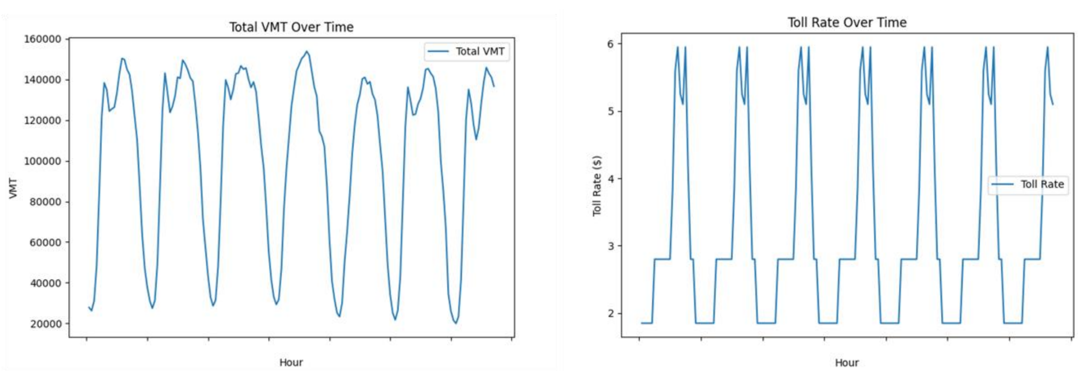


Figure 4. simulation VMT over time (left) & Simulation toll rate over time (right)

JAH causes more severe travel delays. The increase of congestion in the unmanaged lanes results in substantial travel delays. During the simulation, the average travel delay for commuters in unmanaged lanes increases by 40% compared to the baseline scenario without rasing up toll rate before real peak. These delays peaked during the transition from artificially induced off-peak hours to actual peak hours, highlighting the critical impact of the JAH strategy on non-toll road users. The total system travel times (TSTT) were also affected by the JAH strategy. Our simulation showed an increase in TSTT by 12% during the JAH scenario as opposed to a standard tolling schedule. This increase in system-wide travel time reflects not only the congestion in the unmanaged lanes but also the temporary underutilization of the tolled lanes during artificially induced peak pricing.

Table 1. JAH scheme and baseline scenario results

Scenario	Total Revenue ($)	Average Traffic Delay (min)	Congestion Increase in Unmanaged Lanes (%)	Traffic Volume Reduction in Tolled Lanes (%)
Baseline	10,354,993.62	20	0	0
JAH Scheme	22,922,075.68	40	22%	17

JAH allows operators to harvest more revenue during the whole period. From the perspective of toll operators, the JAH strategy results in a notable surge in revenues. The toll revenue increased by an average of 23% during the hours of early toll peaks as shown in Figure 5. This increase in revenue was a direct result of the high toll rates and the subsequent return of vehicles to the tolled lanes as the unmanaged lanes became congested. However, this short-term financial gain for the operators must be juxtaposed against the broader implications for commuter welfare and traffic system efficiency.

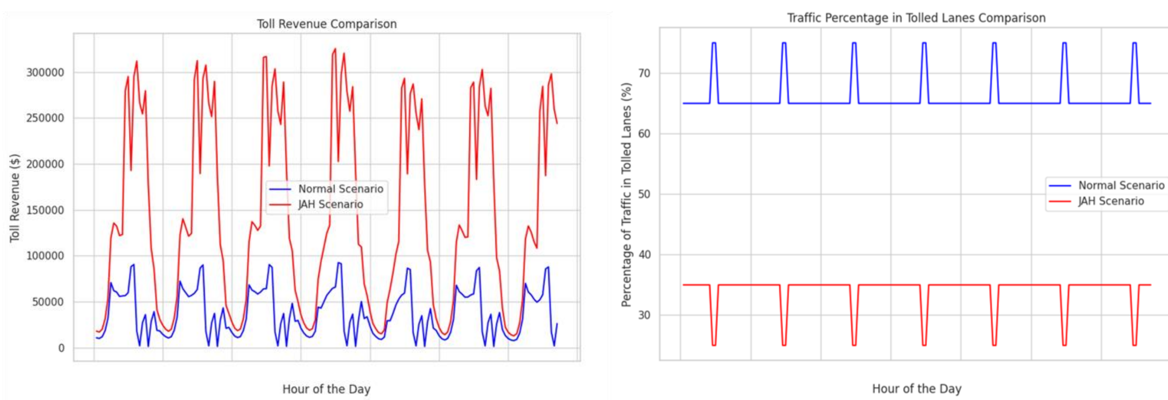
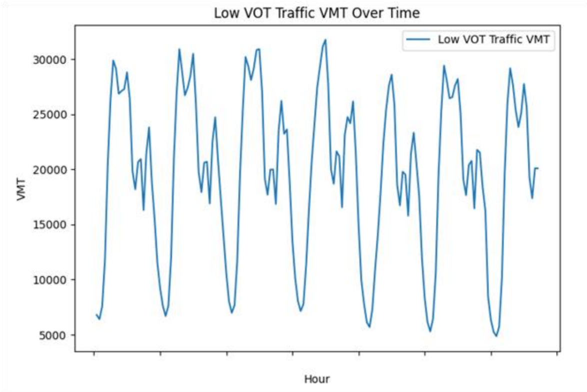


Figure 5. total revenue (left) & traffic diversion percentage

Lower VOT groups suffer longer travel delay. The JAH effect also underscores significant equity concerns. The stochastic simulation results indicate that vehicles with a lower VOT, which often correlate with lower-income commuters, were disproportionately represented in the congested unmanaged lanes. Conversely, those with a higher willingness to pay, often associated with higher-income profiles, could avoid congestion by paying the premium for toll lane access, thereby experiencing reduced travel times. In that case, different VOT groups has totally opposite travel patterns in terms of VMT during time of a day as shown in Figure 6.

To sum up, the results of our stochastic simulations demonstrate the complex interaction between toll rates, commuter behavior, and traffic congestion. The JAH phenomenon, while financially beneficial to toll operators in the short term, raises substantial concerns regarding equitable access to efficient travel, suggesting a need for careful consideration of tolling strategies within urban traffic management policies.



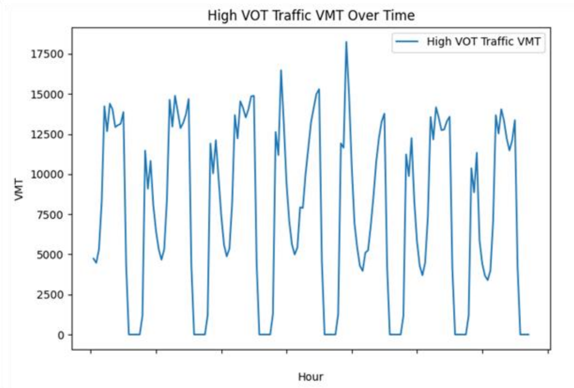


Figure 6. low VOT traffic VMT & high VOT traffic VMT

CONCLUSION

The investigation into the Jam-and-Harvest (JAH) phenomenon through stochastic simulation offers vital revelations on the interaction between tolling strategies and traffic patterns. The core findings indicate that while dynamic tolling can enhance revenue for highway operators, it also leads to more severe congestion disparities and raises concerns about social equity. In addition, the simulation results clearly demonstrate the JAH strategy, which involves raising toll rates ahead of traffic peaks, leads to significant revenue increases. However, this comes at a cost, particularly in terms of equity. Lower-income commuters, who are less able to absorb increased toll costs, suffering heavier travel delay as they are pushed into congested, unmanaged lanes. This worsens socio-economic disparities and underlines the broader social impacts of tolling policies.

Reflecting on these outcomes, it is evident that toll policy plays a very important role in balancing between the financial profit of toll road operations and the equitable access to transportation infrastructure. The challenge for policymakers and stakeholders is to devise tolling systems that are both economically viable and socially responsible. To accomplish this goal, the operators need to consider the full spectrum of commuters' needs and the diverse VOT groups that characterize urban populations(Swami et al. 2021). Herein, we present two policy recommendations:

Equitable discount for low VOT groups. To mitigate the negative impact of JAH on transportation equity, we recommend a dynamic toll pricing strategy that varies not only to traffic pattern but also to the travelers' equity. By incentive low VOT users, the policy framework may further advance the goals of social fairness and transportation efficiency, thereby enhancing the overall sustainability of the urban traffic ecosystem.

Caps on Toll Prices. The caps on toll rates may prevent toll prices from rising to levels that disproportionately impact lower-income drivers, who may have no alternative but to use congested unmanaged lanes. Price caps should be set based on comprehensive cost-benefit analyses that consider the socioeconomic composition of the commuting population, aiming to ensure that toll roads remain accessible to a broad segment of the population.

In conclusion, the JAH effect presents both opportunities and challenges. While it offers a mechanism for managing traffic flow and generating revenue, it also exposes risks to the equitable distribution of transportation benefits. The insights gained from this study underscore the complexity of tolling as a tool for urban traffic management and highlight the importance of pursuing strategies that are sensitive to the diverse needs of the residents from all regions. As road networks continue to evolve and transportation demands grow, innovative and equitable tolling strategies will be critical in shaping the future of urban mobility.

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Scooting towards Equity: A Comprehensive Study of Shared E-Scooter Impact in Chicago

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ABSTRACT

This study explores the adoption of e-scooters as a transportation mode in Chicago and examines various aspects of the mode, including trip patterns, temporal analysis, and the influence of sociodemographic factors on equity. The analysis reveals a diverse user base, with both men and women participating in e-scooter trips, and a mean trip duration of around 19 min. Temporal analysis highlights peak usage during mid-weekdays, especially Tuesdays to Thursdays, and on weekends, particularly Sundays, emphasizing their role in addressing commuting needs. Furthermore, the hour-level analysis identified 5 p.m. to 6 p.m. as the peak usage period, emphasizing the role of e-scooters in addressing commuting needs during rush hours. A Poisson regression model indicates a significant negative relationship between socioeconomically disadvantaged areas and the starting points of scooter trips, suggesting potential disparities in access. This study contributes valuable insight into the evolving understanding of e-scooter usage, emphasizing the importance of collaboration between city planners and policymakers for an equitable e-scooter system.

INTRODUCTION

E-scooter systems are becoming more popular around the world, especially in the U.S. (Yu et al. 2018). Shared electric scooters, often known as e-scooters, have grown in popularity in urban transportation due to their ease and ability to alleviate last-mile connectivity issues. As these systems become more accepted as a main source of transportation in city centers, the metropolitan areas will need to implement changes to allow for the usage of these e-scooters. The current situation that is presented is that most of the areas are not equipped with the necessary environment for the allowance of these systems. Creators of e-scooters need to communicate and connect with city planners to allow for smooth usage of these platforms (Bai et al. 2021; Sorkou et al. 2022; Younes, Noland, and Andrews 2023; Félix, Orozco-Fontalvo, and Moura 2023). Moreover, e-scooters could potentially enhance transportation equity by giving underserved communities more access to public transportation (McQueen and Clifton 2022; Zarif, Pankratz, and Kelman 2018). Shared e-scooters allow users to obtain short-term access to transportation on an as-needed basis and have the potential to help address transportation equity challenges (Shaheen et al. 2017).

However, despite the numerous potential advantages of micromobility services, users, supporters, and public officials have raised significant equity concerns (Department of Transportation 2021). Due to the relative novelty of shared dockless e-scooters, the related work is limited, and only a few studies analyze the spatiotemporal usage and patterns of e-scooter trips (Liu, Seeder, and Li 2019). Therefore, this study aims to examine various facets of e-scooter usage, including trip duration, temporal patterns, spatial distribution, and their influence on transportation equity, with a particular emphasis on sociodemographic factors. The objective of this study is to explore the case study of Chicago to investigate the equitable implications of e-scooter adoption, with a specific focus on sociodemographic factors.

LITERATURE REVIEW

Since e-scooters will be cheaper for riders to use, they will often favor these platforms for day-to-day travel because it will be a quick, easy alternative. People will also favor this type of transportation because they do not have to deal with the maintenance of e-scooters, like they would a personal vehicle. Similarly, the cost of keeping a vehicle is highly expensive especially in the current state of the economy with gas prices, so it is highly likely that individuals would favor the micro-mobility platform. Most people may be concerned about the elimination of jobs with the discontinuation of motor-vehicle travel, but this will not be the case because as demands rise for the e-scooter, similarly, the need for jobs to meet these demands will subsequently increase. The introduction of e-scooters will be a cost-effective alternative to the everyday motor-vehicle, in which people will tend to favor e-scooters more than the current, favored mode of transportation (Aarhaug, Fearnley, and Johnsson 2023).

Moreover, Aarhaug et al. investigated the usage of micro-mobility, more specifically e-scooters, possibly showing a connection between either helping public transportation systems or slowly making public transportation systems obsolete. The result from this study indicated that participants of e-scooter usage would use these micro-mobility vehicles to gain access to other modes of public transportation that otherwise would have taken significantly longer to gain access to through other modes of public transportation (Aarhaug, Fearnley, and Johnsson 2023). The results of another study indicated that e-scooters were typically used as a first and last-mile transportation system (Chicco and Diana 2022).

Studies Related to Spatiotemporal Analysis

According to a study by Abouelela et al., the impact of e-scooter travel is influenced by differing categories. These categories consist of weather, day of the week, infrastructure, sociodemographic, land use, and transit accessibility. This study indicated that most urban infrastructure systems are not readily equipped to allow for the usage of this micro-mobili$f$tabelty platform, but further research will allow these cities to prepare for future micro-mobility platforms to come to these cities (Abouelela, Chaniotakis, and Antoniou 2023).

Moreover, Almannaa et al. concluded that similarly to e-bike users, e-scooter travelers, often traveling at a slower rate, would be grouped on weekends and a cluster of one weekday. The study indicated that plans for micro-mobility platforms would be to increase the travel speed of e-scooters, so users may safely travel to and from work/university to effectively switch to this form of transportation (Almannaa et al. 2021). Another study focusing on Austin, Texas and Minneapolis, Minnesota found that Austin experienced heavier usage on the weekends and afternoon weekdays, while Minneapolis resulted in more traffic throughout every day of the week. The study emphasized the importance of city-to-city uniqueness based on location and distance between public transit stops and compatibility for the usage of e-scooters in the area (Bai and Jiao 2020).

Studies Related to Sociodemographic of Users

Bieliǹski et al. found that e-scooters had a predominant usage among younger male users for first and last-mile transport. The research noted the limitations of the study based on one city instead of focusing on a wide variety of cities (Bieliński and Ważna 2020).

One case research sided with the idea that e-scooter usage was favored by young men. In terms of behavior, the study showed that young men tended to favor the e-scooter because it was similar to an adrenal rush, and they felt that using an e-scooter was more dangerous than using motor vehicles as a travel method (Cubells, Miralles-Guasch, and Marquet 2023). However, some cases found this idea to be very different. Researchers found that e-scooter usage and safety concerns were even on all accounts (Younes, Noland, and Andrews 2023). Both cases represent the difference in the study methods presented by the researchers. This proves to future producers of these e-scooters that there needs to be an equal presentation of their product to consumers to allow for more mass usage of this micro-mobility platform.

Cubells et al. showed that the use of micro-mobility vehicles is currently skewed towards young men, who are more likely to adopt risky behaviors, such as fast or aggressive riding. The results of their study indicated a difference in speed, based on gender and e-scooter travel, but also noticed a non-existent correlation among cyclists. However, Cubells mentioned that there are limitations to the study and that additional research must be conducted (Cubells, Miralles-Guasch, and Marquet 2023).

DATA AND METHODOLOGY

Study Area

This study focused on Chicago as the case study. Chicago, located in the state of Illinois, is the third-largest city in the U.S. The 60,000-hectare City of Chicago is located on the southwest shore of Lake Michigan at an elevation of 176 meters (578 feet) above sea level ("City of Chicago" 2023). Chicago has a population of 2,665,039 residents, of which 51.2% are female. The three largest groups in Chicago are White (45.3%), Black or African American (29.2%), and Asian (6.8%). In 2022, Chicago had 17.1% of residents living below the poverty level ("U.S. Census Bureau" 2022). Chicago has the second-highest percentage of commuters riding their bikes to work, with an average trip time of 23 minutes. Chicago has 303 miles of bike lanes, more than 13,000 bike racks, and 19 miles of lakefront bicycle paths along Lake Michigan ("City of Chicago" 2023).

Data

Shared scooters are available for rent in Chicago through the Divvy bikeshare system, as well as through three companies awarded business licenses to operate in this city ("Scooter Sharing in Chicago" 2023). The data used in this study was obtained from the electric scooter trips taken during the 2020 Chicago pilot program, summarized by a census tract for five months, from August 12, 2020, to December 12, 2020. The data was retrieved from the Chicago Data Portal ("City of Chicago Data Portal" 2023) and includes trip ID, start time, end time, trip duration, the name of the vendor, start community area number and name, end community area number and name, start centroid latitude, start centroid longitude, end centroid latitude, and end centroid longitude.

To investigate the sociodemographic information of where people rode e-scooters in Chicago, several variables were used based on previous travel behavior empirical studies (Jiao and Bai 2020; Ewing and Cervero 2010; Handy, Cao, and Mokhtarian 2005; Sadeghvaziri et al. 2023a) that focused on income and race. The original data were acquired from the U.S. Census Bureau at the Census Tract level.

Data Cleaning

The total number of scooter trips taken between August 12, 2020, and December 12, 2020, was 630,816. Additionally, there are some trip records in which users appear to have encountered technical issues. Specifically, the data was cleaned by excluding trips that had any of the cases mentioned in Table 1. These criteria were collected based on previous studies on the subject (Qian and Jaller 2021; Yan et al. 2021; Tokey, Shioma, and Jamal 2022). After cleaning the data, a total of 601,521 trips were considered for this study.

Table 1. Criteria for Trip Removal from the Dataset

Criteria	Number of Trips removed	% of Initial Number of Trips
Trip distance less than 0.02 miles	0	0
Trip of less than one minute	6,209	0.98
Trip duration more than two hours	23,086	3.66
Total excluded trips	29,295	4.64

Regression Model

Socioeconomically Disadvantaged Areas are areas that are based on census tracts and are the most socioeconomically disadvantaged areas. They are identified as such for the purpose of promoting equitable hiring within areas of economic need. Qualifying areas were identified using three criteria based on data from the American Community Survey: household income, poverty rate, and unemployment. The data were retrieved from the City of Chicago Open Data Portal (“City of Chicago Data Portal” 2023). Figure 1 shows the Socioeconomically Disadvantaged Areas at the Census Tract level in the City of Chicago.

Poisson regression was used to capture the relationship between Socioeconomically Disadvantaged Areas at the Census Tract levels and the geographical location of the starting point of scooter trips in Chicago. Poisson regression is a type of regression analysis that is used to model count data (“STAT” 2018). In this study, the outcome variable is the geographical location of the starting point of scooter trips, and the predictor variables are the Socioeconomically Disadvantaged Areas at the Census Tract level.

ANALYSIS RESULTS

Temporal Analysis

Figure 2 shows the duration of the trips. The results show that the mean trip duration was about 19 minutes; the majority of trips (75.21%) were under 20 minutes. The mean trip duration for women was 14 minutes, and 12 minutes for men.

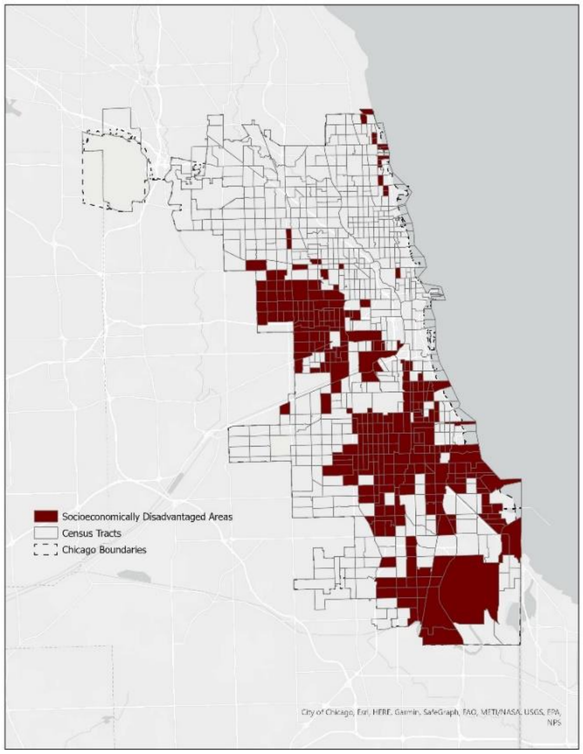

Figure 1. Socioeconomically Disadvantaged Areas

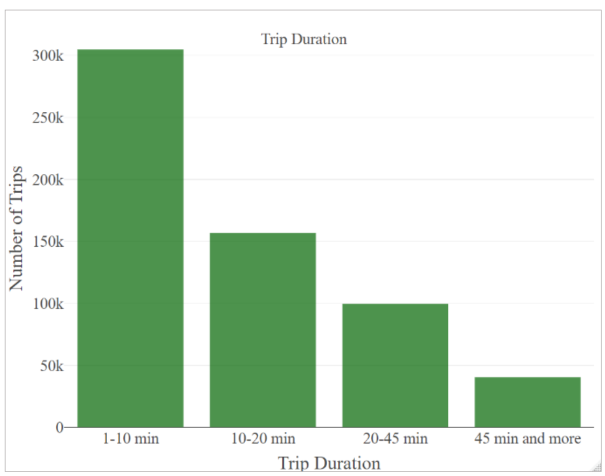

Figure 2. Scooter Trips Duration

Figure 3 and Figure 4 show that 38.66% of the trips took place mid-weekdays (Tuesdays, Wednesdays, and Thursdays). The highest ridership occurred on Sundays (18.54%). Moreover, 27.42% of the trips were taken on shoulder days (Mondays and Fridays), and 33.92% of the trips were taken on weekends (Saturdays and Sundays).

Figure 5 shows that 5 p.m. and 6 p.m. had the highest usage of e-scooters in Chicago. In order to have a better understanding of the usage pattern during a day, the hour of the day was aggregated into Morning (6 a.m. - 12 p.m.), Midday (12 p.m. – 6 p.m.), Evening (6 p.m. – 12 p.m.), and Night (12 a.m. – 6 a.m.). Figure 6 shows that more than half of the trips (51.67%) were taken during Midday (12 p.m. – 6 p.m.).

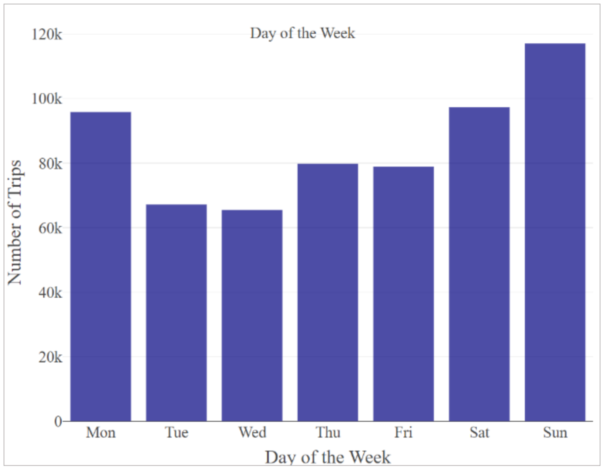

Figure 3. Day of the Week Ridership

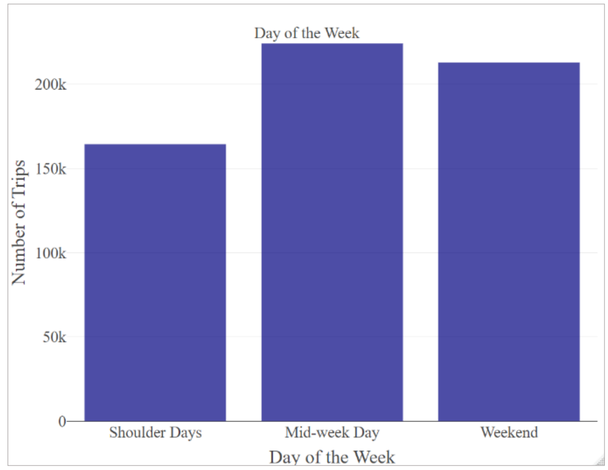

Figure 4. Weekend/Weekdays E-Scooter Ridership

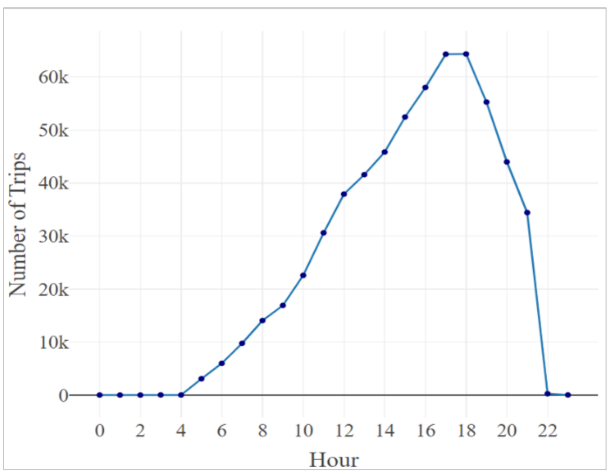

Figure 5. Time of the Day Scooter Ridership

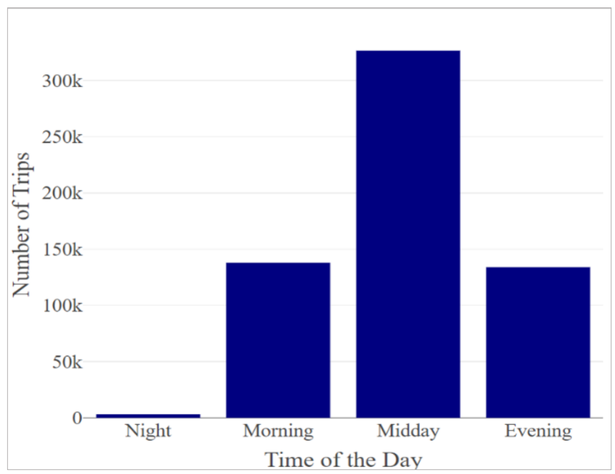

Figure 6. Time of the Day Scooter Ridership

Regression Model Results

Many studies have used statistical models to develop policies to improve traffic safety, investigate and forecast travel behavior, and pinpoint deficiencies in equity and transportation policies (Sadeghvaziri, Javid, and Jeihani 2023; Javid and Sadeghvaziri 2023a; 2023b; Sadeghvaziri et al. 2023b). In this study, a Poisson regression was conducted to examine how the Socioeconomically Disadvantaged Areas at the Census Tract levels can affect the location of the starting point of scooter trips in Chicago. Table 2 shows the results of the regression analysis.

The results of the regression model show that Socioeconomically Disadvantaged Areas have a statistically negative effect on the number of bikeshare stations at the Census Tract level.

Table 2. Regression Model Results

	Coefficient	Std. Error	z-Statistic	Pr(>|z|)
(Intercept)	3.010831	0.009559	314.973801	0.000000
Socioeconomically Disadvantaged Areas	-0.662733	0.021356	-31.032868	0.000000

DISCUSSION AND SUMMARY

The exploration of e-scooter usage in Chicago has provided valuable insight into various facets of e-scooter usage, including trip patterns, temporal analysis, and the influence of equity factors. The study revealed that e-scooter usage in Chicago is characterized by distinct sociodemographic patterns. The analysis found a diverse user base with trips taken by both men and women. The mean trip duration was approximately 19 minutes, with a majority of trips lasting under 20 minutes. Interestingly, the mean trip duration for men was slightly shorter than that for women, indicating potential variations in usage behaviors between genders.

The temporal analysis highlighted the distribution of e-scooter trips across different days of the week and times of the day. Mid-weekdays, particularly Tuesdays, Wednesdays, and Thursdays, accounted for the highest share of trips, comprising 38.66%. Weekends, especially Sundays, exhibited substantial ridership, representing 33.92% of the total trips. The hour-level analysis identified 5 p.m. to 6 p.m. as the peak usage period, emphasizing the role of e-scooters in addressing commuting needs during rush hours. The examination of Socioeconomically Disadvantaged Areas using a Poisson regression model revealed a statistically significant negative relationship between these areas and the location of stating a scooter trip at the Census Tract level. This suggests that areas with higher socioeconomic disadvantages have fewer starting points for scooter trips, potentially indicating disparities in access to micro-mobility services.

The study contributes to the growing body of knowledge on e-scooter usage, particularly in an urban context such as Chicago. However, some areas warrant further investigation. Future research could delve into more detailed sociodemographic factors, such as age groups and occupation, to better understand the diverse user base. Additionally, studying the environmental impact of widespread e-scooter adoption and its integration into existing transportation infrastructure could provide valuable insights for urban planners.

In conclusion, the study provides a comprehensive analysis of e-scooter usage in Chicago, shedding light on patterns, temporal trends, and sociodemographic factors. The findings contribute to the ongoing discourse on micro-mobility and underscore the need for collaborative efforts between e-scooter producers, city planners, and policymakers to ensure the equitable integration of these services into urban transportation systems.

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Segmentation of Vehicle Transaction Propensity: Impact of Neighborhood and Life-Course Events

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ABSTRACT

Vehicle transactions are the events that lead to the modification of household vehicle fleet structure, better modeled in a longitudinal framework. Household composition, life-course events, existing fleet characteristics, and neighborhood characteristics are the time-varying aspects that impact transaction decisions. Heterogeneity and state dependence are the two main issues in such statistical models. To simultaneously account for the heterogeneity and state dependence, this study applies longitudinal latent class cluster analysis to a retrospective response on vehicle transaction behavior from 320 households in Kolkata, India, over the last 10 years. It was found that households can be classified into biographic states and transition from one to another over the years. Apart from that, as societies evolve, biographic states' characteristics also evolve. From 2013 to 2020, two states and from 2021 to 2022, a three-biographic state model could explain the variation in vehicle transaction propensity.

INTRODUCTION

Assessing the quantity and classifications of vehicles a family possesses is essential for estimating vehicular emissions, travel demand, site preferences, accessibility, and other interactions between land use and transportation (Malayath and Verma 2013; Roorda et al. 2009; Whelan 2007). Ownership of a vehicle is a crucial factor in improving individuals' perceived standard of living (Steg 2005; Xiong and Zhang 2017). According to Anowar et al. (2014), car ownership may be categorized into four dimensions: vehicle holding, vehicle type choosing, vehicle transaction, and vehicle usage. Out of the four options, conducting a vehicle transaction alters the household's vehicle fleet. Car ownership and use are the main emphasis in developed nations, serving as a crucial prerequisite for social integration. Conversely, emerging economies are characterized mainly by a prevalence of two-wheelers in terms of vehicle ownership.

Nevertheless, although households in these societies have lower incomes than established economies, they still obtain vehicles as they are considered a prominent commodity. However, the frequency of car ownership is not as high as in developed countries. Considering the various vehicle categories available, the transactions frequently lead to a hierarchical selection of vehicle types. Heterogeneity and state dependence are the primary sources of unobserved variance in longitudinal discrete choice and duration models (Hensher, David A.; Mannering 1994; Kitamura and Bunch 1990). Hence, a longitudinal vehicle ownership model, focuses on emerging economies that simultaneously accounts for state dependence and heterogeneity is needed.

For long-term policy assessment, longitudinal models are more appropriate than cross-sectional models. Along with the enhanced capability, longitudinal models have a couple of issues. Panel data has traditionally been used to estimate longitudinal vehicle ownership models. However, given the time and cost-intensive process of panel data collection, researchers often resort to repeated cross-sectional data (Dargay 2002; Dargay and Vythoulkas 1999). The retrospective data for vehicle ownership has been used in quantitative and qualitative research (Bhui and Pandit 2022; Roorda et al. 2000; Sattlegger and Rau 2016).

State dependence is dealt with by allowing variables with values derived from previous time step(s) in the estimation at a later time (Mohammadian and Miller 2003; Nolan 2010). The inclusion of lagged temporal variables about life-course events in the vehicle ownership modeling framework also accounts for state dependence (Fatmi and Habib 2016; Wang et al. 2018). However, many existing studies overlook the impacts of life-course events in vehicle ownership decisions or transactions, resulting in poor policy formulation. Life-course events encompass critical incidents and key events that can alter mobility resources and travel behavior (Lanzendorf 2010; Waerden et al. 2003). Life-course events such as marriage, childbirth, residential relocation, and changes in employment characteristics can potentially impact vehicle transactions and their duration (Anowar et al. 2016; Brownstone et al. 2000; Cao et al. 2006; Cirillo et al. 2016; Golob et al. 1997; Zambang et al. 2021). While some studies explore the impact of life-course events on vehicle ownership in developed countries (Gu et al. 2021; Khan and Habib 2021; Lanzendorf 2010; Rashidi and Mohammadian 2011, 2016; Waerden et al. 2003; Yamamoto 2008), there is limited research on the same in the emerging economies (Ma and Ye 2019).

On the other hand, heterogeneity has been accounted for by either employing parametric distribution models (Rashidi and Mohammadian 2011) or non-parametric distribution models (E.g., discrete latent groups) (Gu et al. 2021; Wang et al. 2022). However, the latter approach is more straightforward in drawing inferences. Recent studies have made attempts at explaining both heterogeneity and state dependence simultaneously in a longitudinal framework for estimating vehicle ownership, mode choice, and travel patterns (de Haas et al. 2018; Xiong et al. 2018; Yang et al. 2017; Zarwi et al. 2017). The use of hidden Markov model (HMM) is central to the approach in these studies. However, they assume that the number of latent states in each time step is fixed. Although this assumption might hold in developed societies with saturated growth, societies in emerging economies tend to evolve. Consequently, the number of latent classes at each time step may vary. Also, the latent states' characteristics may differ due to the transition of the urban area itself. Hence, examining the number and character of the latent states of an urban area over various time steps based on demographic, economic, and spatial characteristics is necessary. As Ryoo et al. (2018) suggested, a repeated measure latent class analysis (RMLCA) should be employed in case of measurement invariance in the number of latent states.

This paper aims to examine the biographical changes of households and their impact on the propensity to undergo vehicle transactions. In this study, we look into the role of household characteristics, residential location, and vehicle ownership of households each year and classify them into (latent) biographic states. We also examine the occurrence of life-course events in defining the biographic states. Based on these biographic states, we also determine whether membership to a particular biographic state leads to variation in households' propensity to undergo vehicle transactions. The RMLCA approach also enables the detection of the variation in the characteristics of a biographic state, signifying the transition of the character of the urban area as a whole. The constitution of biographic states using both categorical and continuous variables is also an approach that is less explored in transportation literature. In the methodology sections, we discuss the data collection, variables utilized, and tools for analysis. In the results section, we discuss the results and their implications. Finally, we conclude with the need to employ such methods in longitudinal vehicle ownership models using latent transition analysis.

METHODOLOGY

For this study, we conducted a household survey in Bidhannagar Municipal Corporation (BMC) and the area under New Town Kolkata Development Authority (NKDA) between September 2022 and February 2023. This area lies along the eastern fringe of Kolkata, West Bengal, India. Stratified random sampling was employed in the study area, ensuring the representation of each ward (smallest urban administrative unit). A total of 450 surveys were conducted, of which 320 were selected for analysis. Given the unavailability of panel data in India, we resorted to a retrospective survey to obtain the desired longitudinal character in the data. Hence, from 320 households, 3200 household-year observations were collected. Apart from the existing socio-demographic characteristics, several life-course events, like marriage, separation, childbirth, relocation, employment, and demise, in the last ten years and corresponding years of occurrence were collected from every household. We also collected existing and previous vehicle holding, transaction (acquisition, disposal) years, and type choice for the past ten years. Due to the longitudinal character of the data, we could capture the residential relocation characteristics, and subsequently, the corresponding neighborhood densities were also calculated. This ensures that the model developed based on the data is not city-specific and does have some generalization. In other words, a new household coming into the study area at any point in time can be conveniently allotted a biographic state based on the values of the variables in consideration during the immediate past and existing year of the household.

To estimate the LCA models, the StepMix package was used to perform the LCA with covariates and distal outcomes as vehicle transactions. This package is the first open-source platform for bias-adjusted three-step estimation of latent classes with categorical variables and covariates (Morin et al. 2023). For that, the structural model of the latent class is defined manually, following the steps shown in https://stepmix.readthedocs.io/en/latest/api.html#stepmix. Various combinations of variables were tested to constitute the biographic states. Apart from the model fit indices, we simultaneously checked for the coherence of the estimated latent classes. Table 1 shows the list of variables that were used for estimating the biographic states.

The vehicle types were divided into scooter, motorbike (bike), and car. To capture the impact of vehicle vintage (age) on the propensity to undergo transaction, vehicle vintage was coded so that it can categorically record the oldest vehicle in the fleet of all three vehicle types. In this case, new, used, and old signify the age of vehicles under 3, 4-8, and above eight years, respectively. The lagged variables of the three life-course events were recorded as 99 (if no event occurred since the year the survey started). The year of event occurrence was recorded as 0, and the number kept increasing in subsequent years till another event (of the same type) or the end of the survey period. The employment type of the household head was recorded as 0 for no employment; and 1-5 for retired, self-employed, private employee, and government servant, respectively. The presence of children and multiple workers were recorded as binary variables. The number of elderly was recorded as 0 for none, 1-2 for one, and more than one, respectively. Since this study aims to examine the influence of biographic states on transaction propensity, the distal outcome was recorded as ‘1’ if the household underwent either transaction type (acquisition, replacement, disposal). Multiple models were tested for model fit and consistency with various combinations of variables. Figure 1 depicts the final model structure for defining a typical biographic state and its linkages.

Table 1. Variables (categorical and continuous) used in LCA models.

Vehicle ownership			Household characteristics (Categorical variables)					
Variables	Cat.	Code	Variables	Cat.	Code	Variables	Cat.	Code
Vehicle Vintage	No Vehicle	0	Household Size	One	1	Elderly	Absent	0
	New scooter	1		Two	2		One	1
	Used scooter	2		Three	3		More than one	2
	Old scooter	3		Four	4	Emp. type	Unemployed	1
	New Bike	4		Five	5		Retired	2
	Used bike	5		Six	6		Self-emp.	3
	Old bike	6		Seven	7		Private emp.	4
	New car	7		Eight+	8		Government emp.	5
	Used Car	8	Children	Present	1	Multiple workers	Present	1
	Old Car	9		Absent	0		Absent	0
Covariates (Continuous variables)								
Neighbourhood density			Population density of neighborhood					
Residential relocation			Lagged no. of years since last relocation					
Marriage			Lagged no. of years since Marriage					
Childbirth			Lagged no. of years since last Childbirth					

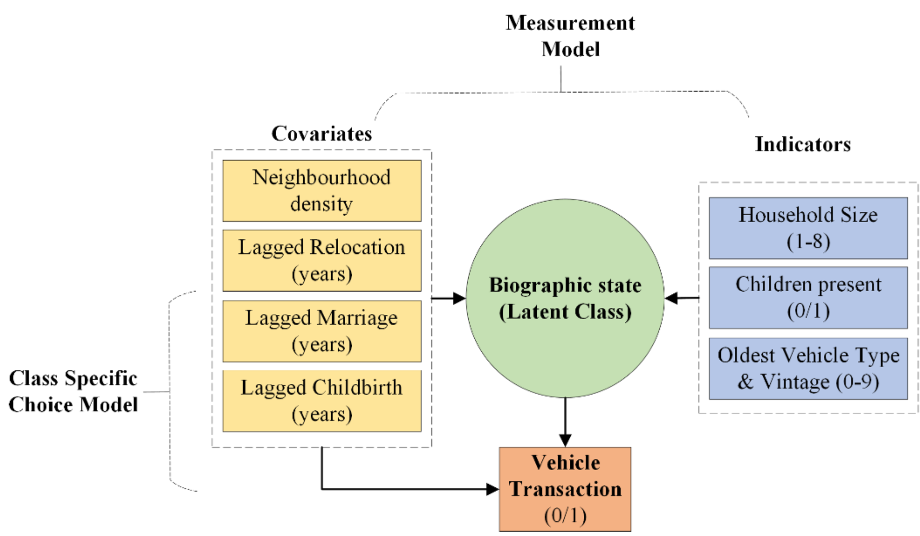

Figure 1. Model structure of LCA with covariates and distal outcome

RESULTS AND DISCUSSION

After arranging the data for each year, four latent class models with 1, 2, 3, and 4 classes for each year were estimated. The 3-step estimation with BCH bias correction was selected to estimate biographic states. Subsequently, fit indices like AIC and BIC were extracted to compare model fit. APPENDIX contains the AIC and BIC values of the estimated models, and Figure 2 shows the change in AIC over the various latent classes across all the years. In most cases, it has been found that both AIC and BIC often indicate similar results. However, in this case, possibly due to too many categories in the categorical variables, the BIC shows a monotonically increasing trend. A similar case can also be found in Schwarzinger et al. (2019), where the decision on the number of latent states was taken only through AIC, as BIC exhibited a monotonically increasing trend. After finalizing the number of biographic states based on AIC, the characteristics of each state were individually examined and were found to be coherent. Hence, a 2-class model for 2013-2020, and a 3-class model for 2021-2022 was selected. Having quantitatively justified the number of biographic states in each year, Table 2 presents the characteristics of the biographic states at each year.

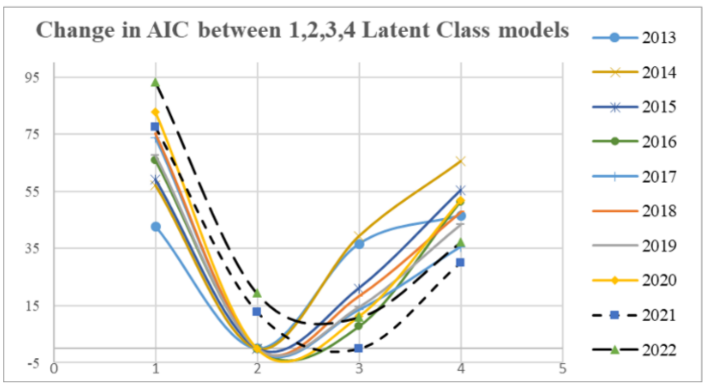

Figure 2. Change in AIC over 1,2,3,4 Latent Class model for all years.

Between 2013 and 2020, households can be divided into two biographic states. Biographic state '1' can be termed '*Mature households*' as households in this state had relatively larger household sizes, and most had children. It was also found that residing in a high-density neighborhood increased the likelihood of a household being in this state. Given the high household size, this could be aimed at optimizing the overall accessibility to amenities. Biographic state '2' can be termed '*Transient households*' as households in this state had relatively lower household sizes and did not have children. It was also found that residing in a low-density neighborhood increased the likelihood of a household being in this state. For mature households, relocation and childbirth could only have been the life-course events in their biography. For transient households, marriage also could have occurred apart from the two events. It was noted that households who experienced recent relocation, recent childbirth, and recent marriage, showed variation in propensity to undergo vehicle transaction. The result for the year 2018 was not in line with the general trend mentioned above for the study area. It was also found that mature households had relatively higher vehicle ownership than the transient ones until 2019.

Table 2. Characteristics of Biographic states at each year

	2013		2014		2015		2016	
State 1	35% Veh. 96% (3-5) ppl. 55% Child $_{present}$ High density Relocation $_{recent}$	***(0.09)***	30% Veh. 98% (3-5) ppl. 50% Child $_{present}$ High density Relocation $_{recent}$	***(0.08)***	41% Veh. 96% (3-5) ppl. 59% Child $_{present}$ High density Relocation $_{recent}$	***(0.11)***	49% Veh. 100% (3-6) ppl. 100% Child $_{present}$ High density Relocation $_{recent}$	***(0.11)***
State 2	26% Veh. 80% (1-3) ppl. No Children Low density Marriage $_{recent}$	***(0.04)***	20% Veh. 75% (1-3) ppl. No Children Low density Marriage $_{recent}$	***(0.04)***	27% Veh. 73% (1-3) ppl. No Children Low density Marriage $_{recent}$	***(0.09)***	38% Veh. 76% (2-4) ppl. No Children Low density Marriage $_{recent}$	***(0.10)***
	2017		**2018**		**2019**		**2020**	
State 1	60% Veh. 99% (3-6) ppl. 54% Child $_{present}$ High density Relocation $_{recent}$	***(0.12)***	65% Veh.$_{2W\ only}$ 99% (3-6) ppl. 79% Child $_{present}$ Low density Childbirth $_{recent}$	***(0.15)***	74% Veh.$_{2W\ only}$ 99% (3-6) ppl. 47% Child $_{present}$ High density Childbirth $_{recent}$	***(0.17)***	$B_{U-O} > S_A >> C_U$ 99% (3-6) ppl. 48% Child $_{present}$ High density Childbirth $_{recent}$	***(0.09)***
State 2	37% Veh. 79% (2-4) ppl. 2% Child $_{present}$ Low density Marriage $_{recent}$	***(0.14)***	51% Veh. $_{2W\ \&4W}$ 75% (2-4) ppl. No Children High density Recent Marriage	***(0.21)***	63% Veh. $_{2W\ \&4W}$ 79% (2-4) ppl. No Children Low density Recent Marriage	***(0.20)***	$S_A > B_A > C_A$ 79% (2-5) ppl. No Children Low density Recent Marriage	***(0.14)***
	2021		**2022**					
State 1	$B_A > S_A >> C_U$ 99% (3-6) ppl. 51% Child $_{present}$ High density Childbirth $_{recent}$	***(0.05)***	$B_A > S_A >> C_{U-O}$ 97% (3-5) ppl. 50% Child $_{present}$ High density Childbirth $_{recent}$	***(0.06)***				
State 2	49% Veh.; $B_O > S_{U-O} >> C_U$ 89% (2-4) ppl. No Children High density (L) Recent Marriage	***(0.27)***	60% Veh.; $S_U >> B_U$ 64% (2-4) ppl. No Children High density (L) Recent Marriage	***(0.18)***				
State 3	$S_A > B_{N-U} >> C_{N-O}$ 70% (2-5) ppl. No Children Low density Marriage $_{recent}$	***(0.03)***	$B_A > S_A >> C_N$ 82% (2-5) ppl. No Children Low density Relocation $_{recent}$	***(0.05)***				

Note:
Values in parentheses represent the propensity to undergo transactions for the corresponding class membership.

Abbreviations:
S= Scooter; B= Bike; C= Car; Veh. = Vehicles; ppl. = people;

Subscript:
N=New, U=Used, O=Old, A=All 3 vintage classes

Due to the impact of the COVID-19 pandemic, combined with the urban metabolism of the study area, from 2020 onwards, vehicle ownership in the study area started tending towards saturation. This change also resulted in the surfacing of a third state '3' similar to transient households, except for the residential location being more likely in low-density neighborhoods. They owned vehicles (especially new cars) to compensate for the low accessibility in low-density neighborhoods. Households in this supposedly 'Affluent-Transient' state were found to have experienced recent relocation and marriage. Although income was not considered in estimating the biographic states, the new state indicates that future studies should include income to understand the biographic states and their variation in choice-making in a better way. The new state rendered the previous 'transient state' an intermediary character, which now comprises households in denser neighborhoods with low vehicle ownership. Such households, in conjunction with a recent marriage event, were found to be more likely to undergo vehicle transactions. Although this study shows that the heterogeneity in choice-making varies longitudinally, exploring the causality of biographic states on choice-making requires further investigation. Figure 3 shows schematically the various biographic states identified in this study.

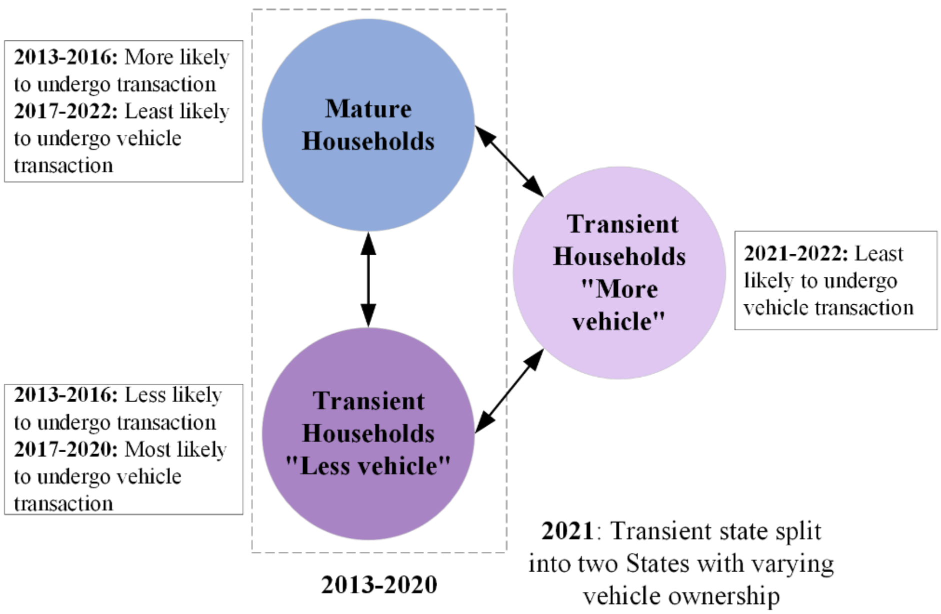

Figure 3. Biographic states and their propensity to undergo vehicle transaction

CONCLUSION

The propensity of households to undergo vehicle transactions is heterogeneous and can be detected by their biographic states at a particular time. In this study, biographic states were constituted as latent classes based on several categorical variables (household size, children, vehicle vintage) and covariates (neighborhood density and years elapsed since relocation, marriage, childbirth). This mixing of variables in the structure of latent states is not widely found in the literature. Also, to the best of our knowledge, this study adds to the scarce literature of LCA with categorical variables and covariates in transportation literature. With the evolution of households, their membership to biographic states and their propensity to undergo vehicle transactions during a given period change. These transitions are mediated by transition matrices, which have been kept out of the scope of this paper. The paper successfully established that in emerging economies, while carrying out a longitudinal latent class analysis, measurement invariance of classes should not be assumed by default. To get a quantitative justification on the number of latent classes for a certain number of time steps, an RMLCA can be instrumental. The primary limitation of this study is that it does not consider the case where multiple vehicles are present in the household fleet. As inferred from the results, income should have also been considered in constituting the biographic states. However, the reluctance and recall bias in obtaining the longitudinal changes in income is one of the prime reasons for not including them. Future studies should consider these.

Apart from the transition of biographic states, households also evolve with time and shift from one biographic state to another. Estimating the transition matrices through a discrete choice model for predicting the transition probabilities is a crucial aspect in operationalizing the outcomes of this study. Subsequently, vehicle transaction propensity can be expanded to capture vehicle transaction and type choices. The impact of biographic states in predicting future choices using stated preference data can be instrumental from a policy formulation perspective. In future studies, more socio-demographic aspects and life-course events can be tested to constitute a higher dimensional and elaborate representation of biographic states.

APPENDIX

Table 3. AIC and BIC of 1-4 latent for each year (2013-2022).

	2013				**2014**				**2015**			
# LC	1	2	3	4	1	2	3	4	1	2	3	4
AIC	2654	**2611**	2647	2657	2771	**2714**	2753	2779	2838	**2779**	2800	2835
BIC	2729	2780	2910	3014	2846	2882	3016	3136	2913	2948	3063	3191
	2016				**2017**				**2018**			
# LC	1	2	3	4	1	2	3	4	1	2	3	4
AIC	2930	**2865**	2872	2916	3049	**2975**	2989	3011	3149	**3074**	3092	3121
BIC	3005	3034	3135	3273	**3124**	**3144**	**3251**	**3367**	**3224**	**3242**	**3355**	**3478**
	2019				**2020**				**2021**			
# LC	1	2	3	4	1	2	3	4	1	2	3	4
AIC	3275	**3208**	3222	3251	3307	**3225**	3236	3277	3352	3287	**3275**	3305
BIC	**3350**	**3377**	**3485**	**3608**	**3382**	**3393**	**3499**	**3633**	**3427**	**3456**	**3537**	**3661**
	2022				*Schwarzinger et al. (2019) also had increasing BIC, possibly due to the high number of categories in the categorical variables, which was also mentioned by Thom Baguley in a personal communication.*							
# LC	1	2	3	4								
AIC	3399	3325	3317	3343								
BIC	**3474**	**3494**	**3580**	**3700**								

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Analyzing the Influential Factors and Dynamics of Bikeshare Utilization in Washington, DC

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ABSTRACT

Bikesharing has emerged as a transformative mode of transportation, contributing to increased cycling, urban mobility, and public transportation use. This study investigates bikeshare dynamics in Washington, DC, focusing on classic bikes, electric bikes (e-bikes), and docked bikeshare options. The analysis of 3,365,045 trips from January to October 2023 resulted in spatial patterns that reveal concentrated trip origins in downtown Washington, DC, emphasizing urban core utilization. Temporal trends highlight peak mid-weekday ridership, aligning with daily work commutes. Multinomial logistic regression discerns nuanced preferences: docked bikes are favored on weekdays, electric bikes on weekends, and members are less likely to choose classic bikes. Findings provide actionable insights for policymakers, informing bikeshare system optimization, station placement, and marketing strategies. Weather-aware planning and promotion, coupled with tailored incentives, are crucial for enhancing bikeshare sustainability and effectiveness in urban transportation.

INTRODUCTION

Bikesharing has swiftly become well established as a new mode of transportation that may increase cycling, enhance urban mobility, and increase the use of public transportation, with over 343 million trips conducted in the United States since 2010. These systems can assist communities in enhancing their sustainability, livability, and safety (NACTO 2015).

Bikeshare programs assist in reducing traffic congestion and pollution brought on by transportation (Wang and Zhou 2017; Zhang and Mi 2018; Hirsch et al. 2019). In several locations throughout the world, bikesharing is expanding quickly as a sustainable and green alternative type of transportation (Fishman 2016; O'brien, Cheshire, and Batty 2014). Almost all major cities in the U.S. currently have bikeshare programs. At least 119 systems nationwide cover only two of the 20 largest urban areas, which shows that almost every large city in the U.S. now has at least one bikeshare system ("Greater Washington" 2023).

With the recent increase in bike use and bikeshare systems, numerous American cities and communities are looking at the use of bikeshare to enhance the transportation system's environmental, social, and health outcomes. To obtain a thorough knowledge of the bikeshare trips in Washington D.C., this study will look at several variables that might explain bikeshare usage in this city. This study delves into the complex dynamics of rider behavior within the Capital City Bikeshare program in Washington D.C., with a particular focus on classic bikes, electric bikes (e-bikes), and docked bikeshare options, aiming to provide a holistic view of their interactions with the diverse bikeshare modalities. By employing advanced data analysis techniques, our study uncovers nuanced patterns that influence the choice of bikeshare mode. The research identifies factors that drive the preference for classic bikes, e-bikes, or docked bikeshare.

LITERATURE REVIEW

Multiple studies were completed and examined to determine the factors that affected and influenced the behavior and preferences of riders who utilized the bikesharing system in Washington, D.C. Specifically, many studies focused on factors such as age, gender, health, income, and other variables. It was apparent that there was a disparity in the usage of bikeshare among income levels, genders, ages, abilities, and races (Dill and McNeil 2021). Many factors affect bikesharing, such as usage-related time, location, weather, system operations, and user characteristics. Studies revealed that cold weather, rain, and high humidity resulted in fewer people using bikes and shorter trip durations. Moreover, during rainy conditions, fewer people used bikes near subway stations, especially at night (Gemmell et al. 2023).

It was found that men were more likely to use the bikesharing system than women because, in general, men used them to travel from work to their cars or vice versa, and women used bikesharing more for grocery shopping and to complete their daily tasks (Nickkar et al. 2019; Kaviti, Venigalla, and Lucas 2019b). The bikesharing system served two main purposes: weekend fun and tourism for non-members, and weekday commuting for members (Kaviti, Venigalla, and Lucas 2019b). System member (subscriber) who has signed up for a membership or subscription plan with the bikeshare service provider, and non-member (nonsubscriber), refers to individuals who use the bikeshare system without having a membership or subscription plan. Non-member users had a more diverse demographic and used bikes for fun and sightseeing (Nickkar et al. 2019; Kaviti, Venigalla, and Lucas 2019b).

There was clear evidence that bikesharing had a positive impact on people's lives in the capital, as it was found that more than 4% of traffic was reduced in neighborhoods, with an even larger effect in highly congested areas (Hamilton and Wichman 2018). Dockless systems had the potential to improve urban multi-modal transportation with behaviors aligning with both commuting and recreation. Many users reported saving time and money, resulting in increased trips using bikeshare with mutual benefits for users and businesses (Hamre and Buehler 2014; McKenzie 2019). There were many suggestions, including that station placement should be near stores, and bike lane improvements were necessary to encourage more users, especially women (Nickkar et al. 2019). It was also suggested that bike system designs should consider diverse weather conditions and user preferences, and proposed infrastructure solutions like climate-sensitive cycling paths and repositioning bikes based on weather forecasts (Kumar 2021). It was also recommended to consider bikeshare station capacity and proximity stops for effective planning during distributions (Younes et al. 2019).

Payment options and pricing had a crucial factor in the number of people who used bikesharing systems. Since there was diversity among those who used the systems, it was important to take a closer look at how these factors influenced the systems and what recommendations there might be to ensure that bikesharing was still an affordable and appropriate choice. Multiple studies focused primarily on how pricing affected bikeshare usage, and it was found that lower-income groups, women, and tourists were more sensitive to price changes (Kaviti and Venigalla 2019a). Multiple articles demonstrated that most users preferred to pay with a credit/debit card since it was easier to pull one out of their wallet or have it on their phone instead of carrying cash. There were multiple recommendations given, starting with a suggestion to adjust prices to attract more users and increase revenue for bikesharing services (Kaviti, Venigalla, and Lucas 2019a; Kaviti and Venigalla 2019b). Another suggestion was to induce an analytical approach for bikesharing evaluations and have a shift from cars, taxis, and public transport by adjusting the costs of bikesharing to ensure they were fair for different individuals, different income levels, and even preferences, as well as understanding activity levels and the financial impacts of bikesharing on active travel (Fishman, Washington, and Haworth 2015).

Overall, bikesharing saved time and money for users and led to an increase in neighborhood development and mutual benefits for businesses and users, creating more trips and economic activity. In conclusion, people were more prone to using bikeshare systems if the prices were appropriate and affordable so people of all income levels and backgrounds could enjoy the variety of benefits that bikesharing had to offer.

Bikesharing systems were frequently changing and adjusting to provide the best solution and ensure that users received the best experience and effectiveness out of their ride. For these bikesharing systems to be kept at an appropriate level while keeping in mind the variety of users who had different backgrounds, characteristics, income levels, and experiences, multiple factors had to be considered and studied. Factors such as age, gender, income, health, and weight were considered (Barbour, Zhang, and Mannering 2020). Additionally, barriers to shared mobility services usage among various demographic groups, helmet use, and trip purposes were also studied (Guo and Zhang 2021). Furthermore, there was a specific pivot on equity and usage patterns in Washington, D.C. that utilized methods to identify factors influencing bikesharing ridership. The information was compared among registered users, and usage frequency and its impact on replacing car trips were also analyzed. Survey data and models were utilized to study socio-demographic, travel behavior, and health-related variables (Barbour, Zhang, and Mannering 2019). Results highlighted the influence of various factors such as gender, age, income, commute type, health indicators and provided insights for policymakers to enhance bikesharing viability (Barbour, Zhang, and Mannering 2019). Rules also promoted shared rides, which were recommended for cost savings and overall transportation improvement.

Additional factors included strategic placement of bike stations, ease of navigation, and careful management of extra charges for enhanced fairness, infrastructure, and pricing for equitable bike-sharing (Su, Yan, and Zhao 2022). It was also recommended to lower prices to attract more users and increase revenue, which emphasized the sensitivity of different demographic groups to pricing changes (Kaviti and Venigalla 2019b). It was proposed to further understand decision-making and ensure equal benefits for all user groups. There was also an emphasis on the need for additional efforts to ensure fairness in transportation, with a highlight on the unknown impacts of station changes on bike usage (Desjardins, Higgins, and Páez 2022; Ma, Liu, and Erdoğan 2015). Furthermore, suggestions included making bikes safer, easier, and more appealing by offering electric bikes and considering diverse needs for increased inclusivity (Rayaprolu and Venigalla 2020; Bateman et al. 2021).

METHODOLOGY AND DATA

Data

This study focused on Washington D.C. as the case study. Washington, D.C., formally the District of Columbia and commonly called Washington or D.C., is the federal district of the

United States. The city is located on the east bank of the Potomac River, which forms its southwestern border with Virginia and borders Maryland to its north and east. Washington D.C. has a population of 671,803 residents, of which 52.4% are female. The three largest groups in Washington D.C are White (46.2%), Black or African American (45%), and Asian (4.7%). In 2022, Washington D.C. had 13.3% of residents living below the poverty level ("U.S. Census Bureau" 2022). Since 2002, the District Department of Transportation (DDOT) has constructed 104 miles of bicycle lanes and currently maintains more than 150 miles of recreational trails and bike lanes in the District ("Greater Washington" 2023).

In the U.S., there have been more than 70 cities and college campuses with bikeshare programs since 2008, and more are expected to be added in the future. The first large bikeshare system in the U.S., Capital Bikeshare, began operations in the Washington, D.C. area in 2010 and now has more than 3,000 bicycles. In May 2013, a more extensive program, Citi Bike, debuted in New York City (NYC) with 6,000 bicycles (Ursaki and Aultman-Hall 2015; Larsen 2013; Bikeshare 2017).

Bikeshares are available for rent in Washington D.C. through the Capital bikeshare system. The data used in this study is the Capital bikeshare trips taken from January 1, 2023, to October 31, 2023. The data was retrieved from Capital Bikeshare System Data ("Capital Bikeshare" 2023) and includes trip ID, bike type (classic bike/electric bike/docked bike), start time, end time, start and end latitude, start and end longitude, and end user type (casual/member).

The total number of bikeshare trips taken during the 10 months was 3,831,691 (This dataset does not include any information on the number of bikes available). After importing these bikeshare trips to ArcGIS Pro, the bikeshare trips that had a start location outside the city boundaries were removed since the goal is to investigate the behavior of riders inside the city. Therefore, after cleaning the data, 3,365,045 trips were considered for this study.

Regression Model

This study used multinomial logistic regression to investigate the factors affecting ride type (classic bike, electric bike, docked bike) in Washington D.C. Multinomial logistic regression is used to model nominal outcome variables, in which the log odds of the outcomes are modeled as a linear combination of the predictor variables ("Stata Data Analysis" 2020).

ANALYSIS RESULTS

Using ArcGIS Pro and the longitude and latitude data of bikeshare trips retrieved from Capital Bikeshare, a heatmap was generated to illustrate areas with a higher concentration or density of trips, utilizing a color gradient. This heatmap, as demonstrated in Figure 1, serves as the purpose for identifying patterns and trends. Locations with a more intense color on the heatmap indicate a higher concentration of crashes. Figure 1 shows that the density of locations where bikeshare trips started over a 10-month period was significantly higher in downtown Washington D.C.

Figure 2 shows that 44.87% of the trips took place mid-weekdays (Tuesdays, Wednesdays, an Thursdays). Moreover, 26.91% of the trips were taken on shoulder days (Mondays and Fridays), and 28.21% of the trips were taken on weekends (Saturdays and Sundays).

Figure 3 shows that 4 p.m. and 5 p.m. had the highest bikeshare usage in Washington D.C. Moreover, 7 a.m. and 8 a.m. had the highest usage of bikeshare in Washington D.C. This could show that people use bikeshare as a mode of transportation to/from work. Figure 4 shows the ridership in each month of the year. It can be concluded from the figure that July and August had the most ridership during this 10-month period.

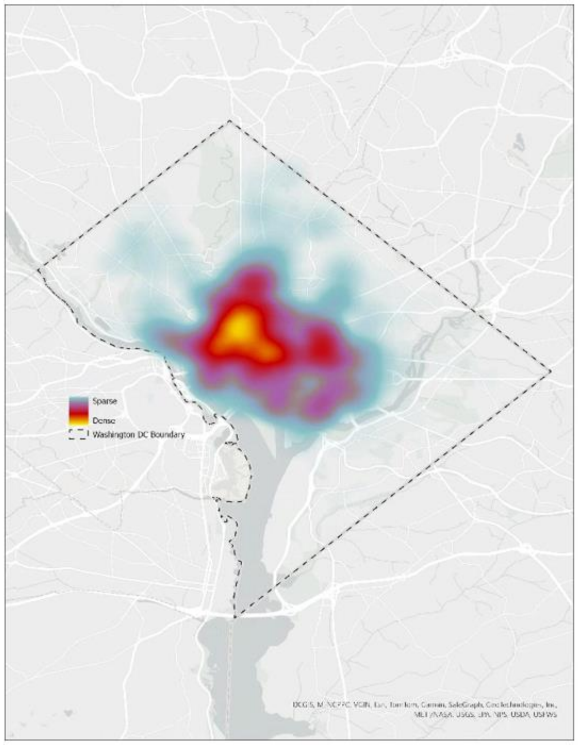

Figure 1. Heatmap of Density of Start Points of Bikeshare Trips in Washington D.C.

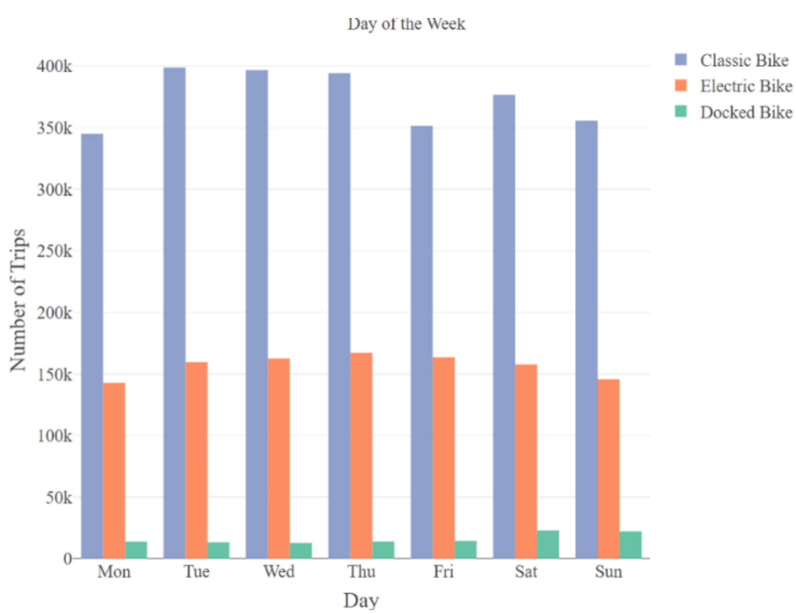

Figure 2. Day of the Week Ridership

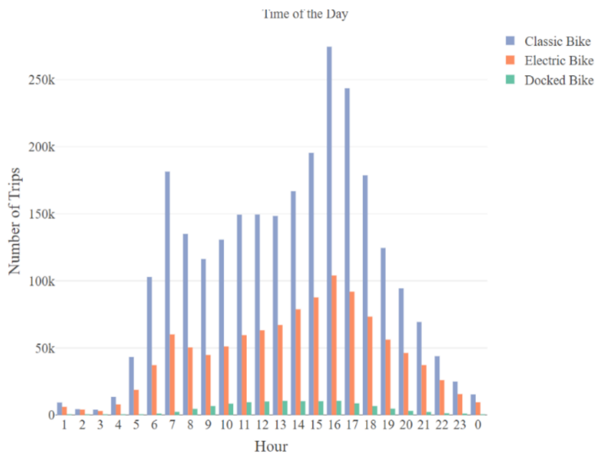

Figure 3. Time of the Day Ridership

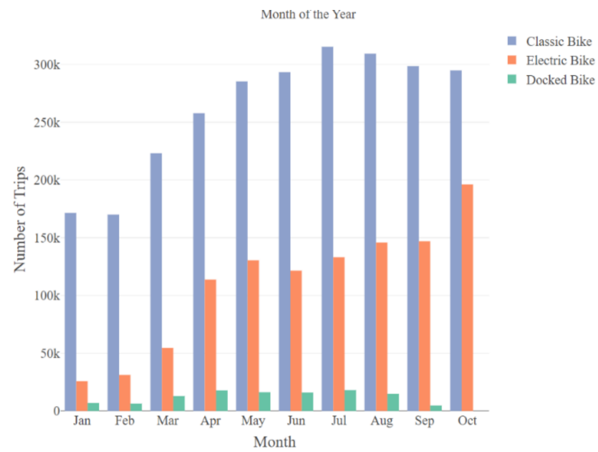

Figure 4. Months of the Year Ridership

Table 1 shows the summary of the variables investigated in this study. More than half of the Capital Bikeshare users (62%) are members. Moreover, most of the trips (45%) were taken during middays.

Table 1. Summary of Variables

Variables	Levels	Percentage
Months	January	5.41%
	February	5.32%
	March	7.57%
	April	10.16%
	May	11.24%
	June	11.27%
	July	12.45%
	August	12.37%
	September	12.28%
	October	11.93%
Day of the Week	Shoulder Days	26.91%
	Mid-weekdays	44.87%
	Weekends	28.21%
Time of the Day	Mornings (6:00 am – 12:00 pm)	31.66%
	Middays (12:01 pm – 18:00 pm)	45.18%
	Evenings (18:01 pm – 22:00 pm)	20.03%
	Nights (22:01 pm – 5:59 am)	3.10%
Membership Type	Members	37.91%
	Casuals	62.09%

This study developed a multinomial logistic regression to investigate the factors affecting ridership type. Table 2 presents the results of the final models. The baseline or usual value (reference level) for the dependent variable (bike type) is classic bike.

Table 2. Multinominal Regression Model

			Hour of the Day			Week		Membership Type
	Bike Type	(Intercept)	Midday	Evening	Night	Mid-week Day	Weekend	Member
Coefficients	Docked Bike	-2.150	0.145	-0.183	-0.550	-0.107	0.157	-10.151
	Electric Bike	-0.885	0.106	0.218	0.547	-0.062	-0.079	-0.069
Std. Errors	Docked Bike	0.008	0.007	0.010	0.024	0.008	0.008	0.358
	Electric Bike	0.003	0.003	0.003	0.006	0.003	0.003	0.002

The results of the model indicate that riders are more likely to choose a docked bike during the midday and evening hours, and an electric bike during the night hours. Riders are more likely to choose a docked bike on weekdays, and an electric bike on weekends. Members are much less likely to choose a classic bike than casual riders. The following is a more detailed interpretation of the results of the regression model:

1. Hour of the day:
   - The positive coefficient for midday hours indicates that riders are less likely to choose a docked bike during the midday hours than during the morning hours.
   - Evening: The negative coefficient for evening indicates that riders are less likely to choose a docked bike during the evening hours than during the morning hours.
   - Night: The positive coefficient for night indicates that riders are more likely to choose an electric bike during the night hours than during the morning hours.
2. Day of the week:
   - The negative coefficient for midweek indicates that riders are less likely to choose a docked bike on weekdays than on weekends.
   - The positive coefficient for weekends indicates that riders are more likely to choose an electric bike on weekends than on weekdays.
3. Type of membership:

The large negative coefficient for members indicates that members are much less likely to choose a classic bike than casual riders.

DISCUSSION AND SUMMARY

The findings of this study shed light on the complex dynamics of bikeshare usage in Washington D.C., providing insight into factors influencing riders' choices among classic bikes, electric bikes (e-bikes), and docked bikeshare options. The discussion encompasses key patterns revealed through advanced data analysis, emphasizing the implications for urban transportation planning and bikeshare system optimization.

The spatial analysis using a heatmap revealed concentrated bikeshare trip origins, with downtown Washington D.C. exhibiting significantly higher trip densities. This spatial concentration aligns with the city's bustling urban core, suggesting that bikeshare systems are predominantly utilized for short-distance commuting and travel within central business districts.

Temporal trends demonstrated in Figures 2, 3, and 4 further contribute to our understanding of bikeshare utilization patterns. Mid-weekdays observe the highest ridership, indicative of the system's integration into daily work commutes. Additionally, the prominence of peak bikeshare usage during morning and late afternoon hours implies a role in facilitating journeys to and from work, potentially contributing to the alleviation of rush-hour traffic. The monthly ridership distribution highlights peak usage in July and August, aligning with favorable weather conditions. This observation underscores the impact of weather on bikeshare utilization, a factor consistent with prior studies (Gebhart and Noland 2014). Such insights are vital for bikeshare operators and urban planners, emphasizing the importance of weather-aware bikeshare planning and promotion.

The multinomial logistic regression model explored the factors influencing bikeshare mode selection, considering the hour of the day, day of the week, and membership type. The results revealed nuanced preferences among riders:

- Hour of the Day: Riders exhibit a preference for docked bikes during midday and evening hours, while electric bikes are more popular during the night. This suggests that the choice of bikeshare mode is influenced by the time of day and, potentially, the purpose of the trip.
- Day of the Week: Docked bikes are favored on weekdays, emphasizing their role in daily commuting, while electric bikes see increased usage on weekends, possibly indicating a shift toward leisurely or recreational trips.
- Membership Type: Members are less likely to choose classic bikes compared to casual riders. This could be attributed to members having a more specific purpose or familiarity with the system, leading them to opt for electric or docked bikes.

The results of this study provide valuable insights for policymakers aiming to enhance bikeshare systems in Washington D.C. and other urban areas. Understanding the temporal and spatial dynamics of bikeshare usage can inform the placement of docking stations, promotion strategies, and infrastructure development. Moreover, the differentiation in bikeshare preferences based on membership type highlights the importance of tailoring marketing and incentive programs to attract and retain both casual and member riders.

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Mapping Urban Mobility: A GIS-Based Analysis of Citi Bike's Accessibility

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ABSTRACT

This study investigates the accessibility of bike infrastructure, including bikeshare stations and bike lanes, in New York City (NYC), with a focus on sociodemographic factors. Utilizing a combination of buffers, the bicycle equity index (BEI) and binary logistic regression, the research analyzes the spatial distribution of bike lanes and bikeshare stations, emphasizing the importance of equitable access. The BEI methodology integrates variables such as minority population, poverty, age groups, and zero-vehicle households to assess equity. Binary logistic regression identifies significant predictors, revealing that households with no vehicles, age-dependent populations, and minorities significantly influence bikeshare station availability. The outcomes provide valuable insights for urban planners, policymakers, and transportation authorities to address sociodemographic disparities and enhance the inclusivity of bike infrastructure in NYC. The research contributes to the understanding of factors shaping bike infrastructure access and informs targeted interventions for creating a more equitable and sustainable urban transportation landscape.

INTRODUCTION

Bikeshare systems are becoming more popular around the world, especially in the U.S. (Yu et al. 2018). With over 343 million rides completed in the U.S. since 2010, bikesharing and shared micromobility have quickly been established as new transportation options that can boost cycling, improve urban mobility, and boost public transit usage. These systems can help communities improve their safety, livability, and sustainability (NACTO 2015). Prior studies have found that rural and minority communities are subject to disproportionately high travel costs (Probst et al. 2007; Javid, Sadeghvaziri, and Jeihani 2023). Age, disability, lack of awareness of programs, having small children, lack of safety and bicycling infrastructure, and bikeshare characteristics such as location, time constraints, cost, ease of use, and availability of bikes are the most prominent barriers to bikeshare usage among different people (Bateman et al. 2021). Nonetheless, bikeshare systems have faced equity-focused criticism for not servicing disadvantaged groups, such as people with physical activity and health disparities, persons of color, women, low-income areas, and the less educated (Hull Grasso, Barnes, and Chavis 2020). To develop bike infrastructure more equitably, policymakers will need new tools and methodologies for identifying and prioritizing high-need regions.

This study aims to investigate the access to bike infrastructure (including bikeshare stations and bike lanes), and the factors influencing the presence of bike infrastructure in New York City.

The methodology included estimating buffers around bike infrastructure by ¼ mile and evaluating equity of access using the Bicycle Equity Index (BEI) methodology. The objectives of this study are:

1. Explore the importance of assessing bike infrastructure and bikeshare station placement in urban areas to enhance accessibility.
2. Learn about the methodology for evaluating equity of access using the Bicycle Equity Index (BEI) and the application of binary logistic regression to examine sociodemographic factors influencing bikeshare station availability.

LITERATURE REVIEW

Bicycling is fundamentally linked to increased physical activity and improved air quality, possibly avoiding illness in cyclists and everyone exposed to pollution (Yu et al. 2018). Shared mobility services such as bikesharing, ride hailing, carsharing, e-scooters, and other types of shared mobility have increased rapidly in recent years in cities (C.-H. Wang, Akar, and Guldmann 2015). With the recent increase in using bike and bikeshare systems, a significant number of U.S. cities and communities are investigating the use of bikes to positively increase transportation systems' environmental, social, and health results (Fukushige, Fitch, and Handy 2021).

There are several barriers to bikeshare/bicycle usage among different groups of people. For instance, Pearson et al. identified some of the barriers to entry for adults as it pertains to using cycling as a form of transport. Barriers to entry included fear of motorist aggression, high risk of injury, poor feelings of safety, worry of bike theft, high traffic density, lack of bike paths, lack of storage on bikes, etc. Enablers of using cycling as a form of transportation included protected bike lanes, good lighting, proper bike route signage, secure bike storage or parking, the ability to take bicycles on other forms of public transport, etc. The team identified that the perceived safety of riding a bicycle was the largest agreed-upon barrier to cycling as a form of transportation (Pearson et al. 2023).

For instance, a study found a trend toward Bike Share System (BSS) appearing mainly in more affluent areas with higher access to resources. These areas are mainly inhabited by young, Caucasian, highly educated people. The researchers then created a framework model to evaluate bike share systems based on equity, equality, and efficiency. This framework was applied to a series of residential blocks inside the service area of a hybrid BSS in Munich, Germany. They found that these areas were underserved due to the traditional-oriented social groups that live in the BSS area. The researchers recommended informing the community of the benefits of changing the perception of the system to increase equity in its uses (Duran-Rodas et al. 2020).

Chen et al. researched southern Tampa bike share systems. This research team analyzes the "walking-cycling-walking" process of bike share systems and the behavior of the individuals who use them. The researchers then used a series of equity measures to determine the equity of each system. The research team's results were that accessibility to bike share systems was not evenly distributed within southern Tampa. Different sociodemographic groups had different accessibility rates to bike share systems. White, Asian, and non-Hispanic groups had higher accessibility to bike share systems. They also found that overall use was low due to the low-density nature of Tampa, Florida. Bike share systems were not located where people were interested in using them. The team recommended using their dataset to reposition the location of bike share stations in southern Tampa (Chen et al. 2019).

Bartolomeo et al. inquired into the equity of free-floating bike share systems. The team proposed that free-floating bike share systems lead to less equity for disadvantaged communities due to the lack of assigned parking spaces where the bikes are to be returned. The findings concluded that free-floating bike share systems have an unbalanced distribution. There were lower amounts of available vehicles in areas with a higher unemployment rate, and the disparity grew during peak hours. Vehicles tended to be concentrated more towards the city's center, away from where disadvantaged residents lived. This study recommended creating a system for redistributing free floating bike share bikes so that there is greater accessibility for all residents (De Bartolomeo, Caggiani, and Ottomanelli 2023).

METHODOLOGY AND DATA

Study Area

New York City (NYC) is the largest and most influential city in the United States. It is located at the mouth of the Hudson River in southeastern New York State. NYC is made up of five boroughs: Brooklyn, The Bronx, Manhattan, Queens, and Staten Island. NYC is home to 8.4 million people, and altogether they speak more than 200 languages. It is a global city with a significant influence on many industries. NYC's economic and administrative center has been described as the cultural, financial, media, and entertainment capital of the world. NYC has a population of 8,335,897, with an area of 305 square miles. The four largest ethnic groups in NYC are White (39.8%), Hispanic (28.9%), Black or African American (23.4%), and Asian (14.2%). About 17% of NYC's population lives below the poverty line (U.S. Census Bureau 2022).

Data

The data used in this study were retrieved from the New York City Open Data Portal (NYC Open Data). The data is publicly available for all bike routes. The datasets consist of the locations of bike lanes and routes throughout the city (NYC Open Data 2021), and it was entered into ArcGIS using the WGS 1984 coordinate system. Figure 1 shows the bike lanes and bikeshare stations in NYC, with the majority of the bike lanes located in the downtown and midtown areas. Moreover, most of the bikeshare stations are located in Manhattan, Brooklyn, and Queens.

The data for bikeshare stations were retrieved from the U.S. Department of Transportation, Bureau of Statistics (BTS) National Transportation Atlas Database (NTAD). The Docked Bikeshare Stations data provides the locations of docked bikeshare stations (BTS 2022). The data was last updated on August 10, 2022, and currently, there are 1,622 bikeshare stations in NYC provided by the CitiBike Bikeshare program.

Bicycle Equity Index (BEI)

In order to investigate access to bicycle infrastructure from the equity point of view, this study adapted the methodology of the Bicycle Equity Index (BEI), which was developed by Rachel Prelog for the League of American Bicyclists (Prelog 2015). This study will consider several variables:

- Percentage of minority populations (non-white and/or Hispanic)
- Percentage of low-income populations (below poverty)
- Percentage of elderly populations (65 and older)
- Percentage of youth populations (under 18)
- Percentage of zero-vehicle household populations

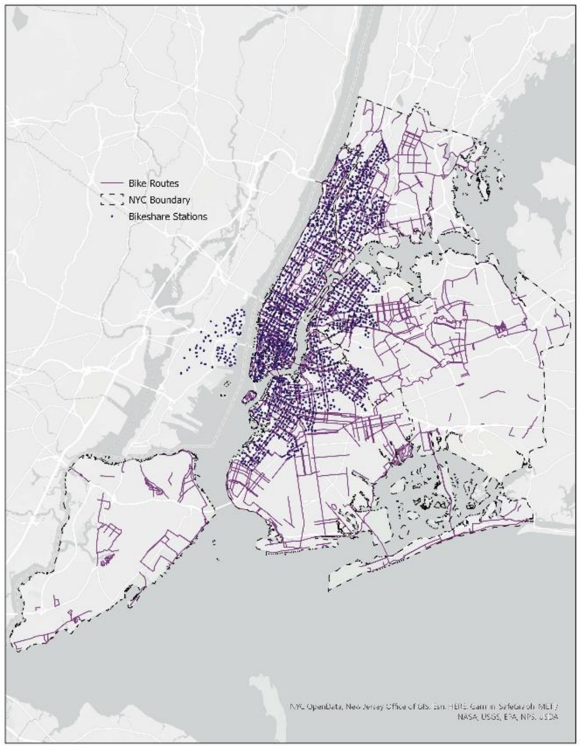

Figure 1. Bike Lanes in NYC

In order to obtain the aforementioned variables, this study used the United States Census Bureau's American Community Survey (ACS) five-year estimate (2017-2021) data for race and Hispanic origins, poverty level status, population variables, and household size by number of vehicles available (U.S. Census Bureau 2022). The index can help communities detect gaps and make better decisions. The BEI is built using the five indicators taken from the ACS data source. To combine various indicators into a single BEI assessment, the z-scores of each indicator were calculated. Positive z-scores indicate a greater proportion of an indicator when compared with the regional mean. The BEI was calculated by adding the z-scores from all five indicators. However, in the index creation, only positive z-scores were employed, and negative scores were turned to zero. This prevented indicators with negative z-scores (values below the average) from reducing the effect of other indicators (Prelog 2015). Additionally, all indications were given equal weight, which meant that none were more crucial to determining equity than the others. The z-score statistic is calculated using Equation 1, where x is the raw score, μ is the population mean, and σ is the population standard deviation:

$$z = (x - \mu) / \sigma \quad (1)$$

Access Coverage

Determining access coverage of the bike lanes and bikeshare stations includes two steps: 1) buffering the bike facilities shapefile; and 2) calculating the coverage zone. A quarter-mile buffer was used to determine whether individuals had access to bicycle infrastructure. Similar studies identified a quarter-mile as a practical access distance for facilities and services related to transportation. Furthermore, research indicates that the likelihood of using a bicycle significantly increases if one lives within a quarter mile of on-street bicycle facilities (Murray 2003; Murray and Davis 2001; Krizek and Johnson 2006; X. Wang et al. 2016; Buck and Buehler 2012; Monsere et al. 2014; McNeil et al. 2017). Figure 2 shows the NYC bike lanes and a ¼-mile buffer. Figure 3 shows the NYC bikeshare stations and a ¼ mile-buffer.

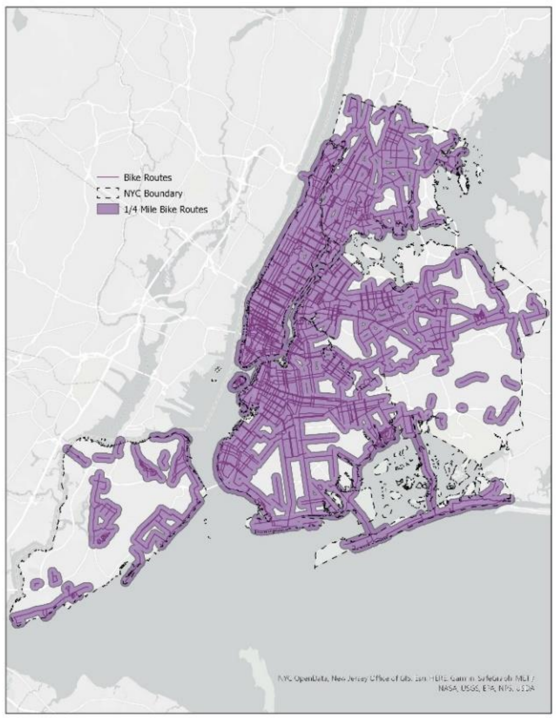

Figure 2. Bike Lanes Buffers in NYC

Regression Model

A Binary Logistic Regression was used to capture the relationship between the sociodemographic of the Census Tracts and bike lanes in NYC. Binary Logistic Regression is a statistical model used to analyze the relationship between a binary outcome variable (i.e., a variable that takes on one of two possible values) and one or more predictor variables (ScienceDirect Topics 2023). In this study, the outcome variable is the binary decision of whether there was a bikeshare station in a census tract, and the predictor variables are the sociodemographic characteristics used in the BEI. Equation 2 shows the mathematical equation of the Binary Logistic Regression model:

$$\log(p / (1 - p)) = \beta 0 + \beta 1x1 + \beta 2x2 + ... + \beta pxp \tag{2}$$

where p is the probability of the outcome variable, β0 is the intercept, β1, β2, ..., βp are the coefficients associated with each predictor variable (x1, x2, ..., xp), and log is the natural logarithm. The logistic regression model is used to estimate the values of the coefficients β0, β1, β2, ..., βp, based on the observed data. These coefficients indicate the direction and strength of the relationship between each predictor variable and the outcome variable. The coefficients are typically exponentiated to obtain odds ratios, which indicate the increase or decrease in the odds of the outcome variable associated with a one-unit increase in the predictor variable.

Analysis results

Figure 2 shows the bike lane distribution and their buffers in NYC. The figure shows that most of NYC's bike lane network radiates out from its downtown area and Manhattan boroughs. As one travels near the city's southwest and east boundaries, the bike lane network becomes more dispersed and lacks linkages to the main network. As a result, the present network does not adequately serve some neighborhoods near the western, eastern, and southern edges of the city (Staten Island and Queens). This study calculated the area coverage and the percentage of the area covered by bike lanes in NYC using ArcGIS Pro. Figure 2 shows that with a ¼-mile buffer, more than 69.5% of the city has access to the bike lanes.

Figure 3 demonstrates that the northern part of Staten Island, the southern part of The Bronx, and the northern part of Brooklyn have the highest percentage of the populations below the poverty level. The map demonstrates that the geographic distribution of the low-income population is mainly uniform, with more clusters of poverty on the northern and eastern sides.

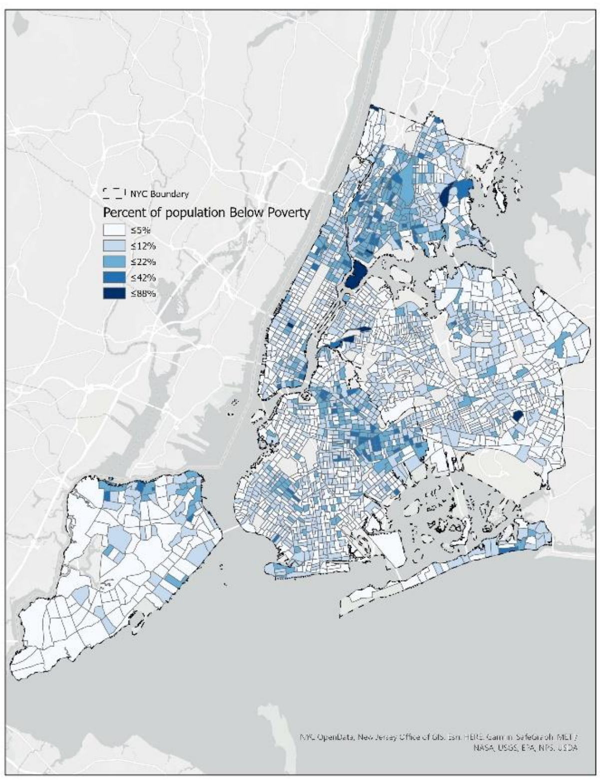

Figure 3. Percentage of Population Below Poverty Level in NYC

Areas of greater disadvantages that might benefit from investments in bike lanes can be identified by combining the z-scores of all BEI Indicators. Figure 4 demonstrates the results of the BEI and the spatial distribution of BEI scores. Areas with brighter shades have a lower need for bike lanes, and the darker census tracts have a higher need for bike lanes. Notable neighborhoods are located on the eastern, northern and southern sides.

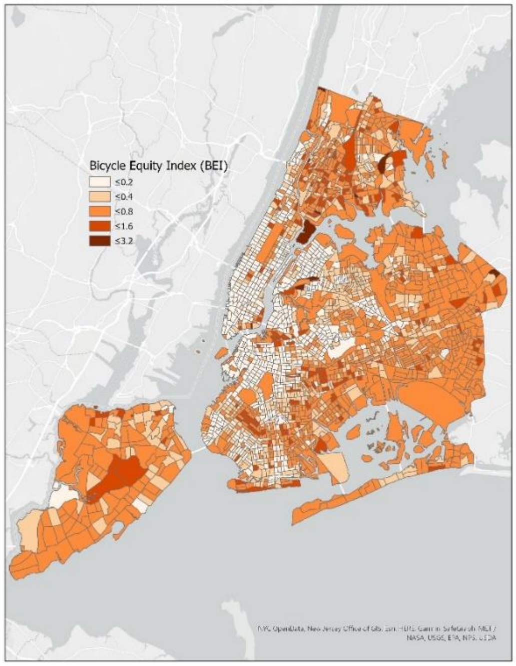

Figure 4. Bicycle Equity Index (BEI) in NYC

Many studies have used statistical models to develop policies to improve traffic safety, investigate and forecast travel behavior, and pinpoint deficiencies in equity and transportation policies (Sadeghvaziri, Javid, and Jeihani 2023; Javid and Sadeghvaziri 2023a; 2023b; Sadeghvaziri et al. 2023). Therefore, in this study, a Binary logistic regression was conducted to examine how the independent variables are associated with the probability or likelihood of having a bike lane at the Census Tract level. Table 1 shows the results of the regression analysis.

Table 1. Regression Model Results

	Estimate	Std. Error	z value	Pr(>|z|)	Signif. Codes
(Intercept)	0.394098	0.294275	1.339	0.1805	
Households with no Vehicles	0.044762	0.002407	18.598	< 2e-16	***
Ages more than 65 and less than 18	-0.02376	0.006273	-3.787	0.000153	***
Below poverty line	-0.01274	0.008633	-1.475	0.140094	
Minorities	-0.01292	0.001865	-6.93	4.21E-12	***
Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1 (Dispersion parameter for binomial family taken to be 1) Null deviance: 3073.1 on 2326 degrees of freedom Residual deviance: 2512.3 on 2322 degrees of freedom (97 observations deleted due to missingness) AIC: 2522.3					

The model's results show that several independent variables are significant predictors of bike lane access. The results suggest that the variables of households with no vehicle, ages more than 65 and less than 18, and minorities are significant predictors of the likelihood of having bike lanes at the Census Tract level. The variable population below the poverty line does not appear to have a statistically significant impact on the presence of stations in the Census Tracts.

DISCUSSION AND SUMMARY

This study aimed to investigate access to bike infrastructure in New York City (NYC), focusing on bikeshare stations and bike lanes, while considering the influence of sociodemographic factors. The methodology included the use of buffers, the Bicycle Equity Index (BEI), and Binary Logistic Regression. The results of the analysis revealed insight into the distribution of bike lanes, bikeshare stations, and sociodemographic factors in NYC.

The analysis of the bike lanes in NYC indicated that the network predominantly radiates from the downtown area and Manhattan, with less coverage in neighborhoods near the city's boundaries. The study found that over 69.5% of the city's area has access to bike lanes within a ¼-mile buffer, emphasizing the importance of evaluating accessibility to promote cycling as a transportation option. The BEI methodology, incorporating variables such as minority population, low-income population, elderly population, youth population, and zero-vehicle households, provided a comprehensive assessment of equity in bike infrastructure. The spatial distribution of BEI scores highlighted areas with a higher need for bike lanes, particularly in the eastern, northern, and southern sides of the city. This information can guide policymakers in identifying regions that may benefit from targeted investments in bike infrastructure to enhance accessibility.

The Binary Logistic Regression model aimed to understand the relationship between sociodemographic factors and the presence of bikeshare stations at the Census Tract level. The analysis identified significant predictors, including households with no vehicles, age groups (more than 65 and less than 18), and minorities. These findings suggest that sociodemographic characteristics play a crucial role in determining the likelihood of bikeshare station availability. However, the population below the poverty line did not appear to have a statistically significant impact on the presence of stations in Census Tracts.

The outcomes of this study contribute valuable insights for urban planners, policymakers, and transportation authorities to enhance the equitable distribution of bike infrastructure. The identification of sociodemographic factors influencing bike infrastructure access can inform targeted interventions to address disparities and promote inclusive bikeshare systems.

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Electric Vehicle Charging Demand Forecasting: Framework and Practical Exemplary Study

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ABSTRACT

While widespread, relevant policies and incentives play an active role in promoting extensive adoption of electric vehicles (EVs), the forecasting of EV charging demand emerges as a crucial consideration with implications for power grid management. This paper addresses this imperative by presenting a research methodology aimed at innovating EV charging forecasting models and integrating them into computational algorithms. This integration facilitates the analysis of overall EV charging demand and distribution issues within a specific geographic area. This study employs a bottom-up heuristic approach to construct a methodological framework for incorporating the developed EV activity-based travel demand forecasting (EVA-TDF) models into a process of trip-chain-simulation based process. To evaluate the effectiveness of the proposed methodology, the greater Cincinnati area in Ohio serves as an exemplary study site. The findings suggest that urban areas characterized by high population density may be optimal locations for deploying level 1 and 2 EV charging stations.

1. INTRODUCTION

Emission impact and energy consumption problems caused by traditional internal-combustion-engine (ICE) vehicles remain stubborn. According to the U.S. Energy Information Administration, the gasoline consumed by light-duty vehicles dominantly occupies 54.2% of total transportation use that is 28% of energy used (EIA, 2022). As a clean transportation mode, electric vehicles (EV) powered with battery has been viewed as a most promising solution to reduce traffic emissions and deplete gasoline dependence. Widespread policy support and incentives promote massive adoption of EVs. It is anticipated that a dramatic growth of the charging-energy demand for EV population across China, Europe, and the US could take place from 2020 to 2030, increasing from roughly 20 billion kilowatt-hours to about 280 billion kilowatt-hours (Engel et al., 2018). As the consequence, EV charging demand puts high pressure on power grid, i.e., power demand exceeds distribution transformer ratings, increased line current and peak-valley difference (Xia et al., 2019, de Hoog et al., 2015). It is observed that in the US, 18% increase of peak load occurs in summer when EV penetration rate is 30% (Abbas et al., 2019, Ma et al., 2010). The reasonable deployments of charging stations highly impact on future power systems operation and construction determining long term planning of EV applications.

A survey conducted by an online car marketplace suggested that the range and price are ranked as the most important factors concerning buyers (about 40%), recharging time and the proximity of available charging stations are also ranked as top considerations (Autolist, 2019). Especially under slow evolution of battery technologies, costly battery replacement and expensive battery lifetime-related cost really matters to EV users (Zhang et al., 2019b). Refueling services provided by charging facilities to prolong driving range has been recognized as a good option to alleviate those concerns. However, unreasonable charging stations planning would bring some problems associated with poor user experience and squandering of land resources (Yi et al., 2019). Limited public charging facilities also lead to longtime charging service due to low charging rate and long waiting time (Zhang et al., 2019a). Meanwhile, location optimization for charging facilities and services would in turn affected by the charging demand forecast; in particular, the charging-station demand is supposed to highly rely on the forecast by using the localized data, along with different levels of EV adoption across regions. The planning and design of the power generation, transmission, and distribution capacity to build the new charging stations also proposes new specifications and requirements. Moreover, inherent random characteristics of EVs (e.g., varying state of charge or SOC, dynamics of charging need for missed trips, different battery performance attributes) make it difficult to accurately predict the spatiotemporal charging demand distribution and charging time, along with many uncertainties on the grid (Chen and Liao, 2013).

Many previous studies indicate that estimating charging demand has been challenging due to lack of realistic vehicle travel data (Cai et al., 2014). EV charging demand forecasting problems may be attributed to uncertainties due to range anxiety, required charging time, and location deployment of the charging infrastructure. Moreover, land-use attributes make the public charging systems different from traditional petrol refueling systems and are also impacted by the home-charging possibility. Greaves et al. (2014) indicated that home charging satisfies more than 90% of day-to-day driving. Xu et al. (2017) further proved that home or workplace charging are much more popular than other options. It would be unacceptable for EV users to spend lots of time on refueling totally against their planned routes. Therefore, those concerned factors should be incorporated into the quantity-based charging demand forecasting methodology and relevant travel demand models, so a solid framework is needed to direct the development of computation algorithms to make the forecasting implementable.

The local-data-based charging demand and associated distribution could provide convincible information in support of smart policy making, charging grid planning, and infrastructure deployment as well. To overcome the identified need, the paper explores the solution through developing a synthetic research methodology to forecast the overall EV charging demand and distribution. The greater Cincinnati area in Ohio is used as a scenario site in a Geographical Information System (GIS) data environment. The bottom-up heuristic approach is used in innovating and integrating the EV Activity-based Travel Demand Forecasting (EVA-TDF) model into the charging demand estimations through running trip-chain simulations. It provides a facilitator to guide the development and update of the involved models and computation algorithms for EV charging demand and distribution forecasting. The method also facilitates broader applications in different sizes of cities, or areas, providing convincible information in support of smart policy making, charging grid planning, and infrastructure deployment as well.

The paper is organized as follows: Methodology and data fusion models are discussed in Section 2. A proof-of-concept study is conducted in Section 3, followed by Section 4 Conclusions.

2. METHODOLOGY

2.1 Overview of the Proposed Methodology

Fig.1 illustrates the proposed EVA-TDF framework to guide development of the detailed models and computation algorithms for forecasting regional EV charging demand and station distributions. This heuristic driven simulated bottom-up EVA-TDF modeling framework consists of four sub models: EV generation model, EV destination distribution model, EV charging demand model and EV charging demand distribution model. This heuristic simulated framework is a problem-solving method employing a sequential model cascading approach where the results from each sub model serves as inputs to the next sub model from bottom to up. This method also uses simplified decision-making to find solutions quickly, especially in complex situations where exhaustive analysis is impractical, which is effective in real-world scenarios where finding an exact solution is challenging or time-consuming. This framework is presented in a real-world TAZ based map for a defined study area, where the spatial boundary of TAZ is well visually predetermined. The results are displayed in a GIS environment to visualize EV charging demands and distributions at the TAZ level for different purposes. In the GIS environment, TAZ based data settings are integrated with diverse datasets from multiple sources, i.e., traffic characteristics, lane use, and socioeconomic factors. Advanced spatial analysis enabled by GIS environment, i.e., feature-to-point analysis and service area analysis, is used to provide guidelines or criteria for further locating charging stations of different types within each TAZ.

Based on the electricity provided by grid systems, charging facilities are usually categorized into Level 1, Level 2 and Level 3, in corresponding to alternating current (AC) Level 1 charging (equivalent to a US household outlet), AC Level 2 charging (240 volts), and Level 3 - direct current (DC) fast charging. According to different voltage and power adapts to different charging facility, and different charging time is needed to charge the EVs' battery to its maximum capacity, charging facility from Level 1 to Level 3 has different practical uses. Fig. 1 summarizes practical uses of charging facilities at different levels. Level 1 is widely used in residential areas and workplace; Level 2 is used in commercial areas such as shopping mall and business center; and Level 3 is used in public places for drivers who need fast charging, such as motorway service area and dedicated charging stations. This framework is implemented in two iterative loops, i.e., algorithm loop and data loop. The algorithm loop demonstrates the logic from EV generation to EV charging demand distribution through performance assessment and scenario-based planning. The number of TAZ-based charging stations at different levels and total number of stations are important outputs for performance evaluations.

It is importantly worthy noting that we are currently in the midst of a gradual shift from partial EV adoption to a complete transition towards a fully electric-powered emission-free environment. To well adapt to the prolonged transition, scenario-based planning at different EV penetration rates could make decision-making and strategic planning effective by exploring a range of potential scenarios. The data loop shows the hierarchy of data flows to obtain EV charging demand and distribution with types of charging facilities, and the procedure of streaming multiple data sources into the EVA-TDF models is illustrated in Fig. 2.

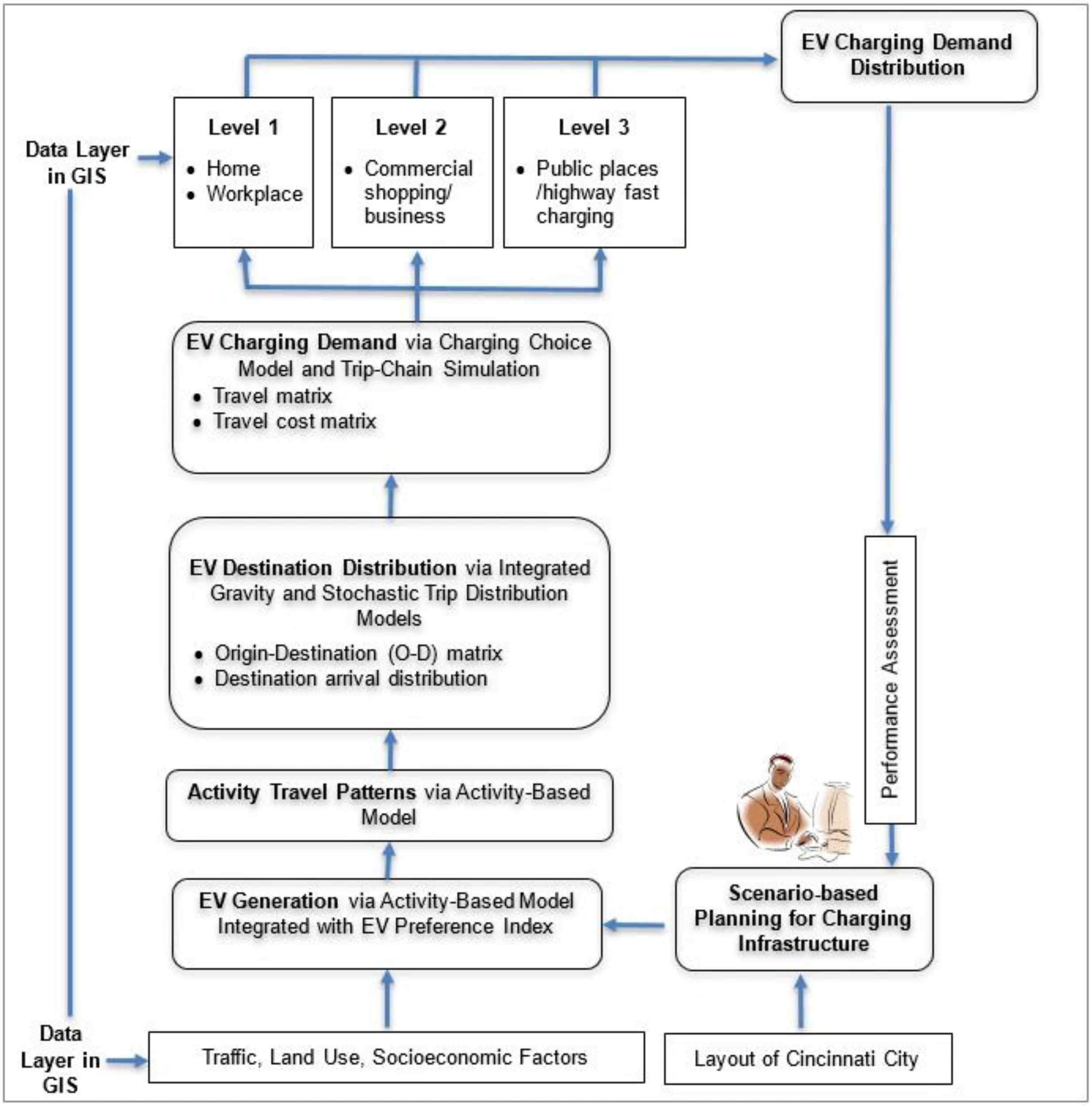

Fig. 1. Flowchart of the EVA-TDF Modeling Framework

Fig. 2 illustrates the hierarchy of the modeling and data flow relationship mechanism to facilitate the development of involved models and their I/O data flow process functions. A real-world TAZ based map of a defined area is integrated into scenario-based planning process at different EV adoption rates. Supportive data, including EV preference, land use, traffic, and socioeconomic factors (i.e., employment, income, household, vehicle ownership) at TAZ level, are inputs to the EV generation model. In this step, trip production and trip attraction of each

TAZ are presented as a matrix, which is calculated in terms of measurements of travel frequency or total volume of EV trips generated given a given time period. Trip production is number of trips generated from households of each TAZ and trip attraction is number of trips destined at each TAZ.

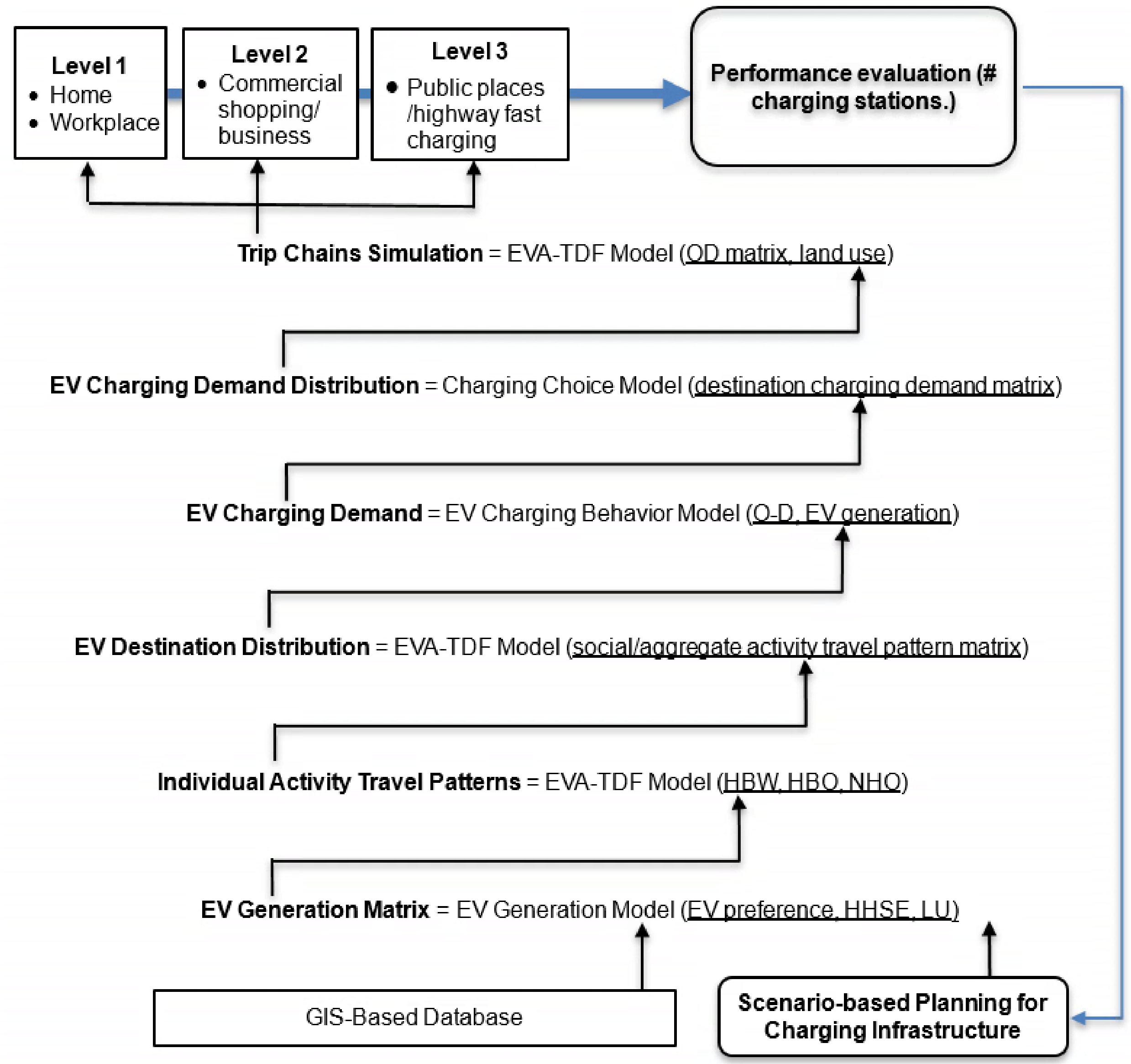

Fig. 2. Hierarchy and Logics of the EVA-TDF Models and Involved Data Flows

Activity-based model is incorporated into the outcomes resulting from EV generation model to evaluate zonal production and attraction with individual activity travel patterns, including home based work (HBW), home based others (HBO) and non-home based (NHB). HBW trip means home at one end (origin or destination) and work at another end (origin or destination) of the journey, wherein journey is one way movement from origin to destination. HBO trip denotes home at one end and non-work is another end of the journey. NHB trip describes neither home at the end of the journey. The individual activity travel patterns matrix is incorporated into the EV generation model through aggregating socioeconomic factors, and they are used as inputs to the EV destination distribution model to evaluate activity travel pattern-based O-D trip matrix.

EV charging demand distribution is estimated on top of the results of EV charging demand and supportive travel time and cost matrixes, which separate activity travel pattern-based O-D trip matrix into various alternative transportation modes. O-D trip matrix and land use data are connected in the trip chains simulation for identifying EV charging stations distributions in a concerned area, and travel cost to access the charging stations can also be estimated in the system. This step generates number of charging stations in each zone for Level 1, Level 2 and Level 3, respectively. These results are incorporated into the performance evaluation to generate feedbacks to the scenario-based planning. Based on the evaluation results, GIS based database is scalable to remove redundant data sources or augment with new data sources. The logics of interactions between data flows within the hierarchy of the EVA-TDF modeling framework enables formulating the scalable data intelligence for EV charging demand and distribution model.

2.2 EV Generation Model

Fig.3 illustrates O-D patterns between TAZs. O (origin) is the starting location of a one-way journey, D (destination) is the ending location of the one-way journey. Each TAZ is either O or D. A journey from $TAZ\ j$ to $TAZ\ j+1$ is presented as O-D patterns $O_j \rightarrow D_{j+1}$. In this journey, it is regarded as production trip from $TAZ\ j$, and attraction trip to $TAZ\ j+1$. A journey from $TAZ\ j+1$ to $TAZ\ j$ is presented as O-D patterns $O_{j+1} \rightarrow D_j$. In this journey, it is regarded as production trip from $TAZ\ j+1$, and attraction trip to $TAZ\ j$. Trip purpose for O-D patterns $O_j \rightarrow D_{j+1}$ ($t_{O_j \rightarrow D_{j+1}}$) is evaluated by Eq. (1), where h, w, o means home, work and non-work, respectively.

$$\begin{cases} if\ ((t_{O_j} = h) \cup (t_{D_{j+1}} = w)) |\ ((t_{O_j} = w) \cup (t_{D_{j+1}} = h))\ , t_{O_j \rightarrow D_{j+1}} = HBW \\ if\ ((t_{O_j} = h) \cup (t_{D_{j+1}} = O)) |\ ((t_{O_j} = O) \cup (t_{D_{j+1}} = h))\ , t_{O_j \rightarrow D_{j+1}} = HBO \\ if\ ((t_{O_j} = O) \cup (t_{D_{j+1}} = O)) |\ ((t_{O_j} = O) \cup (t_{D_{j+1}} = O))\ , t_{O_j \rightarrow D_{j+1}} = NHB \end{cases} \quad (1)$$

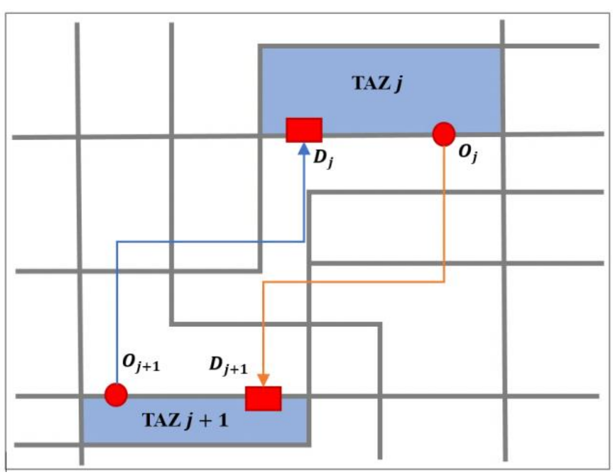

Fig. 3. O-D Patterns among TAZs

Employment matrix E is expressed by Eq. (2). $E^r_{z_i}, E^s_{z_i}, E^o_{z_i}$ presents number of employees work for retail industry, service industry and others (non-retail and non-service) at $TAZ\, i$, rexpectively. Household vehicle ownership is categorized into three types, as shown in Eqs. (3) and (4). Household set at $TAZ\ i$ (H_{z_i}) by car ownership and income is calculated by Eq. (5).

$$E = \begin{bmatrix} E^r_{z_1} & E^s_{z_1} & E^o_{z_1} \\ E^r_{z_2} & E^s_{z_2} & E^o_{z_2} \\ \vdots & \vdots & \vdots \\ E^r_{z_i} & E^s_{z_i} & E^o_{z_i} \end{bmatrix} \tag{2}$$

$$C = [c_1, c_2, c_3], c_i \in C \tag{3}$$

$$\begin{cases} if\ n_v = 1, c_i = c_1 \\ if\ n_v = 2, c_i = c_2 \\ f\ n_v \geq 3, c_i = c_3 \end{cases} \tag{4}$$

$$H_{z_i} = \left[H^l_{c_1}(z_i), H^m_{c_1}(z_i), H^h_{c_1}(z_i), H^l_{c_2}(z_i), H^m_{c_2}(z_i), H^h_{c_2}(z_i), H^l_{c_3}(z_i), H^m_{c_3}(z_i), H^h_{c_3}(z_i)\right] \tag{5}$$

Where, C is household vehicle ownership set. c_1, c_2, c_3 means households with one vehicle, two vehicle and more than two vehicles, respectively. n_v is the number of vehicles owned by households. $H^l_{c_1}(z_i), H^m_{c_1}(z_i), H^h_{c_1}(z_i)$ shows number of households at $TAZ\ i$ own one vehicle and they have low level of income, medium level of income, high level of income, respectively.

Total production trips matrix by incorporating Production trips rate (P_r) at TAZ level is shown in Eq. (6).

$$P_{z_i} = [P_{HBW}\ P_{HBO}\ P_{NHB}] = H_{z_i} P_r \tag{6}$$

Combined with zonal trip attraction models developed by Martin and McGuckin (1998), attraction trips matrix at TAZ level is collectively generated by HBW (A_{HBW}), HBO (A_{HBO}) and NHB (A_{NHB}) (Martin and Mcguckin, 1998). $n_{h_{z_i}}$ is number of households at $TAZ\ i$. Total attraction trips matrix at TAZ level is shown by Eq. (7).

$$A_{z_i} = A_{HBW} + A_{HBO} + A_{NHB} = \begin{bmatrix} 14.55E^r_{z_1} + 4.35E^s_{z_1} + 2.45E^o_{z_1} + 1.4n_{h_{z_1}} \\ 14.55E^r_{z_2} + 4.35E^s_{z_2} + 2.45E^o_{z_2} + 1.4n_{h_{z_2}} \\ \vdots \\ 14.55E^r_{z_i} + 4.35E^s_{z_i} + 2.45E^o_{z_i} + 1.4n_{h_{z_i}} \end{bmatrix} \tag{7}$$

2.3 EV Destination Distribution Model

O-D trip distribution matrix by different trip purpose is calculated by using the EV distribution model. Same logic applies to evaluations of O-D trip distribution matrix for HBW, HBO, NHB. HBW calculation is explained as an example in the following descriptions.

Seed trip (s) is expressed in Eq. (8) by incorporating production trips matrix (($P_{HBW}^{h,c}$) separately generated by HBW (P_{HBW}), to evaluate temporal O-D trip matrix ($t_{i,j}$), as shown in Eq. (9). $c_{i,j}$ is a travel time matrix, where $c_{(1,2)}$ means time taken from TAZ 1 to TAZ 2.

$$s = ({P_{HBW}^{h,c}}^{T} \sum_{i=1}^{i=n} H_{z_i}) / \sum \sum \exp(-0.1 c_{ij}) \tag{8}$$

$$t_{i,j} = \exp(-0.1 c_{i,j}) * s \tag{9}$$

The optimized objective is to achieve balancing factor a equals to b at the same step ($j\ means\ at\ step\ j$). More detailed procedure models are provided upon request.

2.4 EV Charging Demand Model

EV charging demand model delivers number of trips generated by different transportation modes at TAZ level, which is determined by Eqs (10) through (14). $U_{i,j}^{car}$ is utility function of travelers by using car in group i, j. $U_{i,j}^{transit}$ is utility function of travelers by using transit in the same group. $t_{i,j}^{car}$ is travel time needed by car from $TAZ\ i$ to $TAZ\ j$. $t_{i,j}^{transit}$ is travel time needed by transit from $TAZ\ i$ to $TAZ\ j$. $P_{i,j}^{car}$ is probability of a traveler from $TAZ\ i$ to $TAZ\ j$ choosing car. $T_{i,j}^{HBW}$, $T_{i,j}^{HBO}$, $T_{i,j}^{NHB}$ are trips generated by trip purpose HBW, HBO, NHB, respectively. $T_{i,j}^{car}$ is number of trips generated by car from $TAZ\ i$ to $TAZ\ j$. $T_{i,j}^{transit}$ is number of trips generated by transit from $TAZ\ i$ to $TAZ\ j$.

$$U_{i,j}^{car} = -0.139 * t_{i,j}^{car} - 1.032 \tag{10}$$

$$U_{i,j}^{transit} = -0.139 * t_{i,j}^{transit} - 3.315 \tag{11}$$

$$P_{i,j}^{car} = \exp(U_{i,j}^{car}) / (\exp(U_{i,j}^{car}) + \exp(U_{i,j}^{transit})) \tag{12}$$

$$T_{i,j}^{car} = P_{i,j}^{car} * (T_{i,j}^{HBW} + T_{i,j}^{HBO} + T_{i,j}^{NHB}) \tag{13}$$

$$T_{i,j}^{transit} = (1 - P_{i,j}^{car}) * (T_{i,j}^{HBW} + T_{i,j}^{HBO} + T_{i,j}^{NHB}) \tag{14}$$

2.5 EV Charging Demand Distribution Model

EV Charging Demand Distribution Model considers different types of EV charging facility are used to adapt to different practical uses in this area. According to recommendations by the U.S. Department of Energy, more than 80% and 15% of public electric vehicle supply equipment (EVSE) in the U.S. are Level 2 and Level 3. And less than 2% of public EVSE are Level 1 (DOE, 2023). Using this data setting, we adopted 1.5%, 81.5% and 17% for Level 1, Level 2, and Level 3, respectively. Based on the data of registered vehicles, EV charging behaviors (i.e., driving range, charging time) and related traffic characteristics, EV charging demand is expressed by Eq. (15).

$$C_s = \frac{VMT * P_{EV} * n_v * c_h}{d} \tag{15}$$

Where, C_s is total EV charging demand each day. VMT is daily per vehicle miles traveled, 220 miles are assumed. P_{EV} is EV penetration rates. n_v is number of vehicles. c_h is charging time, 6 hours are assumed. d is driving range if battery is to be fully charged, 100 miles are assumed. Those assumed number are refer to Wang et al., (2019).

Deployed plan of charging stations at each TAZ is calculated by Eqs. (16) and (18).

$$T_{i,j}^{car}(\text{EV}) = C_s T_{i,j}^{car} / \sum\sum T_{i,j}^{car} \tag{16}$$

$$C_s^{TAZ,i} = \sum_{j=1}^{j=n} T_{i,j}^{car}(\text{EV}) \tag{17}$$

$$C_s^{TAZ,i} = 1.5L_1 + 81.5L_2 + 17L_3 \tag{18}$$

Where, $T_{i,j}^{car}(\text{EV})$ is number of trips are generated by EV from $TAZ\ i$ to $TAZ\ j$. $C_s^{TAZ,i}$ is number of charging stations are planned to deploy at $TAZ\ i$.

3. CASE STUDY – TESTING OF THE DEVELOPED MODELS

3.1 Scope of Study

The city of Cincinnati area in State of Ohio is chosen as the study site. The city of Cincinnati is located in Hamilton County, the core part of the Greater Cincinnati metropolitan area. The city of Cincinnati is bordered with two counties in Kentucky and one county in Indiana across the Ohio River. The geographical feature makes the city of Cincinnati a transportation bub with great job opportunities. Its rich history, culture and good views also attract lots of visitors.

3.2 EV Demand

Fig. 4 presents statistical trip distributions for different trip purposes, including HBW, HBO, and NHB. The trip patterns for all trip purposes follow normal distribution or Gaussian distribution. The green line demonstrates the normal distribution curve for HBW trips at each TAZ, and red line and yellow line represent HBO trips, NHB trips, respectively. It can be seen that HBW trips have the smallest mean value (1041), followed by HBO (1145) and NHB (1620). The ranking orders of variance from high to low is: HBW, NHB, and HBO. Therefore, trip distributions for HBW are more scattered than the other two types. A more scattered trip distribution indicates a higher level of dispersion in travel patterns within the TAZs. That implies more disperse job opportunities within the city. Where NHB and HBO trips have smaller scattered, the land use for functional areas such as recreational areas, commercial areas and parks are more clustered.

3.3 EV Demand Distribution

Based on the simulated results from running the proposed EVA-TDF model, Fig. 5 demonstrates charging demand distribution in Cincinnati for different facility types, including

Level 1, Level 2 and Level 3. Purplish red circle is charging stations designed for Level 1. Blue circle is for Level 2, and red circle for Level 3. The upper left figure is charging station distributions under EV penetration rates is 0.1, the upper right is for 0.3 of EV penetration rates, and lower left figure, lower right figure is 0.5 and 1 of EV penetration rates. Meanwhile, one dot is presented for 20 charging stations. Charging stations are designed more in CBD than other types of land use. Also, more charging stations are needed in high density of population areas except for the CBD. This phenomenon was also found in Huang and Zhou's study (2015).

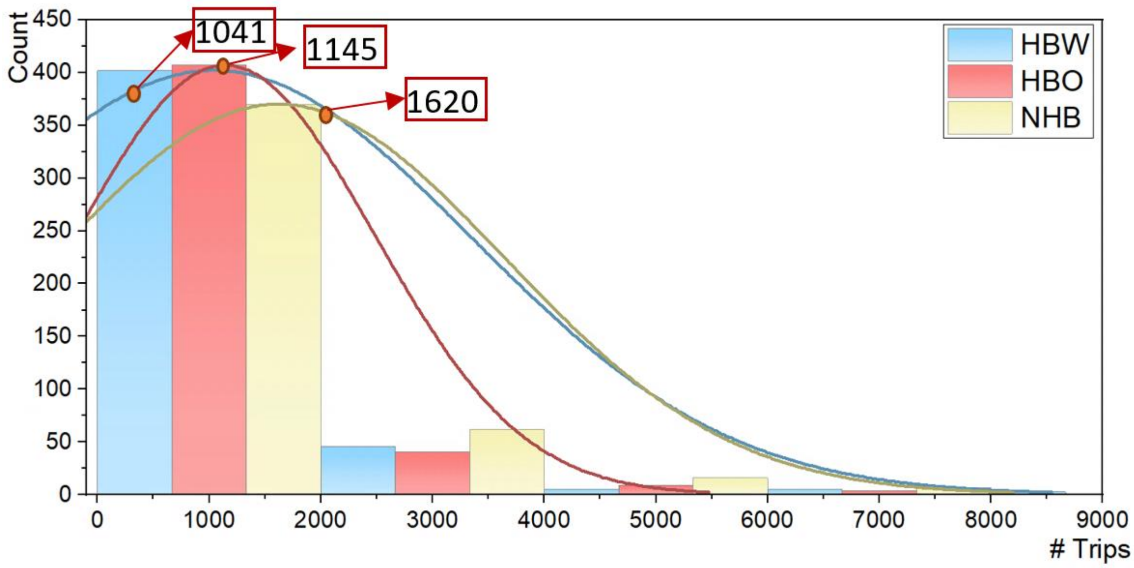

Fig. 4. Number of Trips Distribution by Trip Purpose

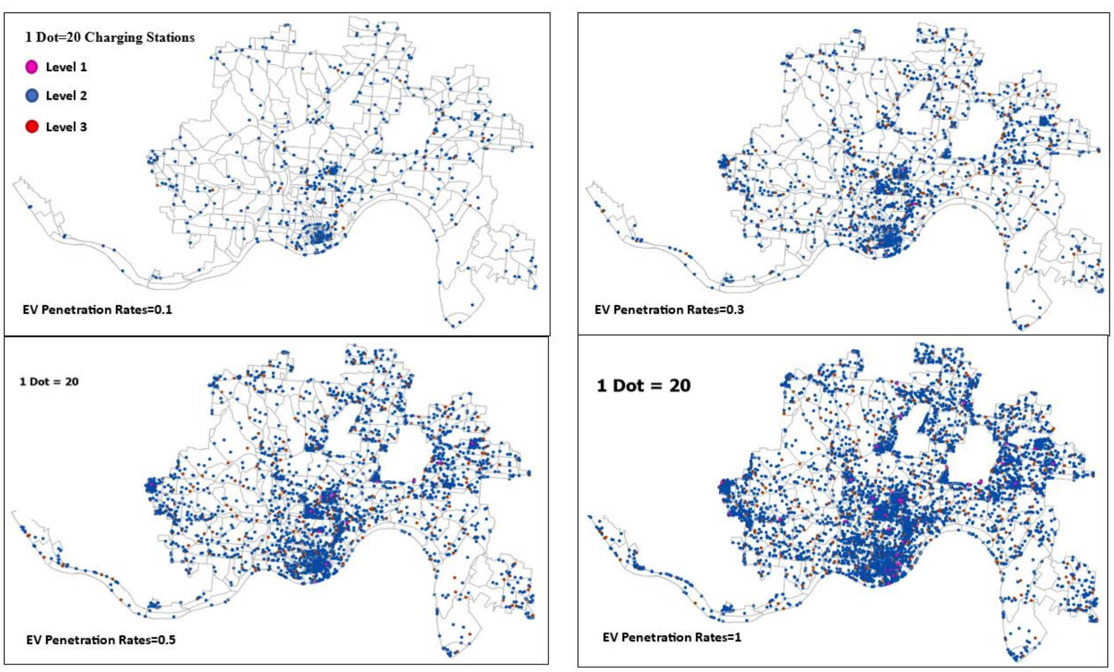

Fig. 5. Charging Stations Deployments by Facility Types

To further demonstrate charging stations distribution for each charging facility type, Fig. 6 through 8 shows design of charging stations for Level 1, Level 2 and Level 3, respectively. Fig. 6 shows Level 1 charging stations designed at each TAZ, where each dot means one charging station. Same as Fig. 5, upper left figure, upper right figure, lower left figure, and lower right figure describe Level 1 charging stations distribution under EV penetration rates are 0.1, 0.3, 0.5 and 1. There are no obvious characteristics for charging stations deployment when EV penetration rate is 0.1. Most TAZs are not designed for locating Level 1 charging stations under very low EV penetration rates. That means that Level 1 charging stations is not the top priority option to deploy charging stations. The CBD and TAZs with high population density above the CBD have larger number of Level 1charging stations under EV environment with penetration rates from 0.3 to 1.

Fig. 7 shows Level 2 charging stations designed at each TAZ, where each dot means twenty charging stations. The upper left figure shows that TAZs within the CBD are candidate locations to deploy large number of charging stations under EV environment with penetration rate is 0.1. The upper right and lower figures show TAZs within the CBD and TAZs with high population density when their types of land use are urban are all candidate locations for EV charging stations deployments. Shahraki et al.'s study (2015) proved that charging stations within a city are more easily to be assessed and frequently used than those areas outside a city. Meanwhile, areas with lots of residents generate more travel demand compared with areas with low density of population. Fig. 8 shows the design of Level 3 charging stations at each TAZ, where each dot means five charging stations. The demand patterns of Level 3 charging stations are similar with Level 2d.

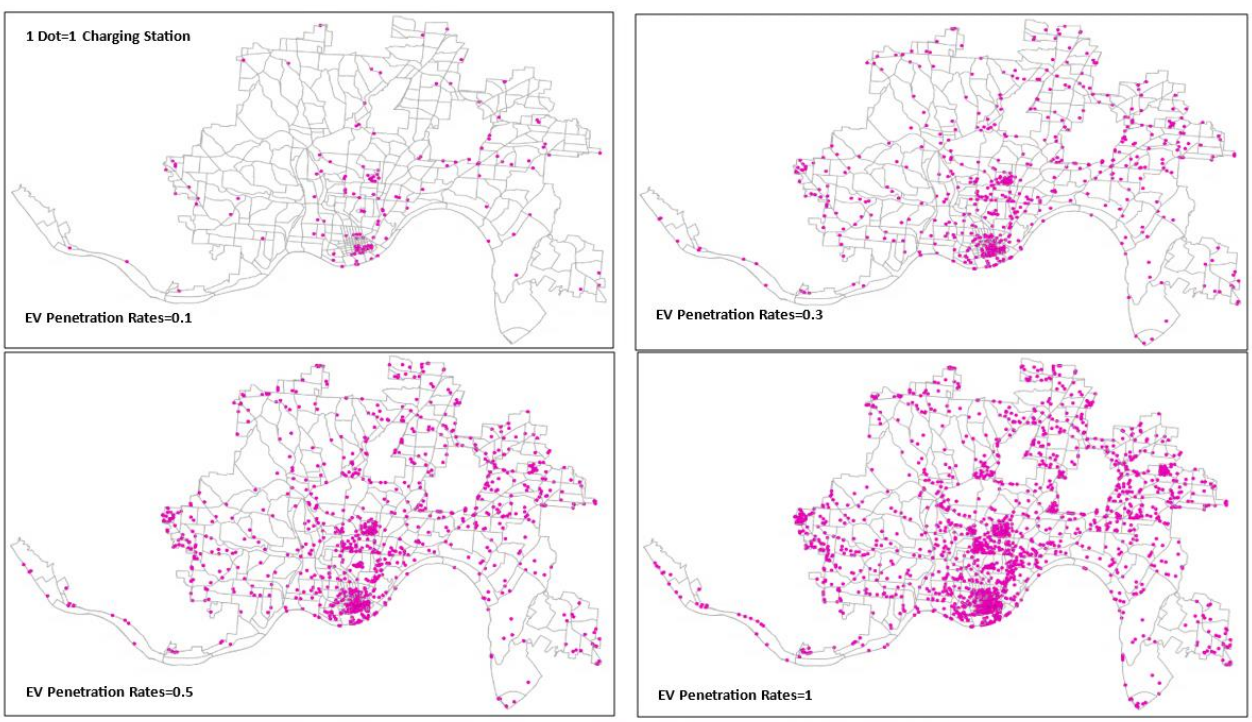

Fig. 6. Charging Stations Deployments for Level 1

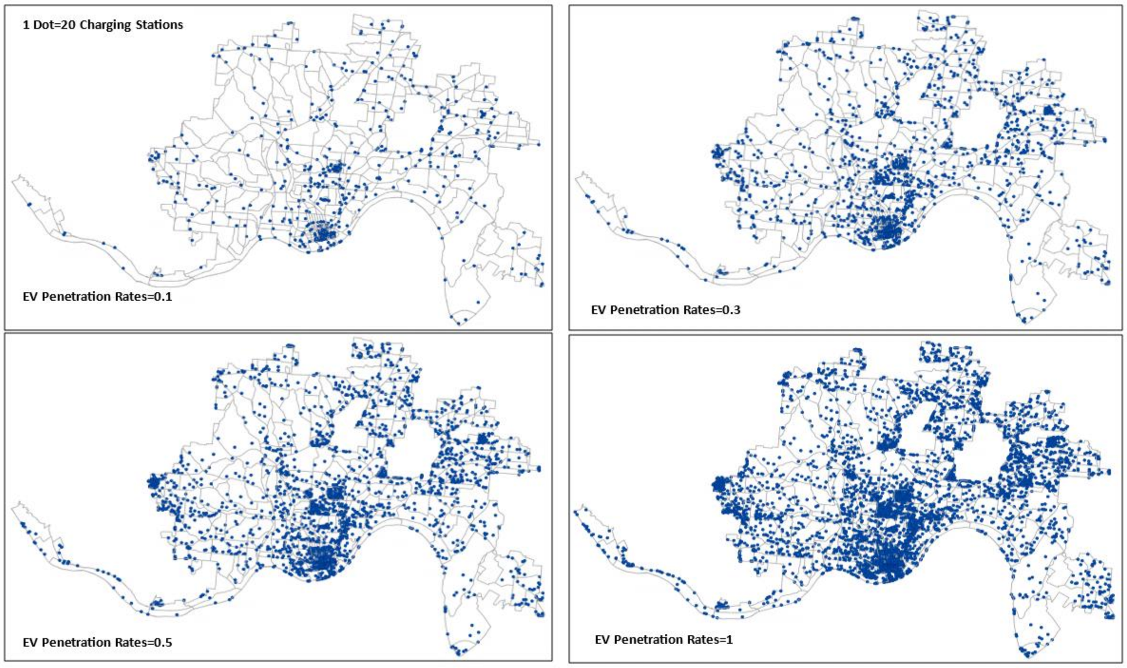

Fig. 7. Charging Stations Deployments for Level 2

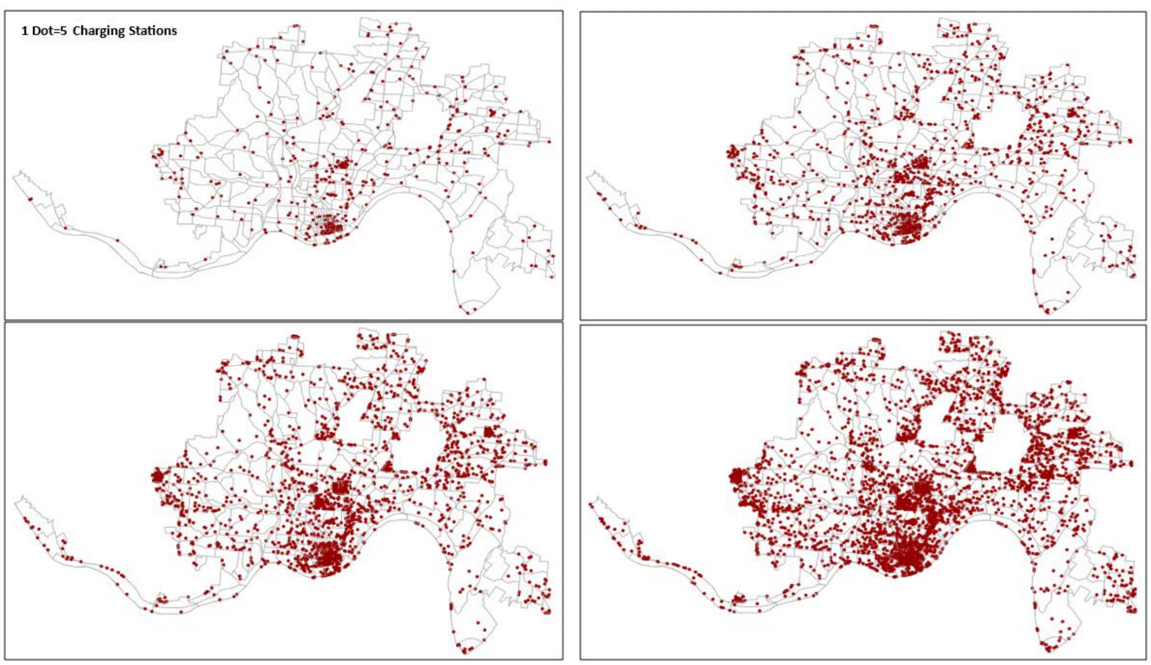

Fig. 8. Charging Stations Deployments for Level 3

4. CONCLUSIONS

For very limited realistic EV travel data with uncertainties of EV uses, estimating charging demand has been recognized challenging. The contribution of this paper is reflected on the development of the EVA-TDF modeling framework to address the issue with the following benefits:

- The developed EVA-TDF framework streamlines the logics of involved sub-models and associated data flows between them. This heuristic structure makes it easier to develop algorithms to check the accuracy at each step for the sequential flow of information.
- With the EVA-TDF framework, algorithmic complexity could be reduced and make the calculation fast through breaking down the EV charging demand and distribution problems into manageable small sub-models so as to eliminate redundant calculations. Such heuristically structured approach also increases the interpretability of the results at each layer to facilitate better understanding of the whole process.
- The EVA-TDF framework increases the scalability and adaptability of the models through making localized variables (i.e., valued by using local data) easily incorporated into the models. Each sub-model is easily scaled down depending on the data scope.
- The case study results suggest that the accuracy of the estimated NHB trips greatly impact the accuracy of the whole travel demand forecasting, followed by HBO and HBW trips.
- The case study results reveal another new finding that TAZs within the CBD or area with high population density are good locations for deploying Level 1 and 2 charging stations.

Future work will be directed to improve the EVA-TDF modeling framework by integrating some data mining techniques, i.e., artificial neural network, support vector machine.

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Development of a Practical Methodology for Evaluating the Conditions of Sidewalks in Dhaka City

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ABSTRACT

In urban settings like Dhaka, the capital of Bangladesh, poor sidewalk conditions pose challenges for pedestrians, affecting usability and aesthetics. This study introduces a novel approach utilizing the sidewalk condition index (SCI) to assess sidewalk conditions. Through a comprehensive methodology involving literature review, walking and video surveys, distress assessment, and SCI calibration, 58 sidewalk segments along key routes were analyzed. The study identifies the top eight hazardous areas, leading to a calibrated SCI that categorizes conditions from excellent to poor. These findings provide actionable insights for local government authorities, facilitating prioritization of sidewalk maintenance and budget allocation. The proposed sidewalk management strategy advocates for policy improvements, emphasizing construction, rebuilding, and maintenance, with recommendations including a five-year planning term and cost analysis for each segment. This research serves as a practical guideline for enhancing pedestrian safety and urban aesthetics, underscoring the importance of adequate budget allocation for improving sidewalk infrastructure in Dhaka and similar cities worldwide.

INTRODUCTION

Background. The global population is burgeoning, with a sixfold surge in growth rates (Islam, 2018), leading to an annual rise of 83 million and an anticipated projection of 11.2 billion by 2100 (United Nations The 2017 Revision, 2017). This rapid expansion, against limited resources, poses significant challenges. Bangladesh, exemplified by the densely populated and challenging city of Dhaka (The World Bank, 2023; The Financial Express, 2021), faces considerable hurdles in accommodating its burgeoning populace. Pedestrian safety, particularly the condition of sidewalks, is a pressing concern in Dhaka. Despite the acknowledged role of walking in mobility and sustainability (Grob et al., 2011), pedestrians encounter adverse conditions and pollution, hindering safe and pleasant experiences (Bari et al., 2018; Morshed, 2018). Pedestrian safety remains a global concern, especially acute in developing countries like

Dhaka, where pedestrians contribute significantly to traffic-related fatalities (Rahaman et al., 2008; Rahman et al., 2007; WHO, 2013). Walkability, encompassing pedestrian facilities, road conditions, and safety measures, is crucial in urban landscapes (Montgomery et al., 2008; Tuydes-Yaman et al., 2017; Ariffin et al., 2013). Despite the pivotal role of pedestrian infrastructure, Dhaka's sidewalks suffer persistent neglect, impeding walkability and citizen safety. This contrasts with the city's substantial reliance on pedestrian transit. Although efforts exist to promote walking as a sustainable mode of transport and foster livable communities in Bangladesh, the quality of pedestrian pathways remains a critical factor influencing walkability.

Objective and Scope. This research aims to comprehensively evaluate sidewalks along selected routes in Dhaka, prioritizing critical aspects of their conditions. By scrutinizing the present state of pedestrian infrastructure, this study lays the groundwork for proposing pedestrian-centric solutions. It endeavors to identify obstacles, segment the best and worst sidewalk conditions, and create awareness among policymakers and city officials to improve walking experiences.

Perceived Benefits. This research's detailed evaluation of Dhaka's sidewalk conditions promises insights to enhance pedestrian safety, inform policy decisions, and improve pedestrian facilities, ultimately contributing to the well-being of pedestrians in Bangladesh.

LITERATURE REVIEW

Pedestrian fatalities, notably prevalent in Dhaka, Bangladesh (Debnath et al., 2021), account for a substantial percentage of traffic-related deaths (Hoque et al., 2003). Dhaka's limited sidewalk coverage - only 13.33% of roads - accentuates the urgent need for safe and accessible pedestrian pathways (Bari et al., 2018). Speck's "General Theory of Walkability" emphasizes sidewalks should maintain a 6-inch height and 4-foot width for continuity and comfort (Weyandt, 2018). However, observed sidewalks in Dhaka lack these qualities, posing challenges for pedestrians. Pedestrian facility design focuses on safety, inclusivity, and cost-effectiveness, fostering walkable urban spaces that enhance societal well-being and economic prosperity. Sidewalks serve as interactive spaces, contributing to city livability, despite Bangladesh's urban areas facing deficiencies in pedestrian infrastructure. Different zones within sidewalks demand specific criteria for safety and comfort. Sidewalk width variations, surface flatness, and drainage affect usability, catering to pedestrian movement and other activities like vending and bus stops. Dhaka's sidewalks suffer discontinuity due to various obstacles, impacting pedestrian movement, particularly affecting the low-income population reliant on walking (Morshed, 2018). Efficient pedestrian traffic signs and compliance significantly affect safety and require emphasis through education and awareness campaigns (FHWA, 2023; Eureka Africa Blog, 2023). Similar to the Pavement Condition Index (PCI), the Sidewalk Condition Index (SCI) evaluates sidewalk conditions are based on the type, frequency and severity of distresses, and subjective assessments for maintenance recommendations (Huang, 2004; Khabiri et al., 2020).

METHODOLOGY

Basic structure. This study was structured around the following three primary tasks:

- Task A: This phase primarily involved collecting secondary data and preparing for the survey. A comprehensive review was conducted on strategic plans and relevant documents concerning pedestrian facilities and streetscapes in Dhaka. Given ongoing development projects like BRT and MRT, often affecting pedestrian facilities in work zones, the essential data and information for strategic planning were gathered to avoid present and future development zone issues.

- Task B: Focused on gathering primary data through videography.
- Task C: Centered on primary data collection through field surveys.
- Task D: Developing a protocol for determining Sidewalk Condition Index.

Study area. To investigate sidewalk problems, two distinct routes were selected for sampling: (1) Mirpur area, and (2) Farmgate and Satmosjid Road area. These routes were divided into 58 segments, identifying 28 pedestrian obstacles. The aim was to evaluate pedestrian facilities, including sidewalks, foot over bridges, zebra crossings, and encroachments, covering 109.34 km of extensively used roads. Hazardous road locations were then prioritized for in-depth analysis. The study locations are shown in Table 1.

Table 1. Study locations (segments)

Segment	From	To	Length (m)
1	Polasshir More, Buet	Dhaka City College (Left)	1600
2	Dhaka College	Polashi Chottor	1600
3	Dhaka City College	Sukrabad Dhanmondi (Left)	2100
4	Sukrabad, Dhanmondi	Dhaka City College (Right)	2100
5	Sukrabad, Dhanmondi	Asad Gate (Left)	1700
6	Asad Gate	Sukrabad, Dhanmondi (Right)	1700
7	Asad Gate	Shamoli Square	1900
8	Shamoli Square	Asad Gate (Right)	1900
9	Shamoli square	Technical (Left)	1600
10	Technical	Gabtoli Ashulia Bridge (Left)	1600
11	Technical	Gabtoli Bridge (Right)	1600
12	Majar Road	Mirpur-1 (Left)	1000
13	Mazar road	Al-Nahiyan High School	1200
14	DMP	Mirpur 14 U- turn	7700
15	Mirpur 14 U-turn	Milk Vita Road	4500
16	Pollobi, Mirpur 6	Mirpur 7 (Left)	1200
17	Block D, Mirpur 11	Mirpur 2 (Left)	2100
18	Rupnagar BUBT, Mirpur 2	Mirpur 8 (Left)	1500
19	Mirpur-2 Residential	Jatio betar Center (Left)	4300
20	Jatio Betar Centre	60ft Road (Left)	2200
21	Jatio Betar Centre	Borobag, Mirpur (Right)	3800
22	Mirpur 8	Rupnagar BUBT (Right)	1500
23	Zoo Road	Sony Cinema Hall	750
24	Sony Cinema Hall	Stadium	2000
25	Borobagh, Mirpur 2	Main road, Shah Ali bagh, Mirpur 1 (Left)	800
26	Main Road, Kalwalipara, Mirpur 1	Darus Salam Road, Mirpur 1 (Left)	1100
27	Technical Mor, Darus Salam, Mirpur 1	Mirpur 1 Over Bridge (Right)	2600
28	Mirpur 1 Over Bridge	Mazar road, Mirpur 1	3900
29	Mazar Road, Mirpur 1	Shyamoli Main Road (Left)	6300
30	Polashir Mor	Kazi Nazrul Islam Avenue(Right)	3100
31	Polashir Mor	Kazi Nazrul Islam Avenue(Left)	3100
32	Kazi Nazrul Islam Avenue	Panthapath Signal (Right)	750
33	Kazi Nazrul Islam Avenue	Panthapath Signal (Left)	750
34	Panthapath Signal	Green Road (Left)	1300
35	Green Road	Panthapath Signal (Right)	1300
36	Panthapath Signal	Anando Cinema Hall, Farmgate (Right)	750

Segment	From	To	Length (m)
37	Panthapath Signal	Anando Cinema Hall, Farmgate (Left)	750
38	Farmgate	Bijoy Sarani (Left)	750
39	Bijoy Sarani	National Parliament Lake Road (Left)	2000
40	National Parliament Lake Road	Farmgate (Right)	1400
41	Asad Avenue	Bus Stand, Basila Road (Left)	2500
42	Bashbari, Mohammadpur	Ring Road, Shyamoli (Left)	1300
43	Shyamoli Square	Shiya Jame Mosque Tajmahal Road (Right)	1800
44	Sher-E-Bangla Road, Mohammadpur	Satmoshjid Road, Mohammadpur (Left)	2200
45	Sher-E-Bangla Road, Mohammadpur	Satmoshjid Road, Mohammadpur (Right)	2200
46	Lalmatia, Satmoshjid Road	Genetic Plaza (Left)	2000
47	Genetic Plaza, Lalmatia	State University of Bangladesh (Right)	1600
48	State University of Bangladesh	Simanto Square (Left)	3000
49	State University of Bangladesh	Simanto Square (Right)	3000
50	Shimanto square	Dhaka City College (left)	750
51	Shimanto square	Dhaka City College (Right)	750
52	Dhaka City College	Elephent Road (Left)	550
53	Elephant road	Dhaka City College (Right)	550
54	Elephent road	Motso Bhobon (Left)	340
55	Elephent road	Motso Bhobon (Right)	340
56	Arong, Lalmatia	Manik mia aveneu West Bus Stop (Left)	230
57	Arong, Lalmatia	Manik mia aveneu West Bus Stop (Right)	230
58	Asad Gate	National Parliament Lake Road (Right)	2200
		Total =	**109340 m**

Developing a protocol for determining Sidewalk Condition Index. The study began with a thorough area survey, assessing sidewalk structure, materials, and distress severity. A matrix for Sidewalk Condition Index (SCI) calculation was devised. SCI ranges for varied sidewalk conditions were tabulated. Expert opinion-based SCI was simultaneously determined based on the opinion of the Engineer/Surveyor ratings on sidewalk condition of the most hazardous sidewalk segments. Both SCI values were then averaged. The mean SCI, amalgamating calculated and Engineer/Surveyor inputs, determined the "Final SCI" for each section. Data validation involved plotting calculated and final SCI values, forming a best-fitted trend line, and statistically validating the SCI range at a 95% confidence level. Subsequently, 20% of location data underwent random selection for validation.

Inclusions and exclusions. Routes covering sidewalks on both sides and consideration of 28 sidewalk distresses were included, whereas the full dataset of the hawkers on the sidewalk and data related to the disruptions caused by bus parking hindering observations in videography were excluded.

Data collection tools. For videography survey part checklists, dash cameras, case studies, Google Maps, and Microsoft Excel were used. For the field survey part digital cameras, related stationeries, measuring tape, compass, Google Maps, and mobile phones were used.

Data management and analysis. Segmented videos were captured by a dashboard camera, supplemented with detailed notes for later analysis. Google Maps facilitated navigation along the routes. Each segment's total problems were calculated and standardized to a uniform value of 100 meters for comparative analysis. From videography analysis, hazardous segments were selected and drawn on art paper during field surveys. Measurements of sidewalk elements, analysis of conditions and problems, and determination of blocked areas were conducted. Parameters like slope, curb, and hawker positions were measured to assess sidewalk conditions.

ANALYSES AND FINDINGS

Problem counts. Primary data was obtained from videography and field surveys conducted by engineers and experts. A comprehensive investigation into various sidewalk safety issues was carried out. The collected data is formatted to provide a clear understanding of these issues, aligning with the research's overarching goal. After numerous viewings of the videography, 28 distinct major problems were identified. Each problem was assigned a weight based on consulting ten experts. The problem types, weights and counts at the preselected 58 segments are shown in Tables 2 through 4.

Table 2. Major problems, weights and counts (for segments #1 through #20)

No.	Problem	Weight	Number of problems (raw problem counts)																			
			Segment #																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Damaged Footpath	4	12	1	7	3	1	1	2	0	17	39	29	11	20	89	8	3	9	4	21	25
2	Pole	3	37	30	20	21	32	36	47	24	29	28	38	14	71	70	37	45	56	48	24	16
3	Hawker	4	0	6	3	8	0	0	1	0	0	0	0	0	7	27		9	20	99	0	5
4	Ramp	3	16	12	35	23	36	35	62	26	46	21	15	36	56	64	76	52	74	11	87	36
5	Tree	2	6	28	21	4	0	8	0	26	4	1	0	0	21	294	22	11	25	12	0	13
6	Railing	-2	4	2	13	6	7	4	0	0	0	0	0	0	0	0	0	3	0	0	0	0
7	Driveway	3	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	7	12	14	1	1
8	Manhole Cover	2	0	0	0	1	0	1	0	0	0	0	0	0	0	1	2	17	29	60	8	1
9	Parking	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	6	4	0	0
10	Obstruction	4	6	0	0	1	0	3	1	3	0	0	1	0	17	36	42	15	20	15	10	1
11	Sign Post	2	13	3	9	5	9	10	10	11	9	3	4	0	2	2	12	0	2	3	0	7
12	Permanent Obstruction	4	0	0	3	0	2	0	1	0	0	0	0	0	0	0	0	5	9	5	0	0
13	Foot over Bridge	-1	3	2	2	2	3	3	3	3	3	0	0	0	2	5	4	0	0	1	1	1
14	Stair	2	0	0	2	0	2	0	0	0	0	0	0	0	2	0	0	0	0	0	2	0
15	Shop Accessories	3	0	0	0	0	0	0	0	0	0	0	0	0	14	19	45	0	0	0	0	0
16	Signal Light	2	1	1	6	5	4	3	4	3	1	0	1	0	0	1	3	0	2	0	1	1
17	Telephone Box	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
18	Construction Materials	4	0	4	4	0	0	0	1	0	0	0	0	1	3	19	20	1	10	18	3	2
19	Hole	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	48	34	2	1
20	Gate	3	2	10	5	5	1	1	0	0	3	3	0	4	7	20	5	6	16	7	3	4
21	Bus Counter	4	0	0	0	0	0	0	5	0	0	0	0	0	1	5	5	0	0	0	0	0
22	Garbage	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0
23	Electric Wire	4	0	0	0	0	0	0	0	0	1	1	1	0	0	0	21	0	1	0	0	2
24	Police Box	4	0	0	1	0	1	0	1	1	1	1	0	0	0	2		0	6	0	0	0
25	Waste Dump	4	1	0	0	0	1	2	0	0	0	0	0	0	1	1	1	1	0	1	0	0
26	Building Corner	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
27	Side Road	5	5	7	8	3	7	3	10	8	5	0	1	0	12	11	32	7	11	22	5	5
28	Passenger Camp	2	2	0	2	0	0	0	0	0	0	0	0	0	1	1	3	0	0	0	0	4

Table 3. Major problems, weights and counts (for segments #21 through #40)

No.	Problem	Weight	Number of problems (raw problem counts)																			
			Segment #																			
			21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	Damaged Footpath	4	10	9	0	2	3	5	10	7	20	2	14	0	8	15	6	3	16	7	7	6
2	Pole	3	26	25	32	67	28	29	26	23	38	133	95	11	30	64	53	22	17	13	21	24
3	Hawker	4	3	52	0	2	19	84	66	65	8	11	30	1	0	5	10	48	0	3	0	0
4	Ramp	3	56	61	4	22	9	15	22	32	71	61	33	6	11	22	15	15	27	7	16	21
5	Tree	2	4	9	5	8	29	4	1	0	11	45	28	15	6	3	1	2	3	2	31	11
6	Railing	-2	0	0	0	0	0	2	38	0	9	17	55	2	22	0	0	7	2	34	0	4
7	Driveway	3	1	7	0	0	5	6	8	6	10	27	12	1	5	8	6	3	1	2	7	2
8	Manhole Cover	2	9	47	0	0	3	10	2	2	4	0	5	0	8	9	10	6	0	5	6	0
9	Parking	3	8	7	6	7	0	3	10	0	3	0	8	1	2	0	2	3	0	3	5	0
10	Obstruction	4	0	20	2	0	2	6	9	3	19	17	27	6	14	8	8	16	2	2	0	1
11	Sign Post	2	0	0	7	15	0	0	0	0	0	4	0	1	0	0	0	0	6	0	0	3
12	Permanent Obstruction	4	0	3	0	0	6	2	1	0	6	0	4	0	0	0	0	0	0	0	0	0
13	Foot over Bridge	-1	0	1	0	0	1	2	2	0	3	2	0	1	3	0	0	0	3	1	0	4
14	Stair	2	0	0	0	0	0	0	0	3	0	1	0	0	0	0	0	0	0	0	0	0
15	Shop Accessories	3	0	0	2	12	0	0	0	0	7	2	0	16	0	0	0	0	0	0	0	0
16	Signal Light	2	0	0	1	2	0	3	0	0	4	3	4	0	1	1	1	0	0	1	1	0
17	Telephone Box	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	Construction Materials	4	1	15	3	0	9	25	5	3	17	3	8	0	2	6	3	2	0	5	3	0
19	Hole	5	0	24	0	0	5	11	0	2	6	0	4	0	3	7	5	2	0	3	2	0
20	Gate	3	3	6	1	14	0	12	7	0	7	27	3	0	0	0	0	0	0	0	0	1
21	Bus Counter	4	0	0	1	0	0	5	5	0	4	0	3	0	2	2	1	0	0	2	1	0
22	Garbage	3	0	0	0	0	2	0	5	0	15	0	0	0	0	0	0	0	0	0	0	0
23	Electric Wire	4	0	0	0	0	0	0	0	0	6	0	3	0	6	10	8	0	0	0	0	0
24	Police Box	4	0	0	1	0	0	0	4	0	1	1	0	1	1	0	1	0	1	1	0	0
25	Waste Dump	4	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
26	Building Corner	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	Side Road	5	4	29	8	17	4	8	9	5	11	26	20	1	9	11	14	5	2	8	4	2
28	Passenger Camp	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Identification of the most hazardous sidewalk segments. The initial problem counts from all 58 segments were standardized to problem counts per 100m. These counts were then multiplied by the respective problem's weightage. The resulting standardized problem counts were totaled to derive the 'hazard score' for each segment. Eq. 1 represents the generalized formula used for calculating this 'hazard score'.

$$Hazard\ score\ of\ a\ segment = \sum\left(\frac{Problem\ count\ from\ Survey\ x\ Problem\ weight}{Segment\ Distance} x100\right) \qquad (1)$$

To identify the most hazardous segments of the sidewalk system of the study area, all 58segments were ranked according to their ‘hazard score’. The top most hazardous segments and their respective ‘hazard score’ are presented in Table 5.

Table 4. Major problems, weights and counts (for Segments #41 through #58)

No.	Problem	Weight	Number of problems (raw problem counts)																	
			Segment #																	
			41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58
1	Damaged Footpath	4	18	16	10	20	6	2	1	0	2	0	1	2	0	4	5	0	0	0
2	Pole	3	41	53	44	28	22	8	18	31	39	19	18	35	27	28	10	26	27	173
3	Hawker	4	27	19	35	17	11	35	0	5	12	0	0	0	1	1	0	5	1	0
4	Ramp	3	32	46	28	26	65	30	35	64	90	44	36	4	22	27	16	4	13	21
5	Tree	2	25	12	6	7	0	8	5	36	8	18	0	0	0	0	15	89	6	4
6	Railing	-2	0	0	0	0	11	2	0	0	0	0	0	3	1	6	3	0	0	0
7	Driveway	3	5	10	7	4	12	4	4	0	0	1	2	2	0	3	1	0	3	1
8	Manhole Cover	2	12	14	12	8	0	1	2	12	18	4	0	0	0	0	0	0	0	0
9	Parking	3	3	6	2	3	1	2	0	1	6	0	0	0	0	0	0	0	0	1
10	Obstruction	4	4	6	8	3	1	8	0	3	1	0	0	0	3	0	5	0	6	1
11	Sign Post	2	0	0	0	0	9	0	0	0	0	4	1	3	5	4	6	4	10	7
12	Permanent Obstruction	4	1	3	0	0	2	0	0	3	3	1	0	1	0	1	1	0	1	0
13	Foot over Bridge	-1	0	0	0	0	1	0	0	1	1	0	0	1	0	2	3	0	0	0
14	Stair	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
15	Shop Accessories	3	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
16	Signal Light	2	1	0	0	0	2	0	0	0	3	0	0	0	2	0	0	1	1	2
17	Telephone Box	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	Construction Materials	4	10	10	13	5	1	2	3	0	3	0	0	0	0	0	0	0	0	0
19	Hole	5	9	5	5	6	0	5	0	0	2	0	0	0	0	0	2	0	0	1
20	Gate	3	3	4	0	0	1	6	8	4	0	5	0	1	0	1	0	0	0	0
21	Bus Counter	4	3	2	3	4	0	3	0	0	0	0	0	0	0	0	0	0	0	0
22	Garbage	3	0	0	3	0	0	3	0	0	0	0	0	0	0	0	0	0	1	0
23	Electric Wire	4	0	8	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	7
24	Police Box	4	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
25	Waste Dump	4	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
26	Building Corner	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2	0	2
27	Side Road	5	7	12	9	16	10	3	3	13	11	2	1	1	2	6	0	0	1	0
28	Passenger Camp	2	0	0	0	1	0	0	0	1	1	0	0	0	1	0	1	0	0	0

Table 5. Most hazardous segments of the sidewalk system studied

Rank #	Segment ID	Segment Name	Hazard Score	Segment Length (m)
1	56	Aarong, Lalmatia to Manik Mia Avenue West Bus Stop (Left)	134	230
2	57	Aarong, Lalmatia to Manik Mia Avenue West Bus Stop (Right)	87	230
3	18	Rupnagar BUBT, Mirpur 2 to Mirpur 8 (Left)	84	1500
4	26	Technical Mor, Mirpur 1 to Darus Salam Road, Mirpur 1 (Left)	75	1100
5	22	Mirpur 8 to Rupnagar BUBT (Right)	73	1500
6	13	Mazar Road to Al-Nahiyan High School (Left)	63	1200
7	36	Panthapath Signal to Anando Cinema Hall, Farmgate (Right)	59	750
8	17	Block D, Mirpur 11 to Mirpur 2 (Left)	51	2100

Road safety inspection findings of pedestrian facilities. The road safety inspection findings of pedestrian facilities for the most hazardous eight sidewalk segments are as follows:

1. ***Segment No. 56 - Aarong, Lalmatia to Manik Mia Avenue West Bus Stop (Left):*** Running 230m from Aarong to Manik Mia Avenue, this segment near Bangladesh National Parliament suffers from tree encroachment, pole obstructions, damaged tiles, and unattended holes. The designated cycle lane often sees car parking, impacting pedestrian access. The multitude of trees significantly narrows the footpath.
2. ***Segment No. 57 - Aarong, Lalmatia to Manik Mia Avenue West Bus Stop (Right):*** Adjacent to parliamentary premises, this 230m stretch is marred by waste dumping, van blockages, open manholes, and non-uniform slopes. The footpath accommodates government facilities and witnesses excessive pole placements.
3. ***Segment No. 18 - Rupnagar BUBT, Mirpur 2 to Mirpur 8 (Left):*** Initiating at BUBT University and concluding at Mirpur 8 Kacha Bazar, this residential area witnesses excessive hawker presence, damaged footpaths, and misplaced trees. Ramp overuse and unwarranted obstruction pose challenges for pedestrian movement.
4. ***Segment No. 26 - Technical Mor, Mirpur 1 to Darus Salam Road, Mirpur 1 (Left):*** Spanning Darus Salam Road, this segment faces extensive blockages by vendors, electric poles, and various obstacles, hindering pedestrian movement. The footpath deteriorates significantly after Tolarbag Residential Area, rendering it unusable.
5. ***Segment No. 22 - Mirpur 8 to Rupnagar BUBT (Right):*** Residential in nature, this segment suffers from vendor encroachment, inadequate ramps, and excessive poles, compromising pedestrian access. The uneven placement of trees and unnecessary ramps impede movement.
6. ***Segment No. 13 - Mazar road to Al-Nahiyan High School Left:*** Commercially active, this segment exhibits damaged footpaths, pole obstructions, and extensive use of footpath space for business, hindering pedestrian movement. Improperly placed drain slabs and waste dumps further compound the issues.
7. ***Segment No. 36 - Panthapath Signal to Anando Cinema Hall, Farmgate (Right):*** This 750-meter segment starts at Panthapath Signal and ends at Ananda Cinema Hall. The 8ft-wide footpath faces several issues: encroachment by vendors, broken tiles hindering pedestrian flow, lack of ramps affecting accessibility, poorly placed manhole covers, and inadequate drainage causing water retention. Educational institutions contribute to high pedestrian traffic.
8. ***Segment No. 17 - Block D, Mirpur 11 to Mirpur 2 (Left):*** Beginning at Block D, Mirpur 11, and concluding at Mirpur 2, this segment witnesses a lack of footpaths in certain areas, ramp overuse, and extensive vendor occupation, compromising pedestrian access. The absence of zebra crossings and improperly placed poles hinder safe passage.

Calibration and validation of the SCI determination protocol. Table 6 and subsequent calculations show the steps of determining the raw SCI of Segment #13 - Mazar road to Al-Nahiyan High School (Left). Table 7 shows the initial (uncalibrated) sidewalk condition of this segment. Similarly the raw SCI and condition of all other seven most hazardous sidewalk segments were determined. The summary of the sidewalk's raw SCI and condition based on SCI and expert opinion, as well as the average SCI are presented in Table 8. Figure 1 provided the predictive equation used for the calibration of the SCI. As noted, 20% of the most hazardous segments were selected randomly for the validation of SCI Protocol Process. The validation process is presented in Table 9.

Table 6. Raw deduct values for raw SCI calculation for Segment #13 (an example)

No.	Distress	Severity of Distress (Si)						Density of Distress (Di)					Raw Deduct Value
	Location: Segment #13	Weightage Value	Very slight	Slight	Moderate	Severe	Very severe	Few	Intermittent	Frequent	Extreme	Through out	Wi*(Si+Di)
	Sidewalk Defects	Wi	1	2	3	4	5	1	2	3	4	5	
1	Damaged sidewalk	4				4				3			28
2	Pole	3			3				2				18
3	Hawker	4					5			3			32
4	Ramp	3	1						2				9
5	Tree	2			3				2				10
6	Driveway	3		2						3			15
7	Manhole Cover	2				4					4		16
8	Parking	3	1					1					6
9	Obstruction	4			3				2				20
10	Sign Post	2		2					2				8
11	Permanent Obstruction	4			3					3			24
12	Stair	2	1						2				6
13	Shop Accessories	3		2					2				12
14	Signal Light	2	1					1					4
15	Telephone Box	4		2					2				16
16	Construction Materials	4				4				3			28
17	Hole	5					5				4		45
18	Gate	3				4				3			21
19	Bus Counter	4			3					3			24
20	Garbage	3					5					5	30
21	Electric Wire	4			3					3			24
22	Police Box	4		2				1					12
23	Waste Dump	4					5					5	40
24	Building Corner	4				4				3			28
25	Side Road	5				4				3			35
26	Passenger Camp	2	1					1					4

Sum of Weight, $\sum Wi = 84$, Raw Deduct Value (RDV), $Wi*(Si+Di) = 515$
where,
Summation of weightage, $\sum Wi = 84$
Raw Deduct Value, $RDV = \sum Wi*(Si+Di) = 515$

Si = Severity of Distress
Di = Density of Distress
Factorized Deduct Value, FDV = $\frac{RDV}{(\frac{Wi}{10})} = \frac{515}{\frac{84}{10}}$ = 61.31
Calculated Sidewalk condition index (SCI) = 100 – FDV = 100 – 61.31 = 38.69

Table 7. Initial (uncalibrated) sidewalk condition (an example)

SCI Range	Average SCI	Sidewalk Condition	Calculated SCI for Segment 13	Sidewalk Condition for Segment 13
85 to 100	93	Excellent	38.69	Poor
70 to 85	77.5	Very good		
55 to 70	62.5	Good		
40 to 55	47.5	Fair		
25 to 40	32.5	Poor		
Below 25	12.5	Failed		

Table 8. Summary of sidewalk's raw SCI and condition based on SCI and expert opinion

Segment	Raw SCI	Condition corresponding to raw SCI	Expert opinion on sidewalk condition	Average SCI value
13	38.69	Poor	Poor	32.5
17	45.83	Fair	Fair	47.5
18	50	Fair	Fair	47.5
22	49.29	Fair	Fair	47.5
26	35.24	Poor	Poor	32.5
36	52.62	Fair	Fair	47.5
56	52.86	Fair	Fair	47.5
57	43.69	Fair	Fair	47.5

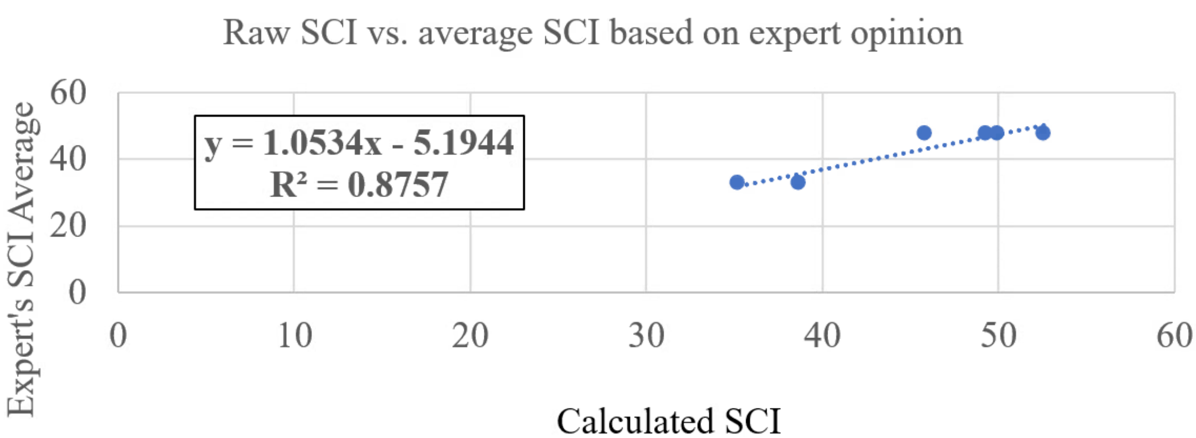

Figure 1. Raw SCI vs. average SCI based on expert opinion.

Table 9. Validation of SCI protocol

Segment	Sidewalk Condition Index (SCI)			Rating		Cross Check
	Raw SCI	Average SCI from expert opinion	Predicted SCI =1.0534x-5.1944	Visual Inspection (Expert)	Predicted Rating (From predictive equation)	✓ = matched, x = not matched
56	52.86	47.5	50.49	Fair	Fair	✓
57	43.69	47.5	40.83	Fair	Fair	✓

CONCLUSIONS AND RECOMMENDATIONS

This research work addresses the urgent need for improved pedestrian infrastructure in Dhaka by assessing sidewalks across 58 segments along key routes. With input from experts, 28 distinct major problems related to sidewalks were identified, and each problem was assigned a weight for evaluation. Extensive videography and field surveys were conducted to gather comprehensive data. Identification of the top eight hazardous areas required detailed surveys and varied calculations, resulting in a calibrated Sidewalk Condition Index (SCI). This calibrated SCI provides categorized insights, ranging from excellent to poor, into sidewalk conditions based on distress severity and density. This study proposes a robust sidewalk management strategy, filling a gap in existing city corporations, with outlined policies for construction, rebuilding, and maintenance. A five-year planning term for sidewalks is advocated, along with a future evaluation strategy to enhance city policies. To implement these recommendations, it is advised to conduct a complete survey using the outlined SCI protocol, prioritize findings, and analyze costs for each segment. The research serves as a valuable guideline for identifying maintenance needs, enhancing safety, and planning standard sidewalks. Allocating a proper budget could ensure a safe pedestrian environment in Dhaka within a few years, addressing the identified problems and necessary developments.

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Effects of Electric Scooter Sharing on Users' Travel Behavior and Urban Mobility Patterns

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ABSTRACT

Electric scooter sharing has emerged as a promising and environmentally friendly alternative for short-distance urban mobility. This research paper aims to analyze the travel patterns and accessibility impacts of electric scooter sharing in low-income neighborhoods of Chicago. Geographic information system (GIS) was used to conduct a spatial analysis of scooter sharing station locations, transportation infrastructure, and socio-economic indicators. The methodology involves data collection on scooter sharing station locations and socio-economic factors, followed by travel pattern analysis. Thematic maps are created to visualize the spatial distribution of scooter sharing stations and identify gaps in service coverage. Network analysis tools are used to assess the accessibility of scooter sharing services in relation to public transit stops and essential destinations. Statistical modeling is employed to evaluate the relationship between scooter sharing adoption and socio-economic factors in low-income neighborhoods. The results reveal insights into travel patterns and accessibility impacts, indicating areas of high scooter sharing demand and potential expansion opportunities in underserved communities.

Keywords: Electric Scooter Sharing, Travel Behavior, Mobility, Lime, Bird, Spin

INTRODUCTION

Electric scooter sharing has emerged as a promising alternative to traditional modes of urban mobility, offering a convenient and environmentally friendly transportation option for short-distance trips. Electric scooter sharing has experienced a remarkable growth trajectory over the past decade, driven by advances in battery technology, the rising popularity of micro-mobility options, and the proliferation of smartphone applications. In 2016, the first wave of electric scooter sharing services emerged, with companies like Bird and Lime launching dockless electric scooters in U.S. cities (Hamer, 2018). These services allowed users to locate, unlock, and rent electric scooters through smartphone apps, providing a flexible and convenient mode of transportation for short trips within urban areas.

One of the key advantages of electric scooter sharing is its potential to reduce greenhouse gas emissions and improve air quality in cities. Electric scooters produce zero tailpipe emissions, unlike gasoline-powered vehicles, contributing to the mitigation of air pollution and the fight against climate change (Fishman, et al, 2019). Furthermore, the compact size and energy efficiency of electric scooters make them an ideal solution for last-mile connectivity, reducing the reliance on private cars and promoting sustainable transportation modes.

Electric scooter sharing has emerged as a viable and sustainable urban mobility solution, offering convenient and environmentally friendly transportation options for short-distance trips.

While challenges such as safety concerns and regulatory frameworks persist, the potential benefits of electric scooter sharing cannot be ignored. As cities worldwide continue to grapple with the complexities of urban transportation, electric scooter sharing services hold the promise of reshaping mobility patterns, reducing congestion, and contributing to a more sustainable future.

While electric scooter sharing holds great promise, it also presents challenges and concerns that need to be addressed for its successful integration into urban transportation systems. One prominent challenge is the issue of safety, as studies have reported an increase in injuries and accidents associated with electric scooters (Bauer, 2020). The lack of dedicated infrastructure for electric scooters, combined with inexperienced riders and conflicts with pedestrians, has raised concerns about the overall safety of these services.

The rapid deployment of electric scooter sharing services has highlighted the need for comprehensive regulatory and policy frameworks to ensure their safe operation and integration into existing transportation systems. Cities worldwide have responded by implementing various regulations, including speed limits, parking restrictions, and licensing requirements for scooter operators (Rios-Torres, 2021 & Freud, 2019). Striking the right balance between promoting innovation and safeguarding public safety remains a critical challenge for policymakers.

Despite the challenges, electric scooter sharing presents opportunities for integration and collaboration with existing transportation modes. Many cities are exploring the integration of electric scooters with public transit systems, creating seamless multi-modal journeys for commuters (Shaheen et al, 2019). Furthermore, a collaboration between electric scooter sharing companies and local authorities can lead to the collection of valuable data, enabling evidence-based decision-making and the optimization of urban transportation networks.

The rapid growth of electric scooter sharing services in urban settings has transformed the landscape of urban mobility, offering a convenient and sustainable transportation option for short-distance travel. As these services continue to expand globally, it becomes crucial to understand their impact on user travel behavior and overall mobility patterns. In recent years, electric scooter sharing has witnessed a significant surge in popularity and adoption. Companies like Lime, Bird, and Spin have emerged as major players in the industry, providing on-demand electric scooters that can be easily rented and used for short trips within cities. The adoption of electric scooters for shared mobility purposes has grown exponentially, with a substantial increase in the number of trips made using these services (Aljadani & Shakhatreh, 2022).

Electric scooter sharing services have the potential to influence user travel behavior in several ways. First, they offer a convenient and flexible mode of transportation for short-distance trips, allowing users to bypass traffic congestion and reach their destinations quickly. Studies have shown that electric scooters are primarily used for trips that are too long to walk but too short to drive or take public transit (Shaheen, et al, 2021). This suggests that electric scooter sharing can complement existing transportation modes and fill the gap in the urban transportation network.

The introduction of electric scooter sharing services has also led to a shift in modal choice and travel patterns among users. A significant proportion of electric scooter trips replaced car trips, contributing to a reduction in private vehicle usage and associated emissions (Zhang & Shaheen, 2020). This finding highlights the potential of electric scooters as an eco-friendly alternative to conventional modes of transportation, especially for short trips.

Several factors contribute to the adoption and use of electric scooter sharing services. Convenience, affordability, and accessibility are among the key factors driving users to choose electric scooters over other modes of transportation (Chen et al, 2021). Additionally, the availability of electric scooters in close proximity to users' starting locations and the ease of unlocking and paying for the service through mobile applications play a crucial role in encouraging adoption and regular usage.

The rapid growth of electric scooter sharing services has transformed urban mobility, offering a convenient and sustainable transportation option for short-distance travel (Baek et al, 2021). This research paper aims to analyze the impact of Electric Scooter Sharing on travel behavior and mobility, contribute to the understanding of the role of electric scooter sharing in urban transportation, and inform future policy and planning decisions. To achieve this goal, the research will adopt the following objectives:

1. Conduct a comparative analysis of the activities of the various scooter vendors around Chicago, especially focusing on Lime, Bird, and Spin;
2. Analyze whether a relationship exists between scooters vendor's commuting time and patronage; and
3. Contribute to the understanding of the role of electric scooter sharing in urban transportation and inform future policy and planning decisions.

METHODOLOGY

In an attempt to conduct a comprehensive analysis of Electric Scooter services in the Chicago area, to analyze the travel behavior and urban mobility pattern. The research focused on three electric scooter service providers in the area; they are Lime, Bird, and Spin. Secondary and Primary data were fundamental to the execution of the analysis. The secondary data was sourced from the official database of the United States on transportation. The obtained data shows the coordinates of the three selected electric Scooter service provider trip analysis, while the primary data involves all Geospatial maps, to display travel behavior of commuters, and spatial distribution of the electric scooter vendor trip across the city.

The coordinates obtained reveal the transportation characteristics across the city, which show the trip distance, trip duration, the trip start-up location and where the trip was terminated, trip distance and duration. Furthermore, the obtained data reveal the number of trips by date, the days of the weeks with the recorded highest trip, the weeks with the highest trips.

The obtained data was helpful in undertaking a spatial analysis of the services distribution across the study area, with a view to analyzing and comparing the services provided by the three selected electric scooter vendors. Thereafter, the data was subjected to descriptive and exploratory analysis. Exploratory data analysis is detailed by means of visualization and by drawing insight from the visualized analysis obtained from the data. The method of visualization is made by comparing variables alongside one another. The data was further subjected to regression analysis. Regression is used to analyze several variables when the focus is on the relationship between a dependent variable and one or more independent variables, which was instrumental to analyzing scooter vendor commuting time and patronage.

Table 1 presented below reveals the holistic view of the trips provided by the three sampled scooter service providers, the information captured starts from the 9th of January, 2020 to 30th of September, 2020. The information also reveals the total trip distance for the period under study, and the trip duration. The table reveals out of the total trip of 569,812,325, 569,810,840 which amounts to 99.99976%, was commuted using SPIN, while 869, which amounts to 0.00013% was commuted using LIME, while 616 which amounts to 0.000011 was commuted while using BIRD. The table thus reveals majority of the scooter trips are commuted using SPIN as presented on Table 1.

Table 1. Tirps' Information

S/No	Vendors	Trip distance	Trip duration	Percentage of trip Distance	Percentage of Duration
1.	SPIN	569,810,840	171,271,940	99.9997	99.99976
2.	LIME	869	222	0.0002	0.00013
3.	BIRD	616	190	0.0001	0.00011
	TOTAL	**569,812,325**	**171,272,352**		

Comparative analysis of scooter vendors' trips to visualize areas with high and low trip concentrations across Chicago

Table 2 presented above reveals the comparative analysis of all obtained data from the three sampled scooter vendors; four types of fundamental data were obtained, which include the distance traveled by various scooters within the sampled period, the trip duration, the start community, and the end community, respectively. In order to provide a holistic view of the sampled variables' trip distance and duration, a descriptive analysis was carried out, which includes Minimum, Maximum, Sum, Mean, Standard Deviation, Skewness, and Kurtosis Test.

Table 2: Descriptive Statistics Table

	N	Minimum	Maximum	Sum	Mean	Std. Deviation	Skewness	Kurtosis
SPIN								
Trip Distance	1609	2	35227	7172408	4457.68	5323.810	2.606	8.262
Trip Duration	1609	0	49838	2692724	1673.54	2570.881	6.062	80.830
Start Community Area Number	1609	1	77	36006	22.38	22.420	1.221	.205
End Community Area Number	1608	1.00	77.00	35850.00	22.2948	22.11511	1.223	.244
BIRD								
Trip Distance	2039	1	40149	8254363	4048.24	5258.821	2.568	8.462
Trip Duration	2039	10	11121	2411446	1182.66	1455.047	2.534	7.863
Start Community Area Number	2039	1	77	45820	22.47	21.503	1.299	.763
End Community Area Number	2038	1.00	77.00	45232.00	22.1943	21.13794	1.321	.890
LIME								
Trip Distance	3309	1	26333	7144393	2159.08	2801.829	2.266	7.456
Trip Duration	3309	7	7792	4160192	1257.24	1497.502	2.153	4.938
Start Community Area Number	3301	1	77	70072	21.23	15.598	1.431	2.012
End Community Area Number	3295	1.00	77.00	69339.00	21.0437	15.67625	1.443	2.057

Source: Researcher output, 2023

The table 2 presented below reveals the mean value of the variables, the mean is commonly called the average, which is a mathematically computed value that represents a central value of a given dataset, and the mean is computed by adding all the data values together and dividing by n; and the mean value of the variables is presented as SPIN (4457.68), BIRD (5258.821) and LIME (2159.08).

The **standard deviation** is a measure of dispersion and gives us a way to describe where any given data value is located with respect to the mean, and the variable has a standard deviation as follows: SPIN (5323.810), BIRD (4048.24) and LIME (2801.829). The table also reveals the data for the **skewness test**: the SPIN has a value of (2.606), BIRD (2.568), and LIME (2.266).

Kurtosis measures the existence of outliers. Kurtosis is a measure of whether the data are heavy-tailed (profusion of outliers) or light-tailed (lack of outliers) relative to a normal distribution. The Kurtosis of the analysis is presented as follows: SPIN (8.262), BIRD (8.462) and LIME (7.456).

The analysis reveals (Tables 3 and 4) that BIRD has the highest trip distance of 39.47% of the total trip made by the various vendors, followed by SPIN with 34.64% of the maximum trip, while the LIME maximum made the minimum trip with 25.89% of the total trip made. Also, BIRD has the highest sum trip distance, followed by SPIN and LIME in that order. In the same vein, SPIN has the highest trip duration with 72.49% of the maximum trip of the entire duration, followed by BIRD with a maximum trip duration of 16.18%, and LIME has the lowest value of 11.33%, respectively. However, BIRD has the highest sum trip duration of 97.67%, followed by SPIN with a 2.02% value, followed by LIME, which possesses the lowest value of 0.32%, respectively, as indicated in Figures 1, 2, 3, 4, and 5.

Table 3: Summary of Descriptive Statistics Table

	DESCRIPTIVE VARIABLES	**SCOOTER VENDORS**		
S/No		**SPIN**	**BIRD**	**LIME**
1.	Maximum Trip Distance	35227	40149	26333
2.	Sum Trip Distance	7172408	8254363	7144393
3.	Mean Trip Distance	4457.68	4048.24	2159.08
4.	Maximum Trip Duration	49838	11121	7792
5.	Sum Trip Duration	2692724	2411446	4160192
6.	Mean Trip Duration	1673.54	1182.66	1257.24

Source: Researcher output, 2023

Table 4: Percentage of Trip Distance and Trip Duration by Various Scooter Vendors

	Spin	**Bird**	**Lime**
Maximum Trip Distance	34.64	39.47	25.89
Sum Trip Distance	31.78	36.57	31.65
Mean Trip Distance	41.80	37.96	20.24
	Spin	**Bird**	**Lime**
Maximum Trip Duration	72.49	16.18	11.33
Sum Trip Duration	2.02	97.67	0.32
Mean Trip Duration	84.74	2.01	13.25

Source: Researcher output, 2023

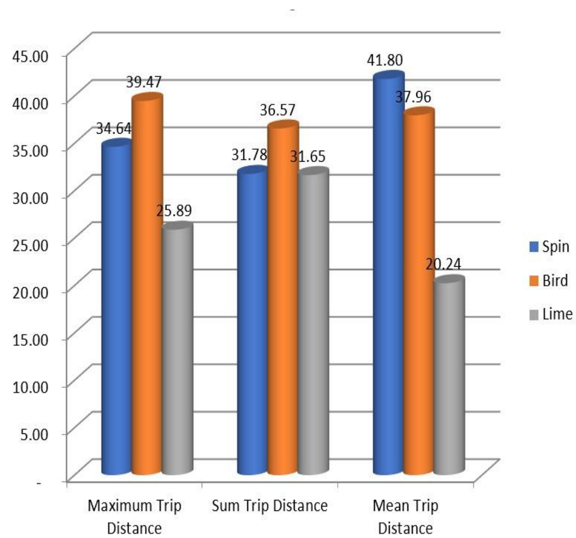

Figure 1: Trip Distance by sampled scooter vendors

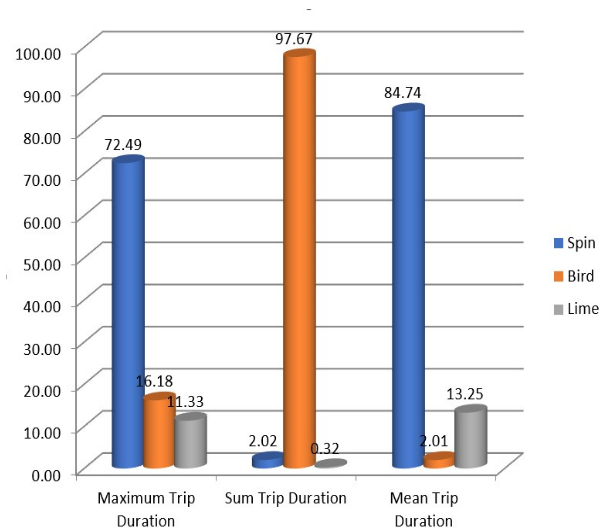

Figure 2: Trip Duration by sampled scooter vendors

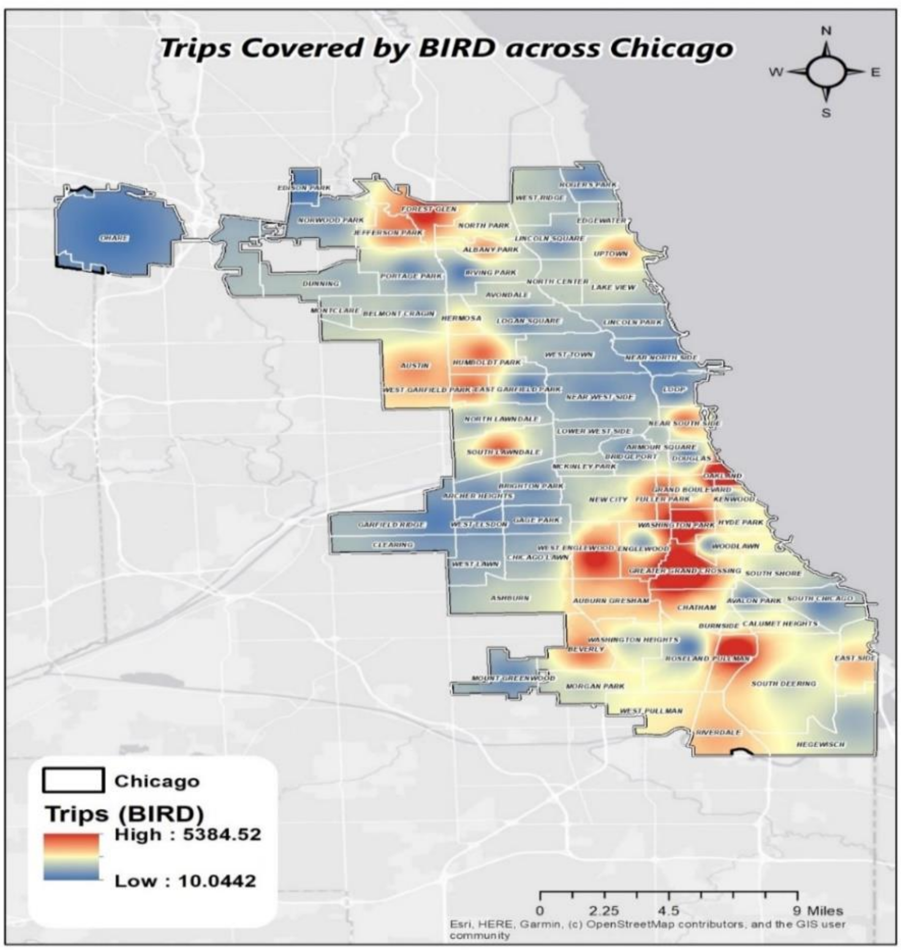

Figure 3: Graphical representation of BIRD Service coverage across Chicago

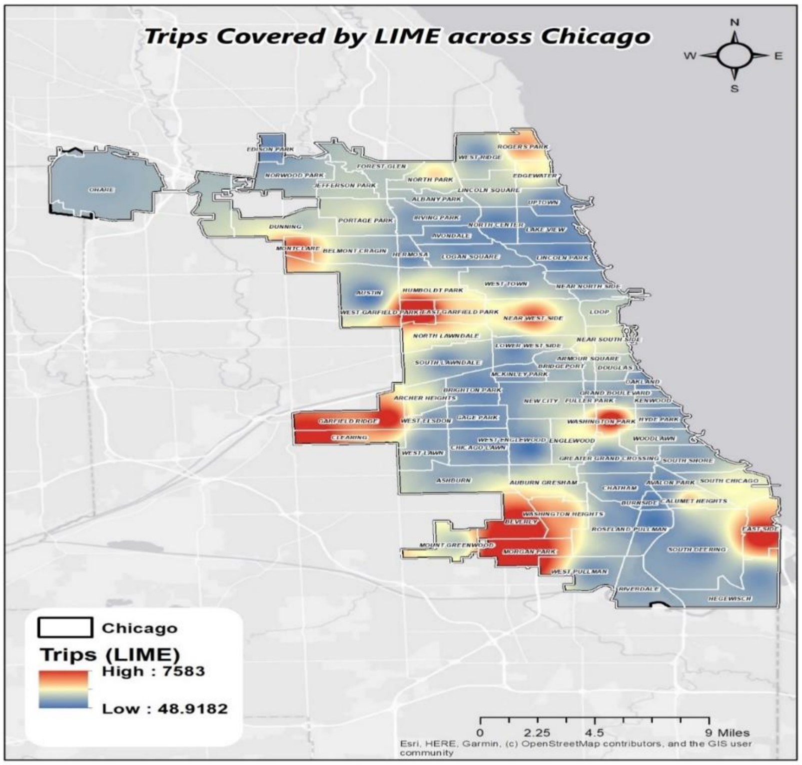

Figure 4: Graphical representation of LIME service coverage across Chicago

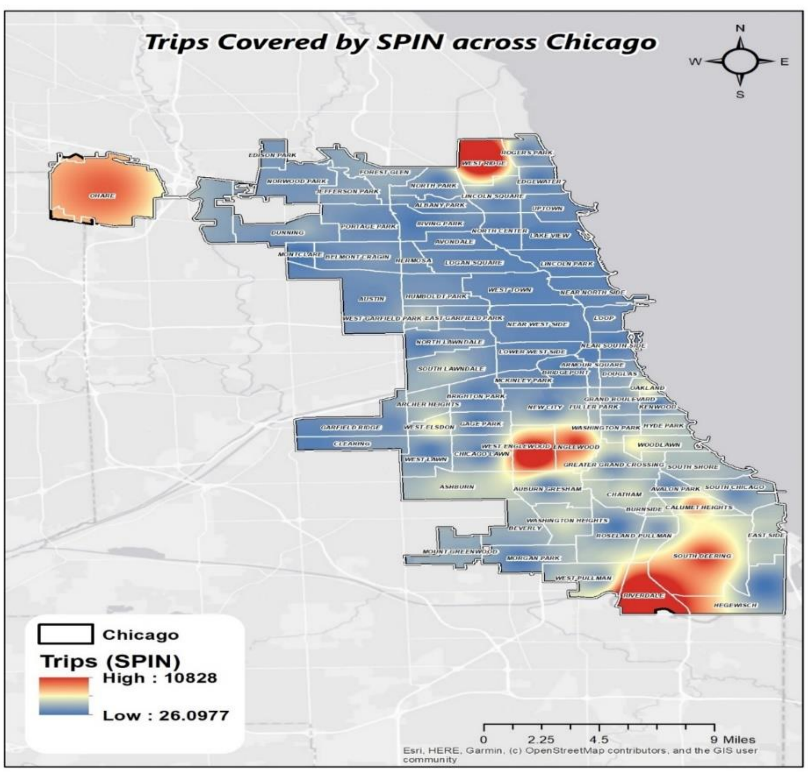

Figure 5: Graphical representation of SPIN service coverage across Chicago

Regression Analysis

R2 Score: The R2 score measures the proportion of the variance in the target variable that can be explained by the model. It ranges from 0 to 1, where 1 indicates a perfect fit. A higher R2 score indicates that the model has captured more of the variability in the data. Since our R2 score is >0.5, it can be concluded the model has captured more of the variability in the data.

Table 5: Regression Analysis Table

	Vendor	R	R-Square	F-Statistics	Significance
1	**SPIN**	.826	.682	1145.149	.000[b]
2	**BIRD**	.839	.705	1618.320	.000[b]
3	**LIME**	.639	.408	755.501	.000[b]

Since R^2 measures the fit of the model, results show that this model is highly fitted, i.e., the data is fitted well with an R^2 value of SPIN (0.682). It can therefore be concluded that holding all variables constant, a percentage shift in trip duration in SPIN will result in 68% of changes in support of the SPIN scooter vendor, while 32% are determined by other changes with variables outside the trip duration. BIRD has an R-Square value of (0.705). Therefore, holding all variables constant, a percentage shift in the trip duration of BIRD will result in 70% changes in support of the BIRD scooter vendor, while 30% is determined by other changes of the variables outside the model and LIME (0.408). It can therefore be concluded that holding all variables constant, a percentage shift in the trip duration of LIME will result in 40% of changes in support of the LIME scooter vendor, while 60% is determined by other variables outside the model.

Table 5 shows that the F-statistics for SPIN is 1145.149, BIRD is 1618.320, and LIME is 755.501. The p-value will be significant in reaching a conclusion to determine if a relationship exists between scooter vendors' commuting time and patronage. This will be tested using the p-value. The analysis shall be considered significant if the significance value is less than 0.05 (p-value <0.05). Hence, the commuting time is considered significant for all the scooter vendors as they all have a p-value less than 0.05.

DISCUSSION

The research conducted a comparative analysis of the activities of all scooter vendors around the Chicago area, including Lime, Bird, and Spin. The data analysis established that the BIRD scooter vendor has the highest distance cover of 39.4% of the total trip recorded over the period under study BIRD has the highest sum trip distance, followed by SPIN and LIME in that order. In the same vein, SPIN has the highest trip duration with 72.49% of the maximum trip of the entire duration, followed by BIRD with a maximum trip duration of 16.18%, while LIME has the lowest value of 11.33%, respectively. It can be concluded the LIME scooter vendor recorded the lowest service in the area during the period under study.

The map analysis presented above reveals the activities of the BIRD scooter vendor trip across Chicago, with a majority of its services concentrated in the Forest Glen and Jefferson Park areas of the city to the north, along with Austin, Humboldt Park, Austin, and West Garfield Park to the west, Greater Grand Crossing, Washington Park and West Engle Wood to the east, and Roseland Pullman to the south, respectively. The activities of LIME scooter vendor has the majority of its activities prominently located in the West at Garfield Ridge, Clearing, Humboldt Garfield Park, and also to the west at Beverly, Morgan Park and Washington Heights, respectively, and has little of its activities dominating in Washington Park. The SPIN scooter vendor has its services concentrated at specific locations such as O'Hare to the west, West Ridge to the north, West Engle Wood to the Central and South Deering and Riverdale to the South, respectively. The map analysis thus shows that the BIRD scooter vendor has a larger concentration of its services across Chicago compared to its two other counterparts.

The significance statistics reveal that there is a significant relationship between scooter vendors' commuting time and patronage. This was evident from the p-value of less than 0.05 (p-value <0.05). Therefore, the scooter service vendor's commuting time is highly significant in the commuter scooter vendor choice and patronage. Thus, these align with the study of *(10)*, who analyzed the shared scooters potential feeder solution for the public transport system, in which a flexible transportation mode will enhance the commuter's mobility and patronage.

SUMMARY AND CONCLUSION

Shared e-scooter services are considered an eco-friendly mode of commuting, and have helped reduce the environmental impact of conventional modes of transportation, which has been a global concern. This research revealed that most of these scooter services are concentrated in central city cores where there is efficient transport accessibility, hence, the service needs to be promoted in other suburbs, to promote awareness among potential users. This can further be encouraged through the subsidization of this type of trip by offering discounts and loyalty programs for regular users, which can increase the attractiveness of such services. The integration of the different shared services operating in the same city on a common platform, as being currently adopted in parts of Chicago, should be sustained and promoted in the entire region to aid efficient service delivery. Through the app, users have the avenue to check the location of available scoters from various vendors on a single map. Once a scooter is selected, the user will be directed through the app to the provider of the scooter. It is also important to note that the spread of the service needs to be controlled, as an uncontrolled spread of the scooter service in cities may further increase the pressure on transportation infrastructure and urban space, thereby creating conflicts with pedestrians and other vehicular activities. Hence, authorities and operators need to pay adequate attention to the interaction between e-scooters services and pedestrians. There is also a need to offer scooter driving education that should enhance the safety of micromobility vehicles. Finally, autonomous rebalancing, according to predicted demand, could increase the usage rates and provide higher levels of service with smaller fleet sizes, as this will provide complete door-to-door trips even at the origin, which would remove the access cost and make the micromobility service more attractive.

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Factors Associated with Motorcycle Fatalities in the US: State-Wise Analysis

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ABSTRACT

Motorcycle fatality rates in the US in 2018 and 2019 based on vehicle miles travelled were 28 times greater than passenger car fatality rates. The objective of this study was to evaluate how socio-economic characteristics, law enforcement, weather-related factors, road-related characteristics, and rider-related factors in each state of the US were associated with motorcycle fatalities in the 2018–2019 period. A multiple linear regression model was developed with a 90% confidence level ($p < 0.1$), and per capita alcohol consumption, annual average temperature, helmet law, percentage of the population aged 25 and over who have completed a bachelor's degree or higher, per capita personal income, percentage of people holding a valid driving license, and overall percentage of acceptable road miles variables were statistically significant in the model with an R-square value of 0.694. These findings would be useful to improve the awareness of motorcycle riders, passengers, and other motorists to improve traffic safety.

INTRODUCTION

Motorcycle fatalities account for 28% of traffic fatalities in the world and it shows an increasing trend annually (WHO 2015*)*. Overall, the cost of motor vehicle crashes was about $340 billion in 2019 in the US, and that cost taxpayers $30 billion (NHTSA 2023). Even though motorcycle registrations account for 3% of total vehicle registrations and 0.6% of total vehicle miles traveled in the US, 14% of total traffic fatalities in 2021 are motorcycle-related (Motorcycles 2023). About 5,500 motorcyclists died and 180,000 motorcyclists were seriously injured in the US in 2020 (Motorcycle Safety 2023). Motorcycle riders are exposed to a wide range of risks on roads (Patel et al. 2019). Compared to other motorists, the likelihood of being involved in a severe crash is 6-13 times higher for motorcycle riders (Halbersberg & Lerner 2019). Compared to car passengers, the likelihood of dying from a crash per mile traveled is 29 times higher for motorcyclists in the US. Figure 1 and Figure 2 show annual motorcycle fatalities in the US during the 2018-2021 period and states with the highest annual motorcycle fatalities in 2021 (Fatality Analysis Reporting System 2023).

Since motorcycle fatalities have become a critical issue in the US, it is essential to identify the factors associated with motorcycle fatalities. The key objective of this study was to identify significant factors associated with motorcycle fatalities in the US based on data from the 2018-2019 period. For a better approach, state-wise data were collected including socio-demographic and economic characteristics, law enforcement, weather-related factors, road-related characteristics, and rider-related factors in each state.

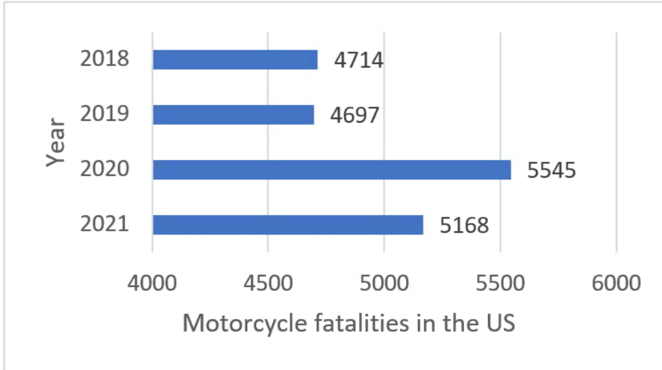

Figure 1. Annual motorcycle fatalities in the US.

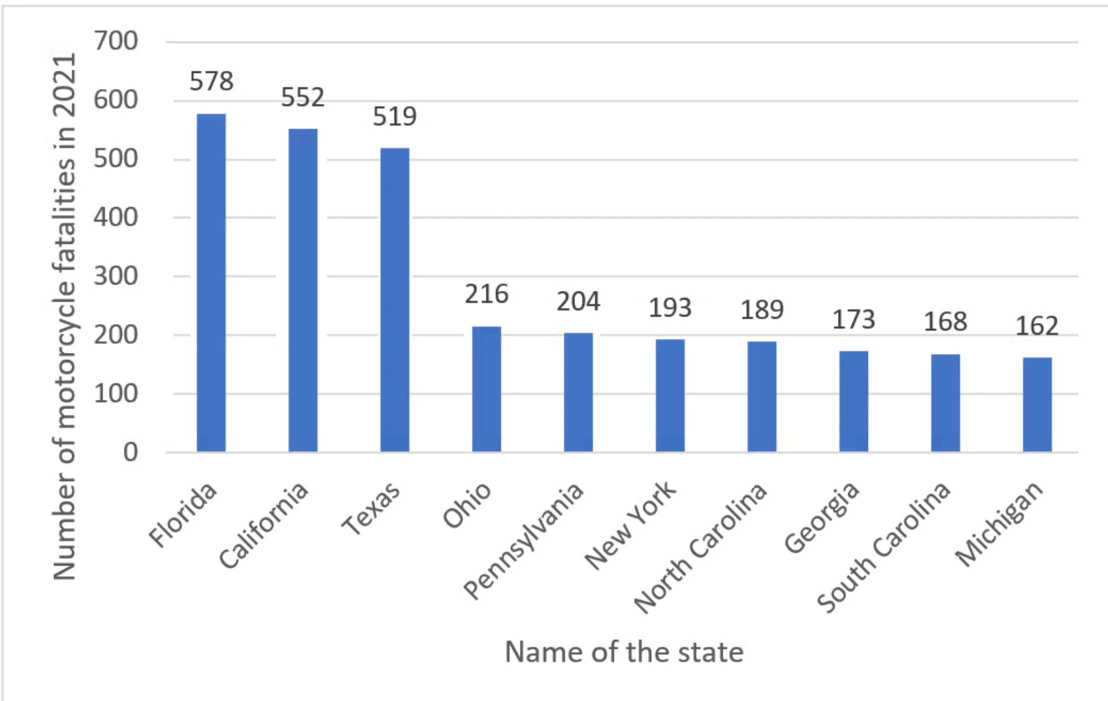

Figure 2. Highest annual motorcycle fatalities reported in 2021 in the US.

LITERATURE REVIEW

The level of injury severity is different in motorcycle-motorcycle collisions and motorcycle collisions with other motor vehicles since motorcycles are relatively small in size and physical characteristics of motorcycles are different (Wang 2022). Motorcycle crash-related factors can be identified as modifiable and non-modifiable and researchers always focus on modifiable factors (Chawla et al. 2019).

In many developing countries, people prefer motorcycles rather than cars due to low operational cost, low fuel consumption, easy maneuverability, and less space requirement for parking (Tamakloe et al. 2022). However, in the US, the opinion of the majority is that motorcycles provide an enjoyable recreational opportunities than cars (Fagnant & Kockelman

2015). Because of that, many motorcycle riders tend to speed up on roads. Speeding is one of the main significant factors which is associated with motorcycle crashes (Yousif et al. 2020). In 2021, 33% of motorcycle fatalities occurred due to speeding in the US and 49% of motorcyclists out of them were in the 21-24 age group (NHTSA 2023). Also, 29% of fatally injured motorcyclists in 2021 in the US had a Blood Alcohol Concentration (BAC) at or above 0.08 grams per deciliter (0.08 g/dL). It is illegal to drive any vehicle with a BAC of 0.08 g/dL or above in all states in the US including Puerto Rico and the District of Columbia, and Utah has more strict rules that do not allow driving when the BAC is at or above 0.05 g/dL (Drunk Driving 2023). Rider distraction is another factor associated with motorcycle crashes (Oregon Department of Transportation 2023). Technology-based distraction becomes one of the key driving distractions that interfere with the attention of the driver and increase the likelihood of occurring a crash (García-Herrero et al. 2021).

Age is a factor associated with motorcycle crashes, that affects the ability to assess risks and safety perceptions of riders (Islam 2021). According to the data of motorcycle-related crashes in the US from 1975 to 2021, fatally injured motorcyclists aged 50 or above have increased from 3% to 35% (Fatality Facts 2023). However, the relationship between the age of the rider and the number of motorcycle crashes is complex, and mixed results can be observed in the literature. The gender of the rider is also a factor associated with motorcycle crashes and it was found that males are engaged in more risky behaviors in riding motorcycles (Fatality Facts 2023). According to the motorcycle crash data in the US in 2021, 96% of motorcyclists who died were males and 92% of passengers who died were females. Motorcycle crashes can end up with the traumatic mortality (Saunders et al. 2019). This mainly happens because of head injuries (Deshapriya et al. 2018). Wearing helmets can reduce the risk of head injuries. In the US, 17 states and the District of Columbia have imposed helmet laws for all riders irrespective of age, 30 states have imposed laws partially that allow motorcycle riders in specific age groups to ride without helmets, and 3 states: Iowa, New Hampshire, and Illinois have not imposed laws to make wearing helmets mandatory (Motorcycles 2023). According to the motorcycle fatality data in the US in 2021, 60% of riders and 46% of passengers were wearing helmets at the time of crash (Fatality Facts 2023).

Road surface characteristics have a significant effect on motorcycle crashes and their severity (Champahom et al. 2023). For example, the possibility of a crash increases on surfaces with potholes when a motorcycle travels at a higher speed. The possibility of occurring motorcycle crashes on rough roads is higher at night when the lighting is inadequate. Mostly in lower-income and middle-income countries, motorcyclists experience critical conditions such as potholes, unpaved road surfaces, and dusty/muddy road surfaces (Wankie et al. 2021). The presence of work zones is another factor associated with motorcycle crashes. Based on the historical data, motorcyclists were associated with more severe injuries and fatalities compared to passenger car drivers in work zones in Florida (Islam 2022). Environmental factors are also correlated with motorcycle fatalities and several researchers have found that extreme hot and cold temperatures and lighting conditions have significant correlations with motorcycle crashes (Abdul Manan et al. 2018, Zare Sakhvidi et al. 2022).

Many researchers have discussed factors associated with motorcycle fatalities through different statistical approaches. However, many studies are specific to a particular county or a state. Also, several socio-demographic and economic factors are underrepresented in the analyses. Even though helmet laws vary from state to state in the US, research studies conducted to find the efficiency of helmet laws in mitigating motorcycle fatalities are limited. This study explored factors associated with motorcycle fatalities through a state-wise analysis that could accommodate more factors into the analysis. Also, this study provides a state-level broader view on motorcycle fatalities that would be useful to make decisions state-level to control modifiable significant factors such as road improvements, helmet laws, etc.

METHODOLOGY

Data Description. In this study, all motorcycle fatality data, and related variables in all 50 states and the District of Columbia in the US were collected for 2 years period from 2018-2019. Table 1 shows the collected data descriptively.

Table 1. Descriptive statistics.

Variable	Variable type	Measure	Min	Max	Mean
Motorcycle fatalities	Count	NA	2	528	92
Log (Motorcycle fatalities per 100,000 population)	Continuous	NA	-0.55	0.46	0.16
Population	Continuous	per square mile	1.1	10,378.7	370.4
Per capita alcohol consumption	Continuous	gallons of ethanol	1.35	4.83	2.5
Annual average temperature	Continuous	Fahrenheit	30.4	78.25	53
Average yearly precipitation	Continuous	inches	9.27	68.35	42.7
Helmet Law	Categorical	0: No laws 1: Partial laws (<18 age) 2: Partial laws (<25 age) 3: Universal law	NA	NA	NA
% of the population aged 25 and over who have completed a bachelor's degree or higher	Continuous	% of the total population aged 25 or over in the state	20.3	57.6	31.2
% of Whites	Continuous	% from the total population of the state	19.61	93.98	70.6
% of African Americans	Continuous	% from the total population of the state	0.35	45.44	11
% of Hispanics	Continuous	% from the total population of the state	1.25	48.18	11.8
Number of all annual property crimes	Count	NA	1,303	921,114	82,373
Total miles of rural roads	Continuous	Miles	0	427,158	118,100.5
Per capita personal income	Continuous	Dollars	38,914	83,406	52,655.5
% of people holding a valid driving license	Continuous	% from the total population of the state	60.13	90.53	71.8

% of older people (65+)	Continuous	% from the total population of the state	10.86	20.66	16.2
% of males	Continuous	% from the total population of the state	44.83	49.45	47.5
Annual Gross Domestic Product	Continuous	in millions of current dollars	33,482.6	3,062,158.9	411,090.05
Unemployment rate	Continuous	% of the labor force from the total population	2.1	6	3.7
Annual motor fuel sale tax collection	Continuous	Dollars	26,268,000	7,557,711,000	1,003,307,902
Overall % of road miles with acceptable road conditions (IRI<170)	Continuous	% of road miles with IRI<170 from total road miles	8.6	94.6	79.5

Motorcycle fatality data in each state for the 2018-2019 period were obtained from the Fatality Analysis Reporting System (FARS) database. It is a nationwide traffic fatality database that provides information to the public, Congress, and the National Highway Traffic Safety Administration (Fatality Analysis Reporting System 2023). Motorcycle crashes can be classified as single motorcycle crashes, multiple motorcycle crashes, and motorcycle versus motor vehicle crashes (Wang 2022). In the study, all motorcycle fatalities were considered in each state. All population-related data were extracted from the United States Census Bureau website. Alcohol consumption data in each state were obtained from the National Institute on Alcohol Abuse and Alcoholism which is operated under the National Institute of Health (National Institute on Alcohol Abuse and Alcoholism 2023). Weather-related information was collected from the National Centers for Environmental Information website. Information on motorcycle helmet laws was obtained from the Insurance Institute for Highway Safety website. Property crime-related data in each state were available on the Federal Bureau of Investigation website. Total miles of rural roads and the number of people having a valid driving license in each state were obtained from the website of the Federal Highway Administration of the US Department of Transportation. Annual Gross Domestic Product (GDP) in each state was available on the Bureau of Economic Analysis website. Rates of unemployment were extracted from the US Bureau of Labor Statistics. Annual motor fuel tax collection in each state and road condition data were collected from the Bureau of Transportation Statistics websites.

Developing the Model. Multiple Linear Regression (MLR) was employed in developing a relationship between the crash rate and associated factors. Here, the dependent variable was motorcycle fatalities per 100,000 population in each state. Predictor variables were the selected factors in each state. The data set consisted of 102 data points for 2018-2019 years including data for all 50 states and the District of Columbia. MLR requires four assumptions to be satisfied before modeling and they are linearity, normality, reliability of measurement, and homoscedasticity (Osborne & Waters 2019). To satisfy the normality assumption, the dependent variable was transformed into its logarithm and used in modeling. All model assumptions were satisfied by the data set. Multicollinearity exists when there are correlations among predictors, and it is important to check multicollinearity in developing statistical models as it leads to unreliable coefficient estimates and weakens model prediction power. Variance Inflation Factors (VIFs) were estimated to check the multicollinearity of predictor variables that were collected over all 50 states and the District of Columbia. VIFs reflect the measure of multicollinearity among observations and VIFs≥10 indicate that multicollinearity exists among predictors

(Shrestha 2020). The Annual GDP variable was omitted from the analysis as it was highly correlated with other predictors. MLR model can be defined as below (Marcoulides & Raykov 2019).

$$y = c + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta_n X_n$$

Where,
y = Log (fatalities per 100,000 population)
c = Intercept
β = Coefficient estimates
X = Predictor variables

Regression coefficients were estimated with a 90% level of confidence. The coefficient of determination (R-squared) was calculated to measure the goodness of fit of the MLR model to the data set. R-squared value can be used as a standard metric to examine the goodness of fit of MLR models in any scientific domain (Chicco et al. 2021). R-squared can be defined as (Chicco et al. 2021),

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(Xi - Yi)^2}{\sum_{i=1}^{m}(\bar{y} - Yi)^2}$$

Where,
X_i = Predicted i^{th} value
Y_i = Actual i^{th} value
$\bar{Y}$ = Mean of the observed data
m = Number of values in the data set

RESULTS AND DISCUSSIONS

Table 2 shows the output of the developed MLR model. According to the model results, 7 variables were statistically significant with a 90% level of confidence. The R-squared value was 0.694 (69.4%) and it indicated a reasonable linear relationship between the dependent variable and predictor variables. The per capita alcohol consumption variable was statistically significant with a 0.049 positive coefficient estimate. It indicates that the number of motorcycle fatalities per 100,000 population in a state increases when the alcohol consumption of that state increases. A study conducted in the US to examine the contribution of alcohol use on motorcycle fatalities found that alcohol use negatively impacted faults, using helmets, and single-vehicle crashes (Sarmiento et al. 2020). Another study found that motorcyclists under the influence of alcohol had a higher probability to involve in crashes compared to alcohol-impaired car drivers (Yang et al. 2021).

The annual average temperature variable was statistically significant with a positive coefficient estimate of 0.008. According to this result, motorcycle fatalities in each state increase when the temperature rises. Similar observations can be found in another study on motorcycle crashes that revealed the frequency of medical attendance increased with short-term exposure to hot temperatures and extreme environmental conditions (Zare Sakhvidi et al. 2022). This may be due to a few reasons. A study conducted on mental health has investigated that hot temperatures could result in a sense of exhaustion, anxiety, and anger leading to risky behaviors on roads (Hrabok et al. 2020). The other reason may be the high usage of motorcycles during periods when rain does not take place. Even though the average yearly precipitation has not become statistically significant in the developed model, the relevant coefficient estimate indicates the likelihood of reducing motorcycle fatalities during rainy seasons. According to the motorcycle fatality data in the US in 2021, motorcycle fatalities that occurred during the June-September months were comparatively higher (Fatality Facts 2023).

Table 2. Results of the developed MLR model.

Variable	Coefficient estimate	P value
Constant	-0.852	0.584
Population per square mile	5.800E-6	0.720
Per capita alcohol consumption (gallons of ethanol)	**0.049**	**0.072**
Annual average temperature (Fahrenheit)	**0.008**	**0.003**
Average yearly precipitation (inches)	-0.001	0.350
Helmet Law	**-0.027**	**0.057**
% of the population aged 25 and over who have completed a bachelor's degree or higher	**-0.010**	**0.007**
% of Whites	0.002	0.127
% of African Americans	-0.002	0.340
% of Hispanics	0.002	0.177
Number of all annual property crimes	-5.199E-8	0.737
Total miles of rural roads	-1.660E-7	0.390
Per capita personal income (dollars)	**-3.733E-6**	**0.087**
% of people holding a valid driving license	**0.006**	**0.016**
% of older people (65+)	-0.004	0.657
% of males	0.006	0.855
Unemployment rate	0.015	0.480
Annual motor fuel sale tax collection	-1.942E-13	0.990
Overall % of road miles with acceptable road conditions (IRI<170)	**0.003**	**0.040**

Wearing helmets is effective for both motorcycle riders and passengers to prevent fatal injuries (Hofmann et al. 2018). A similar result was obtained from the developed model and the helmet law variable was statistically significant with a negative coefficient estimate of (-0.027). It implies that wearing helmets would reduce the motorcycle fatality rate. However, universal helmet law has not been imposed in all states in the US. According to a survey conducted among 127 members/ surgeons of the American Association for the Surgery of Trauma, 82% of surgeons believed that the decision to wear a helmet should not be a personal choice (Hofmann et al. 2018). However, some people resist obeying rules that govern their behavior and believe they should be allowed to do as they please as long as they are not harmful to others (Hook & Rose Markus 2020). Even though many researchers have emphasized the importance of wearing helmets, arguments against helmet laws exist in society.

The percentage of the population aged 25 and over who have completed a bachelor's degree or higher variable showed a statistically significant relationship with a negative coefficient estimate of (-0.010). This result indicates that educated motorcycle riders and other motorists tend to be aware of risky behaviors and avoid them on the road, hence, crashes would be minimized. Also, it can be assumed that people aged 25 and over have a few years of experience in driving. The likelihood of occurring a motor vehicle crash is higher among 16-19 aged teens compared to other age groups (Teen Drivers and Passengers 2023). The education level was found to be statistically significant in road traffic accident mortality rate in a study conducted in Iran (Sami et al. 2013).

Per capita personal income of a state variable was statistically significant in the developed model with a negative coefficient of (-3.733E-6). Per capita personal income is a key indicator in assessing and comparing economic well-being across states and regions in the US (U.S. Bureau of Economic Analysis 2023). This model result can be explained in several ways. Firstly, improved medical care and technology with the economic development of a state could lead to reduced motorcycle fatalities (Law et al. 2009). Secondly, economic development leads to improvement of the quality of political institutions and rules and regulations in road safety resulting in fewer motor vehicle crashes on roads (Law et al. 2009). However, mixed results can be observed in the literature. Increased economic activities could change traffic compositions with increasing numbers of motorists on roads and increased freight movements that could bring a greater risk for motorcyclists (French & Gumus 2014).

According to the model, the likelihood of a motorcycle fatality increases when the percentage of people holding a valid driving license increases in a state. The variable resulted in a positive coefficient of 0.006. This variable indicates that the total number of vehicle riders would increase when the percentage of people holding a valid driving license increases in a state. Hence, traffic crashes and fatalities would be increased, and this applies to motorcycles as well. According to the motorcycle fatality data in 2021 in the US, 61% of motorcyclists who died from fatal crashes had a valid driving license (Fatality Facts 2023). On the other hand, about 39% of motorcyclists have ridden motorcycles without a valid driving license and died in fatal crashes. It has been found that 4.2% of 9 to 11 graders in the US who do not have a valid driving license drove at least 1 hour per week (Fu et al. 2012). Therefore, it can be argued that the number of motorcycle fatalities should be reduced when the percentage of people holding a valid driving license increases in a state. Mixed results can be found in the literature as well. A study found the fact that drivers who did not have a valid driving license were associated with a higher possibility of occurring a motorcycle collision (Lardelli-Claret et al. 2005). Also, unlicensed motorcyclists were identified as a significant factor that contributed to single motorcycle fatalities (Wang 2022).

The overall percentage of road miles with acceptable road conditions variable resulted in a positive correlation with a coefficient estimate of 0.003. Here, acceptable road conditions refer to road surfaces with an International Roughness Index (IRI) of 170 or below. Different results can be found in the literature regarding this variable. One study found that poor road surface conditions with potholes are a cause to improve motorcycle crashes, their injury severity, and fatalities (Tamakloe et al. 2022). Another study found that clean and dry roads were associated with motorcycle fatalities and severe injuries (Santos et al. 2023). Also, motorcycle crashes that occurred in rural areas were higher compared to urban streets. That may be due to two reasons: these roads have higher speed limits and road surface condition is poor compared to urban streets.

CONCLUSIONS

The objective of the study was to identify factors associated with motorcycle fatalities in the US through a state-level analysis based on data from the 2018-2019 period. A multiple linear regression model was developed to find the relationship between the motorcycle fatality rate and predictor variables including socio-demographic and economic characteristics, law enforcement, weather-related factors, road-related characteristics, and rider-related factors in each state. The model resulted in 7 statistically significant predictor variables with a 90% confidence level ($p<0.1$) which are associated with motorcycle fatalities in the US. The motorcycle fatality rate was reasonably explained by the predictor variables with an R-squared value of 0.694. Per capita alcohol consumption, Annual average temperature, Percentage of people holding a valid driving license, and overall percentage of road miles with acceptable road conditions (IRI<170) variables had positive correlations with the motorcycle fatality rate. Helmet law, Percentage of population aged 25 or over who have completed a bachelor's degree or higher, and Per capita personal income variables had negative correlations with the motorcycle fatality rate. These findings would be useful to improve the awareness of risk factors of motorcycle riders and other motorists. As this is a state-level approach, the relevant agencies can make decisions to improve safety measures based on the requirements of a particular state. For example, states where helmet laws are not imposed can give priority to implementing helmet laws. Also, this model approach can be used to compare motorcycle fatality rates in different states.

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Assessment of Emergency Services Accessibility to Universities: A Case Study of Islamabad, Pakistan

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ABSTRACT

Educational institutions often face unforeseen situations that necessitate rapid access to emergency services within their vicinity. However, in larger cities with extensive urban sprawl, universities encounter challenges in accessing healthcare facilities. Therefore, this study aims to analyze the accessibility of emergency care services to universities. The research adopts the gravity model as a framework for assessing accessibility and uses real travel time as the primary dependent variable. The results indicate that universities located in the central area of the city exhibit higher accessibility compared to those situated in the periphery. The results highlight an imbalanced spatial distribution of emergency care services in relation to universities, emphasizing the need for additional measures. The study holds significant implications for decision-makers, enabling them to identify areas with limited accessibility to emergency services and plan for new or relocated emergency care services to meet standard minimum response time. Furthermore, universities are encouraged to integrate the findings into their emergency plans, enhancing their preparedness and response strategies.

Keywords: accessibility, gravity model, emergency services, universities, hospitals, fire brigade, travel time

1. INTRODUCTION

Higher education institutions play a pivotal role in shaping the future of a nation, serving as hubs for intellectual and personal development. The creation of a secure and nurturing educational environment is essential for students' physical and mental well-being, enabling them to actively contribute to society. However, educational institutions worldwide have experienced distressing incidents in recent years that have necessitated the utilization of emergency care services, often resulting in loss of life. Particularly in Pakistan, educational institutions have become prime targets of terrorist attacks, underscoring the urgent need for effective safety and emergency management protocols.

Major incidents in the country exemplify the severity of the situation. In 2009, a suicide blast at the International Islamic University Islamabad (IIUI) resulted in the tragic loss of nine students' lives and caused injuries to 34 individuals (Anwar H.S., 2009). Similarly, the tragic attack on the Army Public School in 2014 led to the grievous loss of more than 141 students, with 131 of them being children (Ismail K., 2014). Furthermore, the Agriculture Training Institute in Peshawar faced an unfortunate incident of a terrorist attack in 2017, resulting in the tragic loss of nine students' lives and inflicting injuries upon 37 individuals (Hassan F. et al., 2017). Moreover, the security challenges persistently manifested in the region. In October 2020, an explosion at a religious school in Peshawar resulted in the fatalities of at least 8 students, while 110 others sustained injuries (Ali A., 2020). These incidents highlight the urgent need to address safety and emergency management in educational institutions, encompassing a spectrum of potential traumas, including but not limited to fires, physical incidents, and terrorist attacks.

Traditionally, two types of emergency responses are employed for such incidents: the involvement of the fire brigade and the dispatch of emergency healthcare services, including ambulances to the incident site and subsequent transportation to hospital emergency departments (Arentze et al., 2019; Higgs, 2009;). Prompt access to emergency services is crucial in optimizing benefits and minimizing harm (Hu et al., 2020). The availability of healthcare facilities and easy accessibility to such services are vital for fostering a healthy community (McGrail & Humphreys, 2009). These aspects collectively contribute to the preparedness and effectiveness of emergency response systems, ensuring the provision of timely and appropriate care in emergencies within educational settings.

Given the pressing need to address safety and emergency management in educational institutions, this research aims to evaluate the accessibility of emergency services for universities in Zone-1 of Islamabad, the capital of Pakistan. By identifying existing inequities in emergency services accessibility, the outcomes of this study would assist city planners and decision-makers in establishing new emergency services at strategic locations or relocating existing ones. Such insights can contribute to enhancing the overall safety and well-being of universities in the area.

1.1 Accessibility

The concept of accessibility, as introduced by Hansen in 1959, pertains to the opportunity for individuals or specific groups to engage in particular activities or sets of activities within a given location (Hansen, 1959). Guers and Wee (2004) further define accessibility as the degree to which a land-use-transport system enables individuals or goods to utilize transportation and reach desired activities or destinations (K. T. Geurs & Van Wee, 2004). Several factors contribute to accessibility, including the spatial distribution of origins and destinations, transportation system performance, characteristics of the transportation infrastructure, and the attractiveness of the destination (Liu & Zhu, 2004). In the context of healthcare, accessibility can be defined as the relative ease of accessing potential healthcare services. Improving accessibility to healthcare facilities is critical for saving lives (Haddad & Mohindra, 2002). Therefore, understanding the accessibility of emergency care services in relation to universities is vital in promoting the well-being and safety of students and staff.

2. RELATED WORK

Research has been carried out to assess the accessibility of emergency services and their response performance, specifically in developing countries. Various factors have been considered in evaluating emergency response performance, including timely response to incidents in rural areas (McGrail & Humphreys, 2009), mitigating congestion in urban areas to improve response times (Knox, 1978), and enhancing ambulance services through reasonable coverage (Higgs, 2009). Various techniques, such as set-coverage, facility location problems, and accessibility analysis using geographic information systems (GIS), have been employed to measure emergency response performance (Higgs, 2009). For instance, Radke and Mu (2000) used a spatial decomposition approach to predict the accessibility to social services and ensure equal opportunities for the public, specifically in underserved areas (Radke & Mu, 2000). Lee (2014) developed a method to analyze the potential accessibility of ambulance services by considering the demand-covered ratio and ambulance-covered ratio. Their findings indicated that urban areas generally had better access to emergency sites compared to rural areas due to factors such as reduced volunteer services and longer travel times (Lee, 2014). Hu et al. (2020) utilized a simulation model to examine the impact of traffic congestion on the spatial accessibility of emergency medical services (EMS) in Shanghai's inner-city. The results indicated a significant reduction in EMS accessibility when traffic congestion was taken into account (Hu et al., 2020).

Access to healthcare facilities and emergency services plays a significant role in alleviating the burden of diseases and maintaining a healthy community (Gulliford et al., 2002). Extensive research has demonstrated that spatial accessibility directly influences the utilization and effective provision of medical services (Delamater et al., 2012; Raza, et. al., 2022). Particularly in low- and middle-income countries, the challenges associated with accessing healthcare can result in severe consequences (Pu et al., 2020). Therefore, it is crucial to estimate spatial accessibility in order to assess disparities in healthcare facility access and develop targeted public health intervention strategies (Wang et al., 2018). Advancements in spatial analysis and the use of geographic information systems (GIS) have led to the development of various accessibility metrics (Gong et al., 2012; Luo & Qi, 2009; Raza & Bham, 2018). These metrics enable researchers to quantify and evaluate the accessibility of healthcare facilities. Among the commonly employed methods are gravity models, which consider factors such as distance and population size to estimate accessibility (Schuurman et al., 2010), and kernel density models, which assess accessibility based on the concentration of healthcare facilities in specific areas (Guagliardo, 2004). These sophisticated analytical approaches have proven valuable in assessing spatial accessibility, providing insights into the distribution and availability of healthcare services within a given region.

A limited number of studies have examined the accessibility of emergency services in relation to educational institutions. For instance, an investigation in North Dakota estimated the accessibility of emergency services to K-12 schools based on different travel time thresholds for two scenarios: overall accessibility, encompassing the route from ambulance services to K-12 schools and then to a trauma center, and quick response service (QRS) accessibility specifically to K-12 schools. The analysis employed a gravity model and found higher accessibility in urban areas compared to rural areas (Motuba & Khan, 2017). In another study by Jie Yin and Yameng Jing (2019), the vulnerability of central schools and educational facilities in Shanghai to urban flooding was assessed in terms of emergency response. The findings showed significant safety concerns for schools and students, even under normal flood conditions (Yin et al., 2019). Similarly, Shah et al. (2018) investigated the emergency preparedness of schools in flood-affected areas of Pakistan. The study highlighted that only a small fraction of schools in the sampled study group had taken measures towards flood preparedness (Shah et al., 2018). These studies shed light on the challenges and deficiencies in emergency response capabilities within educational institutions during various crises, emphasizing the need for improved preparedness and accessibility.

In urban environments, ensuring easy access to healthcare facilities and emergency services remains a significant challenge. Addressing geographical disparities and improving accessibility to healthcare facilities can contribute to reducing mortality rates, preventing epidemics, and mitigating the spread of infectious diseases (Ahmad, 2012). While the availability of quality healthcare facilities is crucial, easy access to such facilities is equally important (Levesque et al., 2013). This study aims to evaluate the spatial accessibility of emergency services to universities in an urban environment, contributing to the understanding of healthcare accessibility and its implications for the well-being of university communities.

3. METHODOLOGY

3.1. Study area and data

The study area for this research is the Zone-1 area of Islamabad. Islamabad is the capital city of Pakistan and is located at coordinates 73.04°E and 33.43°N. Islamabad is divided into five distinct zones, with Zone-1 being further segmented into sectors ranging from Sector D to Sector I. The geographic data (in shape file) of Islamabad were obtained from the Pakistan GIS survey database and subsequently digitized using ArcGIS software. Figure 1 illustrates the delineated study area of Islamabad Zone-1, providing a visual representation of the region under investigation.

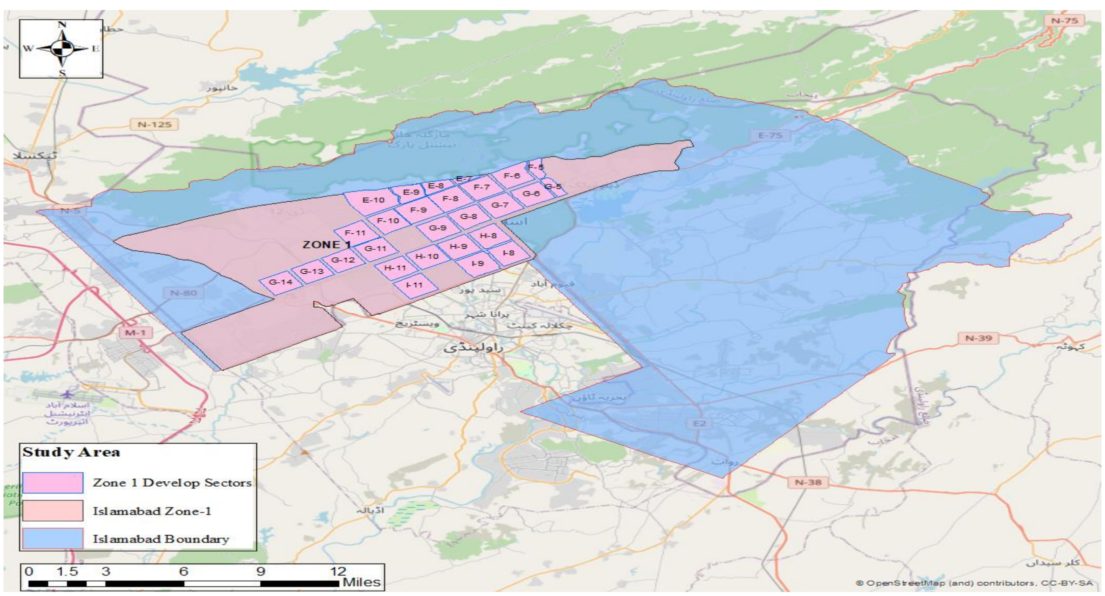

Figure 1. Islamabad Zone-1 Study Area

The study area, Islamabad Zone-1, encompasses several healthcare and emergency service facilities. According to the available data, there are fifteen universities, twenty-six hospitals, five emergency services with ten sub-stations, and one fire brigade with three sub-stations distributed across various locations within the city. The locations of these healthcare facilities, emergency services, and universities were digitized using ArcGIS open street maps as shown in Figure 2 and Figure 3. To establish different levels of hospitals, several factors are taken into consideration. These include the hospital's bed capacity, the presence of seven emergency-related departments (such as accident & emergency, critical care/burn unit, cardiology, orthopedics, general surgery, neurology, and gastroenterology), the number of specialized doctors, and the number of ambulances on-site. The presence and specialization of doctors in fields such as cardiology, neurology, orthopedics, general surgery, and gastroenterology played a significant role in determining hospital levels. Based on the predefined conditions outlined in Table 1, the hospitals were assigned levels ranging from 1 to 5. These levels were assigned attraction factor values of 6, 4, 2, 1, and 0.5, respectively, based on the criteria defined in the literature (Boisjoly et al., 2020; Chen et al., 2015; Motuba & Khan, 2017). In this study, there are 10 Level-I hospitals, 4 Level-II hospitals, 2 Level-III hospitals, 4 Level-IV hospitals, and 6 Level-V hospitals.

Table 1: Hospital Levels Formulation

Sr. No	Bed Capacity	Departments	Doctors	Number Of Ambulances	Hospital -Level	Attraction Value
1	>200	6-7	>25	>10	I	6
2	100-200	4-5	16-25	5-10	II	4
3	50-100	3	10-15	4	III	2
4	21-50	2	5-9	2-3	IV	1
5	1-20	0-1	1-5	0-1	V	0.5

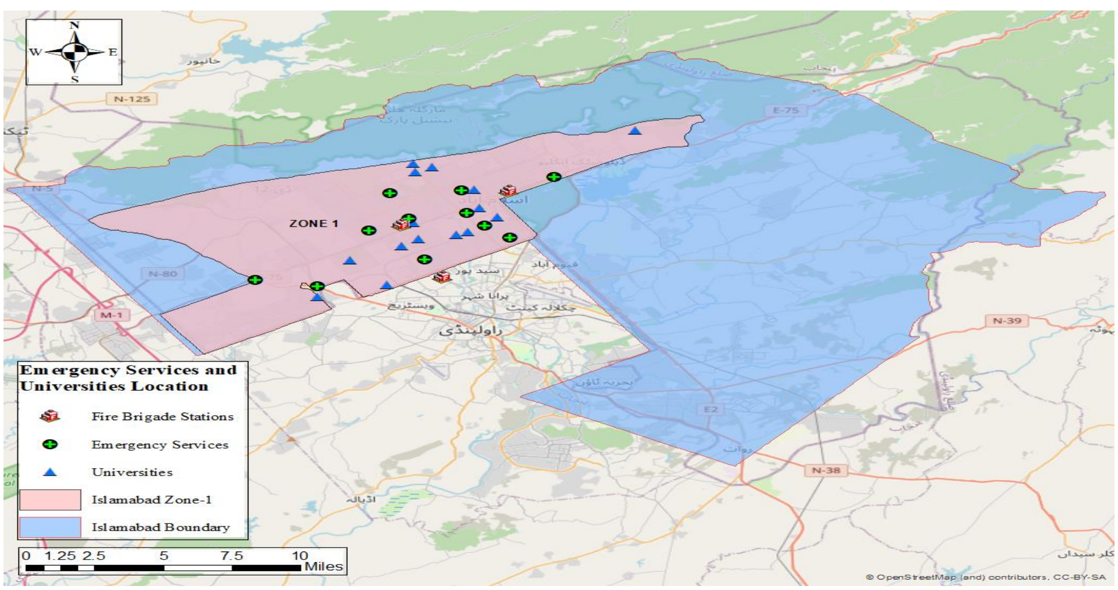

Figure 2: Location of Emergency Services, Fire Brigade Stations, and Universities

3.2. Travel Time Estimation by Online Google Map Application

Traditionally, researchers have relied on the ArcGIS-Network Analyst tool to calculate travel time by considering the distance between the origin and destination and the posted speed limit assigned to each route (Ni et al., 2015; Tao et al., 2014). However, this method has limitations in accurately estimating travel time due to its reliance on arbitrary posted speed limits in practice

(Tao & Cheng, 2019; Raza et al., 2019). In recent years, online map Application Programming Interfaces (APIs) such as AutoNavi map API, Baidu map API, and Google map API have gained popularity for calculating real-time travel time data between origins and destinations (Cheng et al., 2016; Tao et al., 2018). These APIs provide access to dynamic and up-to-date information, allowing for more accurate travel time calculations.

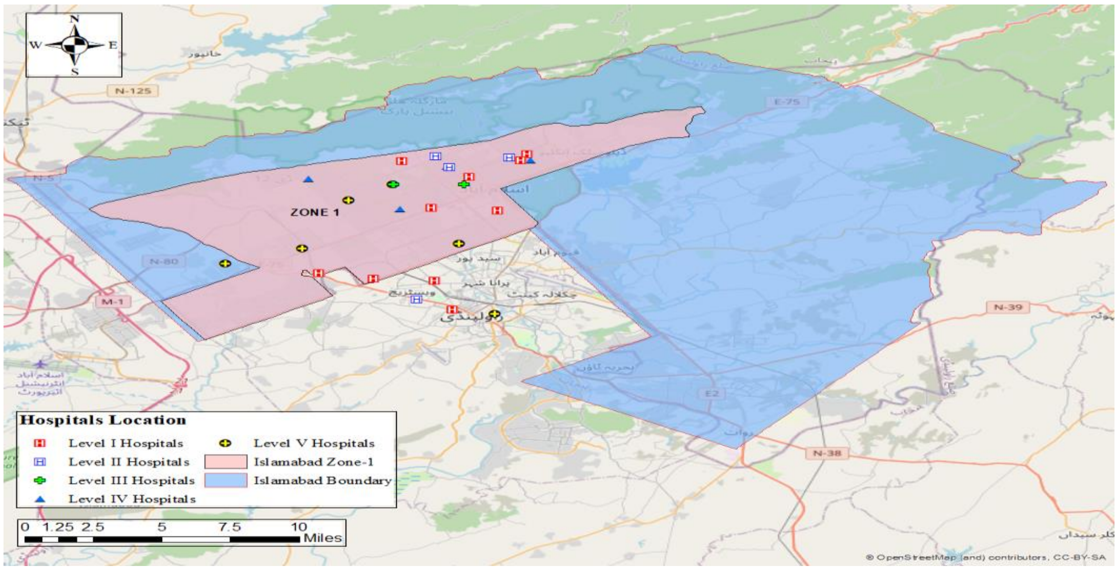

Figure 3: Location of Hospitals in Islamabad Zone-1 and Adjacent Border Area

In this study, the online Google Map API was utilized to estimate travel time during different traffic conditions. Specifically, the car mode of Google Maps was selected to calculate the travel time between 11:00 AM to 1:00 PM on weekdays. This time period was chosen based on the assumption that most of the students, faculty, and teachers would be present inside the university campuses during these hours. To determine the travel time from each hospital, fire brigade, and emergency service location to the universities, the respective origins and destinations were used in the online Google Maps application. In this study, the online Google Map application was employed to overcome the limitations of traditional methods and obtain more accurate and dynamic travel time estimates for the analysis.

3.3. Calculation of accessibility index using gravity model:

Gravity-based method is the most commonly used method to measure accessibility (Song, 1996). Using the gravity model to measure accessibility has two major components: the impedance function, which reflects the accessibility of the transport component, and the opportunity weight, which reflects the accessibility of the land use component (Briceño-Garmendia et al., 2015). The impedance function describes the travel cost from the starting point *i* to the destination *j*, which can be expressed in terms of time, money cost, or other effort measures (K. Geurs & van Wee, 2013). The gravity model can also be adjusted to consider the individual's mode choice and travel distances on the mode-specific networks (Cebelak, 2013). The gravity model accessibility function has been used to access the accessibility measure to medical facilities (Knox, 1978), grocery stores (Handy, 1992), railway stations (Giannopoulos &

Boulougaris, 1989), employment (Cervero et al., 1999; Maria Kockelman, 1997; Niemeier, 1997) and shopping (Bhat et al., 1999; Guy, 1983). The gravity model has been used in this study to estimate accessibility and is described below.

The accessibility of emergency services to a university can be estimated as follows:

$$\mathrm{AU}_i^{ES\rightarrow U} = \sum_{t\leq to} \frac{ES_j}{t^{\beta}} \quad (1)$$

Where $\mathrm{AU}_i^{ES\rightarrow U}$ represents the gravity-based accessibility index of a specific university "i" to emergency services ES_j at location j within a certain travel time threshold value (t_o), and β represents the travel friction coefficient. The travel friction coefficient "β" values of 0.5, 0.7, 1.3, and 1.9 for travel time threshold ranges of 0-8, 9-15, 16-30, and 31-60 minutes, respectively have been used (Chen et al., 2015; Luo & Wang, 2003; Motuba & Khan, 2017).

The accessibility of universities to hospitals can be estimated by using the following formulation:

$$\mathrm{AU}_i^{U\rightarrow H} = \sum_{t\leq to} \frac{L_H . H_j}{t^{\beta}} \quad (2)$$

Where $\mathrm{AU}_i^{U\rightarrow H}$ represents the gravity-based accessibility index of a specific university "i" to hospitals H_j at location j within a certain travel time threshold value (t_o). L_H is the level of the specific hospital accessible in the specified travel time threshold value (t_o).

The overall accessibility index (emergency services to universities and then to hospitals) was estimated as follow:

$$AU_{oi}^{ES\rightarrow U\rightarrow H} = \mathrm{AU}_i^{ES\rightarrow U} + \mathrm{AU}_i^{U\rightarrow H} \quad (3)$$

Where $AU_{oi}^{ES\rightarrow U\rightarrow H}$ represents the overall accessibility of university "i" from emergency services to the university and then to a hospital within a certain time threshold value (t_o).

The accessibility of the fire brigade to universities can be estimated by using the formulation given below:

$$\mathrm{AU}_i^{F\rightarrow U} = \sum_{t\leq to} \frac{F_j}{t^{\beta}} \quad (4)$$

Where $\mathrm{AU}_i^{F\rightarrow U}$ represents the accessibility of university "i" to a fire brigade F_j at a location j within a certain time threshold value (t_o). The accessibility of universities to fire brigade stations was examined in this study to assess whether these fire response services can reach on time in case of a fire incident.

With an increase in travel time the accessibility reduces, so the travel friction coefficient increases with an increase in threshold travel time range. In order to account for different travel coefficients for the different time ranges, the following methodology has been adopted in this study to estimate the accessibility values.

$$AU_{t_{on}} = AU_{t_{o1} \to t_{o2}} + AU_{t_{o2} \to t_{o3}} + AU_{t_{o3} \to t_{o4}} \dots \dots \dots \dots \dots + AU_{t_{on-1} \to t_{on}} \quad (5)$$

Where $AU_{t_{on}}$ represents the accessibility index of a university to emergency care services for the "nth" travel time threshold value, $AU_{t_{o1}}$ represents the accessibility index at the first/initial travel time threshold range settled, $AU_{t_{o1} \to t_{o2}}$ represents the accessibility index between the first and second threshold travel time range settled and so on up to the nth threshold travel time range. The accessibility index will be measured within 0-8, 9-15, 16-30, and 31-60-minute travel time threshold value ranges.

4. RESULTS AND DISCUSSION

The proximity between origins and destinations has emerged as a crucial determinant of accessibility, with travel time serving as a critical indicator of proximity for such origin-destination pairs. In this study, accessibility indexes were calculated for threshold travel times ranging from 0-8, 9-15, 16-30, and 31-60 minutes, specifically focusing on the accessibility of emergency services to universities. Two distinct scenarios were considered for estimating accessibility indexes: (1) overall accessibility encompassing the journey from emergency services to universities and subsequently to hospitals, and (2) accessibility from fire brigades to universities. The estimation of overall accessibility values, representing the journey from emergency services to universities and then to hospitals, was performed and the results are presented in Figure 4.

The findings revealed that the lowest accessibility levels were observed within the 8-minute travel time threshold, with only six universities demonstrating a medium level of accessibility: Bahria University (BAHRIA), Muslim Youth University (MYU), Shaheed Zulfiqar Ali Bhutto Medical University (SZABMU), Allama Iqbal Open University (AIOU), Shifa Tameer-e-Millat University (STEM), and National University of Technology (NUTECH), as illustrated in Figure 4. Subsequently, a slight increase in accessibility was observed within the 15-minute travel time threshold, with five universities achieving very high accessibility levels (BAHRIA, SZABU, MYU, AIOU, and STEM). The Air University (AIR), National Defense University (NDU), National University of Modern Languages (NUML), and Iqra University (IQRA) exhibited high accessibility, while NUTECH and FAST University (FAST) demonstrated medium accessibility to hospitals. Conversely, the remaining universities exhibited low accessibility.

Further marginal improvements in accessibility were observed within the subsequent travel time thresholds of 30 to 60 minutes, with the accessibility of the National University of Sciences and Technology (NUST), Islamic International University Islamabad (IIUI), Riphah University (RIPHA), and Quaid-e-Azam University (QEA) showing signs of improvement. This enhancement of accessibility could be attributed to the accessibility of hospitals located near the border within travel time thresholds exceeding 15 minutes. Generally, accessibility increased with longer travel times, enabling greater access to hospitals and emergency services for the universities. Universities located at the city center exhibited better accessibility compared to those situated on the periphery, except for NUTECH which displayed favorable accessibility despite its peripheral location in Islamabad Zone 1. This exceptional accessibility can be attributed to its proximity to hospitals located at the border in Rawalpindi city. Notably, both

Quaid-e-Azam University and Riphah International University demonstrated low overall accessibility across all travel time thresholds considered in this study.

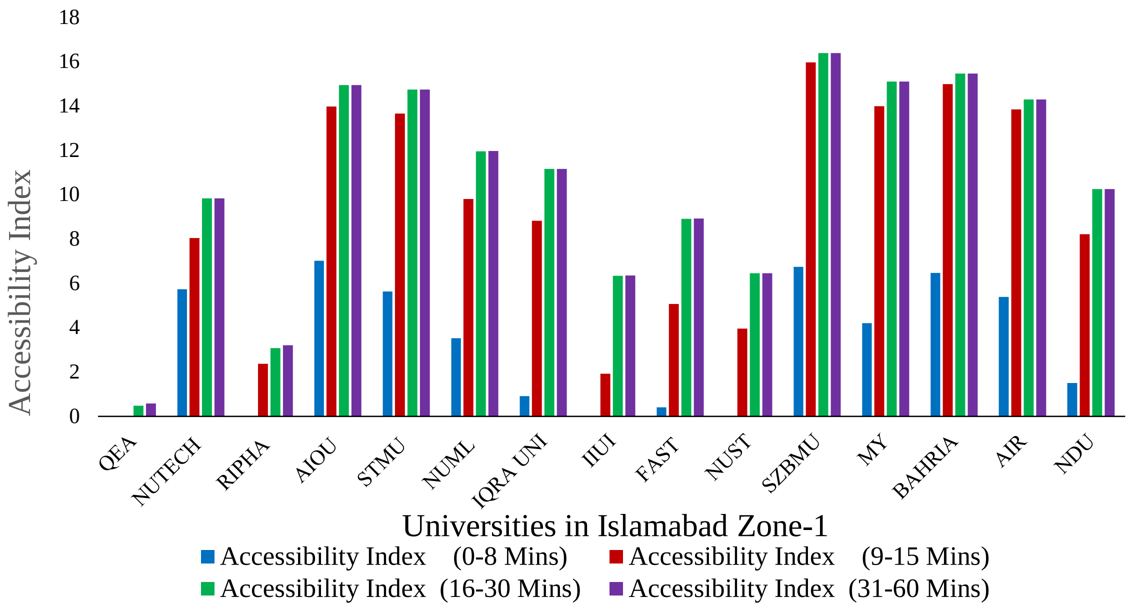

Figure 4: Accessibility of Emergency Services to University and then to Hospitals

Furthermore, the analysis indicates that within the 60-minute travel time threshold, the accessibility of universities to emergency services exhibited improvement. In general, the overall accessibility was relatively better, with only Quaid-e-Azam University and Riphah International University experiencing notably low accessibility levels. It is imperative for the administrations of these universities to implement appropriate measures to address emergency-related incidents and enhance accessibility. By taking proactive steps, such as improving transportation infrastructure or establishing partnerships with nearby emergency service providers, these universities can enhance their emergency response capabilities and ensure the safety and well-being of their students and staff in critical situations.

Similarly, the accessibility analysis results for fire brigade services to universities are presented in Figure 5. Results show that only four universities, namely Allama Iqbal Open University (AIOU), Shaheed Zulfiqar Ali Bhutto Medical University (SZABMU), Shifa Tameer-e-Millat University (STEMU), and Muslim Youth University (MYU), have access to the fire brigade within an 8-minute travel time threshold. Additionally, a majority of the universities demonstrate low accessibility to fire brigade services. Within a 15-minute travel time threshold, the number of universities with access to fire brigade stations increases to seven, including AIOU, SZABMU, STEMU, MYU, FAST, NUTECH, and BAHRIA.

The analysis highlights a changing trend in accessibility as travel time thresholds vary. There is a slight variation in the accessibility index scores between the 15- and 60-minute travel time thresholds. Notably, Quaid-e-Azam University, Riphah International University, National University of Science and Technology (NUST), and the International Islamic University Islamabad (IIUI) are not accessible within the first two travel time thresholds, i.e., 8 and 15 minutes. Overall, the accessibility remains low for all travel time threshold values. Similar to the previous analysis, the accessibility of fire brigade services to universities follows the trend of universities located in the center exhibiting higher accessibility compared to those situated in the periphery of Islamabad Zone-1.

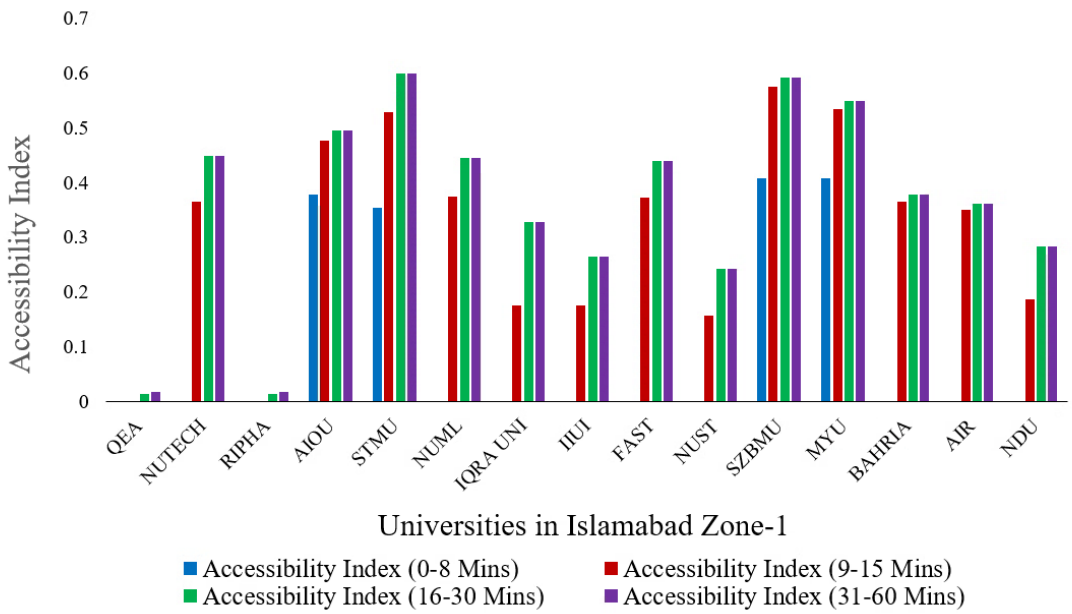

Figure 5: Accessibility of University to Fire Brigade

Results in Figure 5 highlight a concerning situation where only a limited number of universities are accessible within the first two travel time thresholds of 8 and 15 minutes. This poses a significant risk to university administration and policymakers, as it indicates potential challenges in effectively responding to fire-related emergencies within universities. In the event of such emergencies, prompt action becomes crucial, and the current accessibility levels may hinder timely response.

To address this issue, it is imperative for policymakers to prioritize the enhancement of fire safety infrastructure and services. This includes increasing the number of fire brigade stations and strategically locating them throughout the city to ensure improved accessibility to universities. Simultaneously, university administrations must take proactive steps to manage fire-related emergencies internally. By providing necessary fire safety equipment and ensuring appropriate training and awareness programs, universities can enhance their capacity to handle fire emergencies promptly and effectively.

5. CONCLUSIONS

In conclusion, the findings of this study emphasize the spatial disparity in the distribution of hospitals, emergency services, and fire brigade stations within the study area. Universities located in the central region exhibited higher accessibility across all scenarios, while accessibility to emergency services and fire brigade stations was generally lower compared to hospitals. The limited accessibility of fire brigade stations to universities raises concerns regarding the ability to effectively respond to fire emergencies. Policymakers should prioritize the establishment of additional fire brigade stations in strategic locations to ensure timely access to universities. Furthermore, universities situated on the periphery, such as Quaid-e-Azam

University and Riphah International University, require special attention from government agencies and policymakers to provide adequate emergency service units nearby. Overall, while the accessibility indexes of universities to emergency services and hospitals are favorable, there are notable exceptions that call for targeted improvements. It is recommended that university administrations take proactive measures, such as equipping departments with fire extinguishers, to mitigate fire-related risks on campus. By addressing these accessibility challenges and implementing comprehensive emergency preparedness strategies, universities can enhance their resilience and ensure the safety of their students and staff.

This study utilized the gravity model to assess accessibility, yet this method has certain limitations. Assumptions regarding travel friction coefficients, and prioritizing travel time over distance, pose limitations. Moreover, the model assumes a simplistic representation of spatial interactions, disregarding the intricate geographical and topological features that may influence accessibility. Its static nature disregards dynamic changes in transportation networks, land use, and population distributions over time. To enhance understanding, future research is recommended to incorporate topological features like transportation network and connectivity. Additionally, exploring and comparing various accessibility models is recommended for a more comprehensive analysis of emergency service accessibility to universities, ensuring methodological robustness.

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Innovative Funding and Financing Strategies for Enhancing Broadband in Underserved Communities

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ABSTRACT

Many communities have underserved broadband service. With a wide variety of broadband technologies, funding sources, development models (e.g., city-owned, and operated infrastructure with a single internet provider), and revenue models, it is unclear which ones allow broadband to reach underserved and disadvantaged communities. The objectives of this research are to capture the successes and challenges of developing broadband projects and to acquire information about the funding, financing, development, and revenue of different broadband development projects. The approach is comprised of developing and distributing a structured survey that aims to investigate the funding sources, and financing and revenue models utilized for broadband projects, with a critical focus on their success and failure lessons. The survey targeted participants from private and public sectors experienced in broadband projects. A total of 36 responses were collected from 17 states and the District of Columbia. The study identified a broad range of public and private funding sources, as well as the development and revenue models adopted in broadband projects. Moreover, barriers, successes, and strategies for enabling broadband market entry were identified and can be used as lessons learned for future broadband projects. For example, survey results show that private entities own the last mile in most projects which creates the barrier of broadband reaching underserved and disadvantaged communities. However, the results also reveal measures that can be taken to prevent the emergence of broadband monopolies and expand broadband to underserved and disadvantaged communities (e.g., the use of open access networks).

INTRODUCTION

Broadband relies on infrastructure, where the network plays a major part in the markets (Cambini and Jian, 2009). With the significant impact of internet on the economy and society, governments and regulators are more focused on broadband investments than ever before. However, the high cost of developing the middle- and last-miles still creates funding limitations (Katz, R., 2014). The middle-mile is the part of the infrastructure that is not directly connected to the end-users (DOC, 2023). The last-mile is the last part of the network that connects to the end-users (CA GOV, 2023).

The Federal Communications Commission (FCC) has developed an online national broadband map that displays all the US locations where broadband is or could be installed (FCC, 2023). The transparency the map provides pressures internet providers to expand their coverage and helps policymakers target investments to develop broadband in unserved and underserved areas (Rosenworcel, J., 2022). The Infrastructure Investment and Jobs Act (IIJA) defines unserved as locations that have no access to broadband or access to broadband speeds below 25/3 Mbps (Pewtrusts, 2023). The FFC and IIJA define underserved as locations with broadband speeds between 25/3 and 100/20 (FCC, 2018; Pewtrusts, 2023).

A study by the FCC revealed that, in rural areas, less than 69% of Americans have access to both fixed and LTE broadband (FCC, 2018). This is statistically observed in Arkansas, Mississippi, and Montana (BroadbandNow, 2018); they have large rural areas and low broadband access. Despite the critical role broadband has in the growth of economy, investments to deploy broadband services are considered on of the major issues facing the telecommunications sector (Cambini and Jian, 2009; Katz, R., 2014). The high capital costs and low population in rural areas result in a low return on investment (Canfield et al., 2019).

The success of a broadband development project mainly depends on the investment and financial models adopted for the project (Katz, R., 2014). The viability of financing models relies on geography, market, and reliance on debt, equity, or public funds. Innovative infrastructure projects are becoming more challenging, especially with the gap between public needs and available public funding increasing (Zahed et al., 2018[a]). New financial mechanisms may be adopted to expand in rural areas, such as bonds, tax incentives, and rebates (Canfield et al., 2019). Additionally, broadband development projects have no unique financing model; the optimal model will depend on the market it is applied in (Katz, R., 2014). The Broadband Commission has synthesized a large number of financing models for broadband development projects (Broadband Commission, 2021). They can be divided into public financing models (e.g., government operation subsidy, PPP), private financing models (e.g., project bonds, syndicated loans), and community financing models (e.g., community funding). Public-private-partnerships can be suitable for rural areas (Katz, R., 2014). Furthermore, models that involve cost-sharing between competitors may be the only type of models suitable for rural areas.

Additionally, many state and federal programs and funding opportunities keep emerging to address the digital divide. The funding opportunities include the American Rescue Plan Act (ARPA) Capital Projects Fund (CPF), Appalachian Regional Commission (ARC), Through the IIJA, congress has appropriated $65 billion to address the digital divide and ensure accessibility to high-speed internet across the United States (NTIA, 2023; Pipa et al., 2023). States and local municipalities must remain up to date and track the funding opportunities as they emerge (Connected Nation, 2022).

The type of deployed network and contribution (development) models also play a role in broadband development projects. The environment, funding availability, market, and other factors determine which model is suitable for a project (Magellan Advisors, 2015). Development models in this paper refer to the type of network being deployed and each party's contribution to the network (public and private parties). For example, an open-access network may be owned and operated by a private entity or a public municipality. Moreover, a public entity may own the network infrastructure but hire a private entity to maintain and operate the network.

The relationship between regulation and investments in broadband services is a growing concern (Cambini and Juan, 2009). Laws and regulations can positively or negatively influence a firm's telecommunications investment choices and hinder innovative solutions (Cambini and Juan, 2009; Canfield et al., 2019). Furthermore, over-optimism in acquiring subscribers, lack of focus on a business plan, and the project sponsor's lack of commitment contribute to the failure of a broadband project (Katz, R., 2014). The financial model also affects the viability of a project.

The broadband commission has summarized broadband development issues into 4 categories (Broadband Commission, 2021): (1) stakeholders' contribution and involvement, such as lack of initiative and need to improve attractiveness of projects; (2) demand-side issues, such as low affordability of devices and lack of digital literacy; (3) operational hurdles, like high licensing costs and issues with public and private permit acquisition; and (4) other project risks, such as political risk and demand volatility risk. Not meeting the take rate and facing time and cost overruns also risk the success of a broadband project (Loveland Water and Power, 2018).

Additional research related to adoption and management needs to be conducted and surveys are necessary to identify the range of perspectives on broadband investments in rural areas (Canfield et al., 2019). Therefore, the objectives of this research are to capture the successes and challenges of developing broadband projects and to acquire information about the funding, financing, development, and revenue of different broadband development projects.

METHODOLOGY

Based on the literature describing broadband projects and programs, a nationwide survey was created to investigate projects' fundings, financing and revenue models, successes, and failures. Each question had a predefined set of answers which made the survey quick and concise. Participants were also able to provide their own answer for each question if they chose to do so. The questionnaire consisted of x questions organized as follows:

1. Contact information
2. Project location.
3. Respondent position.
4. Type of broadband technology.
5. Middle-mile ownership.
6. Last-mile ownership.
7. Development (contribution) model.
8. Private sector financing models.
9. Public sector financing models.
10. Community financing models.
11. Revenue models.
12. Users' financing support.
13. Measures for enabling market entry of ISPs.
14. Barriers to reaching underserved communities.
15. Measures of success.

Before distributing the survey, the content and protocol of the survey received approval from the University of Texas at Arlington's Institutional Review Board (IRB). The survey was distributed using the online survey questionnaire platform, QuestionPro. The survey reached private and public sector broadband project experts located in many US states.

RESULTS

CTEDD #022-05 project report contains the survey questionnaire as well as the results (Ashuri et al., 2024). Thirty-six responses were collected from seventeen states and the District of Columbia (DC). Twenty-two responses were collected from public sector experts and fourteen responses from private sector experts. Figure 1 illustrates respondents' states, sectors, and positions. Most private sector respondents were chief officers at broadband companies (11 respondents). City managers made up the majority of public sector respondents (7 respondents).

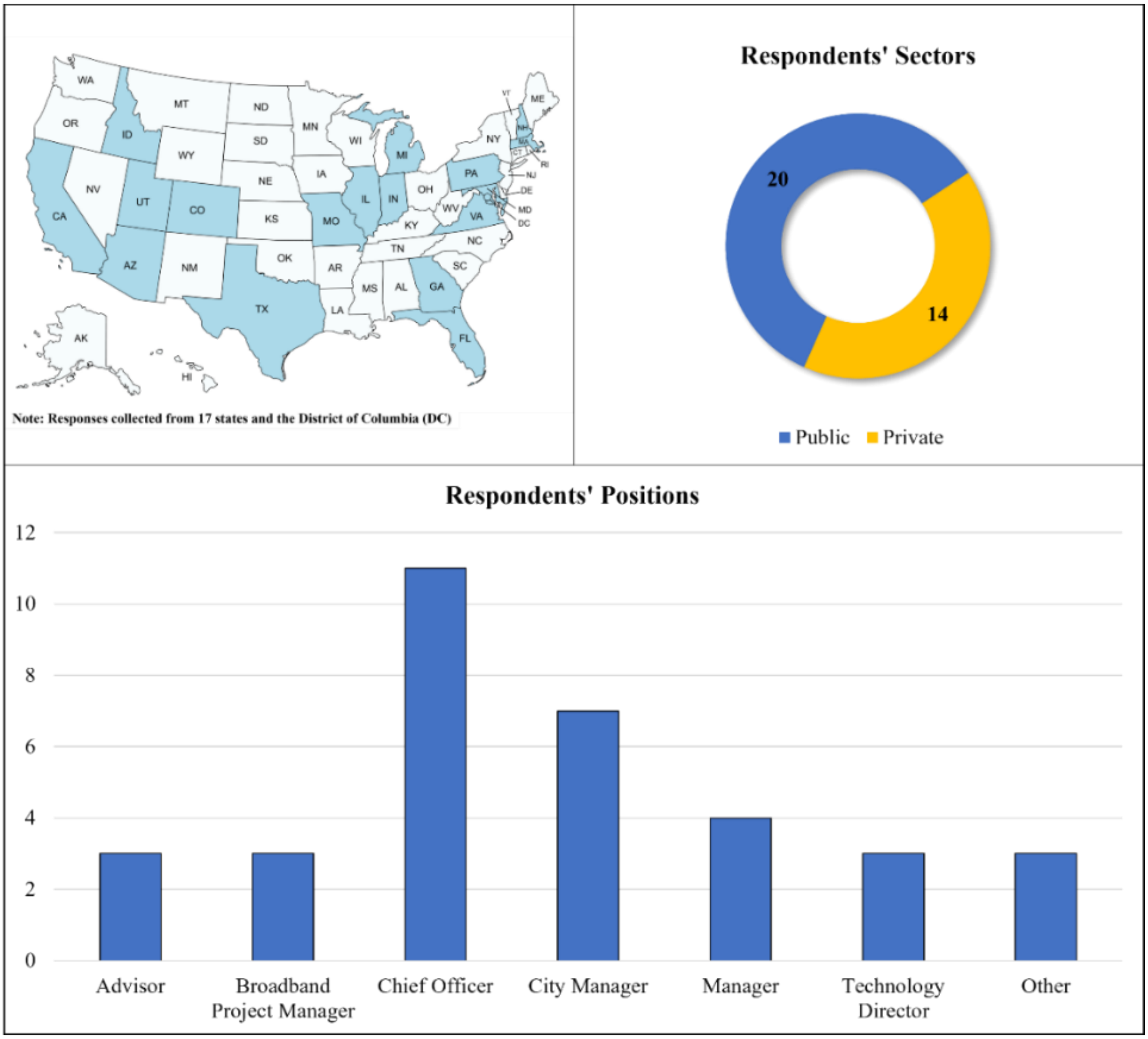

Figure 1. Respondents' states (top left); sectors (top right) and; positions (bottom)

Participants were asked to identify the broadband technology developed or under development in their broadband projects. Table 1 summarizes the projects' broadband technologies. The majority of responses received indicated Fiber to the Home (FTTH) as the broadband technology (25 responses), followed by 7 responses representing Wireless Assets as the project broadband technology. The additional 5 responses received were (1) expansion of existing fiber; (2) fiber to an arena; (3) middle-mile backbone fiber; (4) middle-mile dark fiber; and (5) small cell.

Table 1. Broadband technologies in broadband development projects

Broadband Technology	Responses
Fiber to the Home (FTTH)	25
Cable Internet (COAX)	2
Copper Based Internet (xDSL)	1
Wireless Assets (e.g., fixed wireless)	7
Satellite	1
Other	5

The two following questions inquired about the party that will assume/assumed ownership of the middle-mile and last-mile, respectively. Table 2 lists the responses collected for the two questions. Results indicate that, in most projects, the last-mile is privately owned (19 projects). Public ownership of the last-mile is only assumed in 10 projects. Ownership of the middle-mile is evenly distributed between public (14 projects) and private sectors (15 projects). One respondent mentioned that the middle-mile was state owned but operated and maintained by a private entity. Another respondent mentioned their project only involved the middle-mile which was owned by the municipality. Lastly, a respondent mentioned that a public-school corporation owned both the middle- and last-miles in their project.

Table 2. Middle- and last-mile owners in broadband development projects

Middle- and Last-Mile Owner	Middle-Mile Responses	Last-Mile Responses
State, city, or municipality owned, operated, and maintained	14	10
Private operator or service provider	15	19
Shared between public and private	4	3
Privately owned, then flipped to public	0	1
Other	2	2

The survey then requested the participants to identify the development model for the broadband development projects. The development models identified in the survey results are summarized in Table 3. Thirteen responses indicated a private sector owner and operator. Among the thirteen projects, five were open access networks, while the other eight were single Internet Service Provider (ISP) networks. Dark fiber open access (hybrid) was deployed in six projects. The six additional responses received are as follows: (1) ARPA funds provided to ISP (private, single ISP); (2) ARPA funds to build wireless towers to be leased to ISPs; (3) Municipality owned infrastructure, private provider anchor tenant; (4) P3 model; (5) Private LTE network owned by a public school corporation; and (6) State owned open access middle-mile backbone lit fiber, privately operated, maintained, and commercialized to attract ISPs and lower service cost.

The survey moved on to ask about the financing models of the private sector, public sector, and community, respectively. Results showing private sector financing models are listed in Table 4. ‘Private operator funds’ was selected by the majority (11 respondents). Five respondents selected ‘Federal or state grants’ as the private financing model. One respondent mentioned the

California Advanced Services Fund (CASF) and another mentioned county funds as private financing models.

Table 3. Broadband projects' development (contribution) models

Project Development Model	Responses
Private sector owner and operator, single ISP	8
Private sector owner and operator, open access	5
Dark fiber open access (hybrid)	6
Municipal utility owned and operated, single ISP	3
City owned and operated, single ISP	2
Manual open access, multiple ISPs	2
Automated open access, multiple ISPs	3
Other	6

Table 4. Private sector financing models

Private Financing Models	Responses
Federal or state grants	5
Project bonds	1
Direct loans	4
Syndicated loans	1
Corporate bonds	1
Subordinated bonds	1
Listed equity capital	4
Unlisted equity capital	3
Vendor financing	3
Strategic investors	3
Private operator funds	11
Corporate social responsibility grants	1
Other	2

Respondents also identified public sector financing models (Table 5). Eight responses indicated that a Public-Private Partnership (P3) model is utilized as the public financing model. P3 was followed by 'Government operation subsidies' with 4 respondents selecting that. Five additional answers were acquired: (1) CARES funds and private philanthropy; (2) Financed by a private company; (3) Public grant; (4) State grant and town program; and (5) US EDA grant.

The third financing model participants were asked about was the community financing model. As summarized in Table 6, the majority of this question's respondents indicated that the community did not contribute to financing their projects (14 respondents). Four respondents selected 'Infrastructure transfer (ROW)' as their answer. Additionally, one respondent mentioned the community and businesses provided donations and sponsorships, respectively. Another respondent mentioned that, for their project, homeowners paid they could, and a county grant covered the remaining cost. Finally, a respondent mentioned temporary tax increase as a community financing model.

Table 5. Public sector financing models

Public Financing Models	Responses
ARPA funds	2
Equity capital market	2
Debt capital market	3
Minimum revenue guarantees	3
Government operation subsidies	4
Off-take agreements	1
Federal government loan	1
Local government loan	1
Government equity participation	1
Government roll-out subsidies	1
Infrastructure bonds	3
Cities or counties' pooled fund	3
P3 project finance	8
Other	5

Table 6. Community financing models

Community Financing Models	Responses
Infrastructure transfer (ROW)	4
Community bonds	2
Community funding	3
Subscriber equity	1
No community contribution	14
Other	3

The questionnaire moved on to ask about revenue models adopted for the broadband development projects. Table 7 presents the responses collected regarding adopted revenue models. Thirteen and eleven respondents selected 'Demand aggregation' and 'Anchor tenant contract', respectively. 'Pre-sales' was selected by nine respondents. The five additional answers provided are: (1) Future commercial value; (2) Government subsidy of capital funds and subscriber fees to cover business operations and profit; (3) No revenue model used; (4) Not applicable because the project only served public sector locations (e.g., parks); and (5) Reallocation of existing budgets from anchor institutions for connectivity.

Table 7. Broadband projects' revenue models

Revenue Models	Responses
Pre-sales	9
Demand aggregation	13
Anchor tenant contract	11
Demand side subsidies for users	3
Other	5

Participants were also asked to identify any financing support for broadband users their projects received. The responses are summarized in Table 8. The majority (23 respondents) indicated that their projects did not receive any financing support. 'Subsidies reducing the cost of devices' was selected by 7 respondents. The three additional responses received are: (1) ISPs paid a subsidy to connect customers with high building costs; (2) Network and devices were provided for free; and (3) Town's revenue used to pay for drops.

Table 8. Financing support for broadband users

Financing Support for Users	Responses
Microfinancing of devices	1
Demand aggregation for devices	1
Subsidies reducing the cost of devices	7
Reuse of discarded devices	1
No financing support received	23
Other	3

The survey aimed to identify measures taken in broadband projects to enable the market entry of ISPs. The measures identified by the respondents are summarized in Table 9. 'Deployment of open access network' was selected by 13 respondents. 'Parameters preventing monopolization' and 'Streamlining processes for local ISPs' were selected by 10 respondents. The 4 additional responses received are: (1) Federal government support; (2) Not applicable since the services were provided by the state network; (3) Public funding of middle-mile to ensure lower cost dark fiber leasing rates; and (4) Transparency and months of community outreach and education.

Table 9. Measures for ISP market entry

Market Entry Measures	Responses
Deployment of open access network	13
Parameters preventing monopolization	10
Streamlining processes for local ISPs	10
Waving fees for local ISPs	3
Overbuilding the middle-mile	9
Other	4

The participants were also asked to identify barriers that prevented development from reaching underserved communities. Results received are listed in Table 10 below. 'High development costs' and 'Distance and/or terrain' were indicated by 22 and 19 respondents, respectively. The 4 additional barriers identified are: (1) Construction delays limiting access; (2) Lack of vision and political will; (3) Project would not have been possible without ARPA and BEAD funds; and (4) Reaching the elderly population who did not have internet and therefore no emails.

The final question aimed to identify the measures that indicate a successful broadband development project (Table 11). 'Broadband quality for users' and 'Capacity of deployed network' were selected by 22 and 19 respondents, respectively. 'Broadband price for users' and

'Service coverage' were selected by 18 respondents. On-budget and on-time project completion were selected by 17 and 15 respondents, respectively. The 6 additional responses received are: (1) Adoption and utilization; (2) KPI analytics relative to outcomes, as well as alignment to budgetary pro-forma; (3) Documented changes in community outcomes and mission advancements relative to anchor institutions; (4) Helping non-users explore the possibilities that broadband offers; (5) Publicly owned infrastructure to assure open access; and (6) Upfront payment to offset public subsidy.

Table 10. Barriers preventing broadband from reaching underserved communities

Barriers to Reaching Underserved Communities	Responses
High development costs	22
Distance and/or terrain	19
Lack of public financing	9
Difficulty attracting private financing	5
Level of profit uncertainty	12
Unwillingness of private entities to allow open access	6
Difficulty attracting service providers	11
Inexperience of public entity to build and maintain infrastructure	7
Inexperience of public entity to provide services	7
Other	4

Table 11. Broadband projects' measures of success

Projects' Success Measures	Responses
On-time project completion	15
On-budget project completion	17
Capacity of deployed network	19
Lifespan of deployed network	14
Broadband quality for users	22
Broadband price for users	18
Service coverage	18
Service gap reduction	12
Suppliers' level of profit	3
Other	6

CONCLUSIONS

The last-mile in broadband development projects is typically owned by service providers. Local governments will face difficulties preventing the rise of monopolies in those areas. Open access networks and public ownership of the last-mile can prevent the rise of monopolies and lower user costs. However, it is costly for local governments to solely fund both the middle- and last-miles. On the other hand, numerous broadband program funds and grants are available for local governments to apply for and use. It is possible that municipalities in some cases were unaware of many of the funding sources defined and identified through the survey. Additionally, local communities can contribute to funding broadband projects through, for example, temporary tax increases.

Furthermore, for projects where broadband will be developed by a private entity, it is vital that contracts include clauses that ensure broadband reaches underserved communities. For areas with high development costs (e.g., rocky terrains), it is recommended that local governments and communities contribute to the development of open access infrastructure, regardless of whether private funds will be used or not. Additionally, broadband development projects can undergo cost-benefit analysis to inform decision makers and planners about the feasibility of such projects and provide clues on the type of investors to attract (Zahed et al., 2018[b]). Finally, quantified uncertainty-based real options analysis may be conducted for broadband projects (Kashani et al., 2014). With the proper integration of uncertainties in broadband projects' investment valuations, investors can make better informed decisions.

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A Survey of Preliminary Cost Estimating Approaches across State Transportation Agencies

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ABSTRACT

A successful transportation project's planning and execution depends on accurate cost estimation. This paper focuses on the preliminary cost estimation techniques used in transportation projects and provides the results of an extensive survey targeting transportation professionals at state departments of transportation (DOTs) in the United States. The purpose of the survey is to learn about the practices, methodologies, tools, and challenges associated with preliminary cost estimation as it is employed across various states. The survey's methodology and participant demographics are covered in full in the first section of the paper. The survey findings are then explored in detail, indicating the variety of practices employed by DOTs in terms of estimation methods, data sources, and degrees of satisfaction with the current procedures. It also emphasizes the types of estimating tools utilized, the procedures applied to contingency cost estimation, and whether agencies adhere to federally authorized approaches. The research further investigates how agencies handle unit costs, inflation, and cost indices, offering light on regional factors. About 36% state DOTs responded to the survey, and according to the survey, there was no federally prescribed preliminary cost estimating approach and the most common tool was Excel-based tool. It is clear from the survey responses that there is wide variation in practices across the various state DOTs. This study contributes to the field of transportation project management by offering the current state of practice when it comes to preliminary cost estimating approaches for transportation projects. The paper also presents future directions for developing risk-based cost estimating approaches that are suitable for practical usage.

KEYWORDS: Preliminary Cost Estimates; Transportation Projects; Bid Data Utilization; Accuracy in estimates.

INTRODUCTION

Accurate cost estimating is crucial for successfull planning and implementation of transportation projects since it forms the basis for sound budgeting and decision-making practices at every stage of the project's development. Public transportation agencies can allocate limited construction funds more efficiently if they have a better understanding of top-down methods of estimation and the ways that they contribute to budget accuracy (Karaca et al., 2020).

Many studies have demonstrated the importance of accurate cost estimation and its critical role in transportation projects. Previous research conducted questionnarrie survey targeting experts of State DOTs to gain a comprehensive understanding of the prevailing practices and recommendations for public transportation agencies (Abdelaty et al., 2022; Gardner et al., 2012). According to Flyvbjerg et al., (2018), inaccurate cost estimation contributes to project inefficiencies, budget overruns, and delays. This study attempts to give a thorough review of the current procedures used by state DOTs in the preliminary cost estimation of transportation projects, emphasizing the necessity for reliable estimating processes on a global scale. Additionally, the research explores the application of estimating tools, complexities of contingency cost estimation, compliance with federally approved techniques, and effective control of unit costs, inflation, and cost indexes, offering perspectives on specific factors. Based on the survey responses from 36 percent of State DOTs, there is no federally approved preliminary cost estimating method that is universally employed. Instead, Microsoft excel-based tools developed locally are most commonly used approaches.

By providing an overview of the state of preliminary cost estimation techniques used in transportation projects, this study not only presents empirical support to the body of existing knowledge but also establishes a framework for future research efforts. In order to improve the practical effectiveness of risk-based cost estimate methods in the constantly evolving industry of transportation project management, the study concludes with some recommendations for advancing these strategies.

RESEARCH METHODOLOGY

The primary goal of the questionnarrie survey was to synthesize practices of other state DOTs in terms of approaches and tools used for developing cost estimates and how those estimates were used, considering the risks involved. The methodology entailed selecting participants and sending out survey instruments to be completed.

Participant Selection

The survey was distributed electronically to 50 State DOTs' Value Engineering and Estimate Coordinators, Statewide Project Management Specialists, State Estimating Engineers, Research Implementation Managers, Project Managers, Independent Cost Estimating Coordinators, Engineering Supervisors, Engineers, Director of Preconstruction, Contracts and estimates Engineer, Civil Engineer IV, Chief Road Design Engineer, Bidding and Contract Services Engineer, Assistant State Materials Engineer, and Assistant Director of Planning across the United States. Participants were encouraged to provide detailed responses to maximize the richness of the data collected.

Survey Sections

The survey was distributed through secure online survey platforms, ensuring data integrity and confidentiality. It was consisted of closed-ended and open-ended questions. The survey questionnaire comprised seven sections, each addressing specific dimensions of preliminary cost estimating approaches. These sections included participant's basic information, agency practices in preliminary cost estimation, contingency and risk management, types of cost estimates, inflation considerations, collaboration and knowledge sharing, and recommendations and suggestions.

RESULTS AND DISCUSSION

Question Asked

Participant's Agency?

Responses

Nineteen participants from fifteen different state DOTs and three unknown state DOTs in the United States of America (USA) provided comprehensive responses for this study. Sixty-three percent of the nineteen complete responders consented to a future follow-up interview. The location of the respondents is represented graphically in Figure 1. The data indicated that 18 states, comprising 36% of the total states DOT represented by all survey respondents were Oklahoma, Wyoming, Missouri, North Carolina, Idaho, Utah, Delaware, Nevada, Kentucky, Georgia, Michigan, Minnesota, New York, Illinois, South Dakota, and three unknown states that were not included in the list.

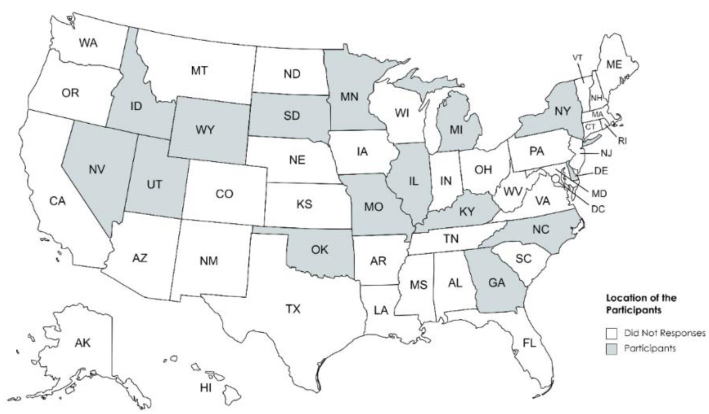

Figure 1. Location of the Prticipants

Question Asked

Does your agency currently implement a systematic method for developing preliminary cost estimates in the planning phase of transportation projects?

Responses

Seven SHAs (State Highway Agencys) had a systematic approach, seven did not have a standardized procedure, one did not respond, and four responded with detailed guidelines to cost estimation methods among transportation agencies (Figure 2). According to four comprehensive responses, the original STIP project estimates were based on SY unit costs and change as plan sets do. The scoping process and completed studies influenced detailed estimates. Notably, there's a distinction between long-range planning and project development groups in establishing project costs before advancing onto the STIP, emphasizing the complexity of the approaches.

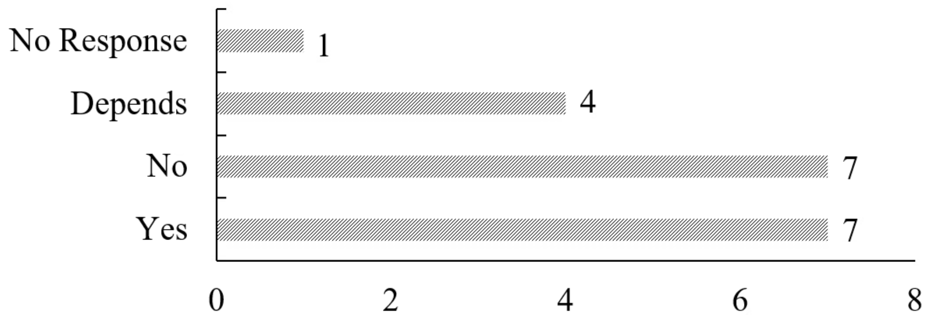

Figure 2. Existence of Systematic Method for developing Preliminary Cost Estimation

Question Asked

How satisfied are you with the preliminary cost estimating process at your agency?

Responses

Two respondents were neutral, two were highly satisfied, and six were moderately satisfied. Remarkably, one respondent expressed dissatisfaction, and eight did not react, adding uncertainties (Figure 3). This variety brought diverse viewpoints regarding the effectiveness of the agency's preliminary cost estimation procedure.

Figure 3. Existence of Preliminary Cost Estimating Process's Satisfaction

Question Asked

Is the preliminary cost estimating approach used by your agency developed in-state or adopted from federal guidelines?

Responses

The majority of respondents (10) to the survey stated that their agency developed its preliminary cost-estimating approach in-state, either in-house or with a consultant or researcher

(Figure 4). Eight responders, nevertheless, chose not to reply, indicating a lack of interest. One responder provided an extensive reply that was state-specific but might differ slightly depending on the area, region, or TSC implementation because there was no set estimating tool and no requirement for particular excel formats, which could result in variations in the forms used for implementation.

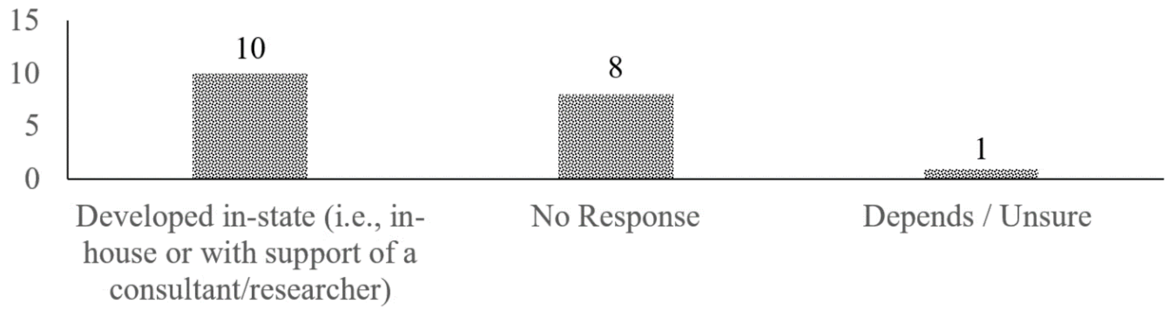

Figure 4. Existence Preliminary Cost Esimation Approaches Developing Process

Question Asked

Is the preliminary cost estimating approach used by your agency in the form of an excel tool or a stand-alone software?

Responses

According to the survey, the majority of the agencies (10 respondents) employed excel tools for initial cost estimation (Figure 5). Only one responder mentioned using stand-alone software, and eight did not answer, indicating a lack of understanding or interest in the issue. The responses highlighted the general dependence in the surveyed setting on spreadsheet-based techniques for initial cost estimation.

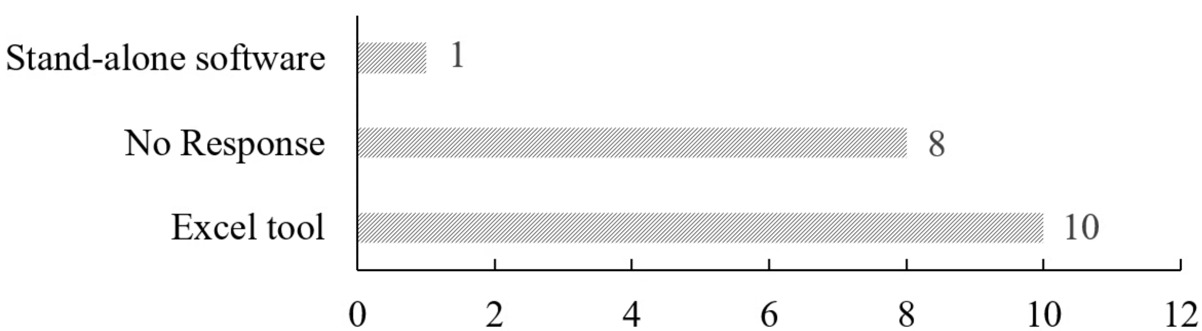

Figure 5. Existence Preliminary Cost Esimation Approaches Formation

Question Asked

Briefly describe the preliminary cost estimating approach used by your agency (e.g., unit price, linear regression, machine learning-based).

Responses

Figure 6 showed that the agencies utilize a variety of preliminary cost-estimating techniques. One respondent employed bid-based and cost-based pricing, while six utilize a unit price approach. Two organizations set prices based on actual high-level quantities. Notably, twelve organizations chose not to reply, indicating a lack of participation or clarity in their approaches. These responses demonstrated how different early cost-estimating techniques are in the survey context.

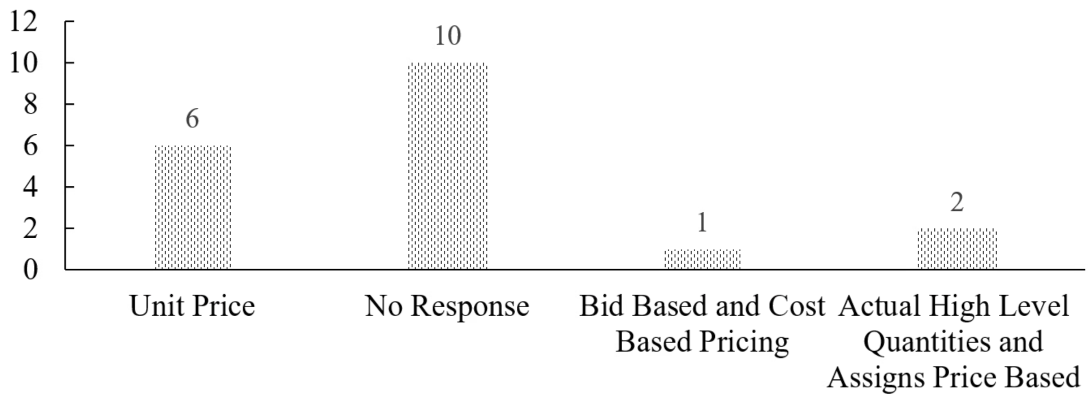

Figure 6. Existence Preliminary Cost Estimating Approach

Question Asked

How are contingency costs estimated in the preliminary cost estimates used by your agency?

Responses

The survey showed different approaches to estimating contingency costs in preliminary estimates. A proportionate relationship was demonstrated by the eight agencies that used a percentage of the base estimate (Figure 7). Three agencies use different techniques, highlighting the unpredictability of the process, and their grading plan estimated usually did not account for contingency. A percentage-based contingency calculation was included in the initial scoping estimates; however, as projects moved through the development phase, pay items were used to calculate updated construction costs. The nature of the project and its location were the main factors influencing the contingency percentage. Notably, eight agencies chose not to respond, suggesting a lack of understanding or involvement with this issue.

Question Asked

What type of a preliminary cost estimate is produced by your agency?

Responses

According to the survey, most agencies (11 out of the total) generated a deterministic cost estimate comprising a set value and a suitable contingency (Figure 8). Notably, eight agencies chose not to reply, suggesting a lack of understanding or involvement with this issue. These revealed a similarity in how the studied agencies approach preliminary cost estimates, emphasizing fixed value and contingency concerns.

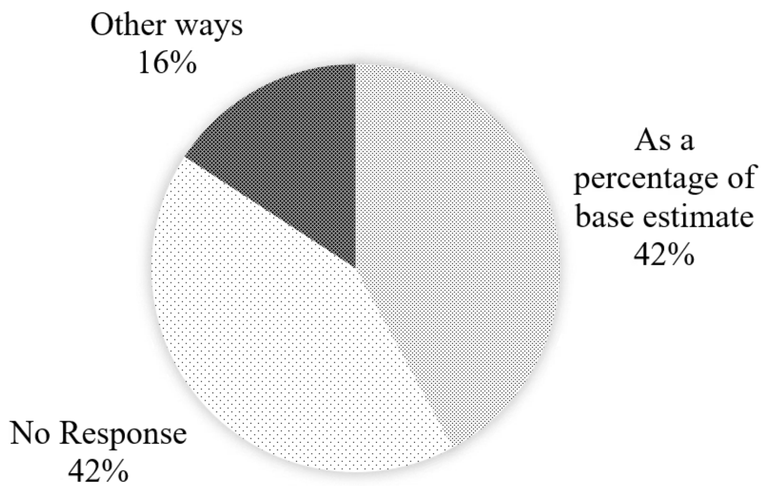

Figure 7. Contingency Costs Estimated in the Preliminary Cost Estimates

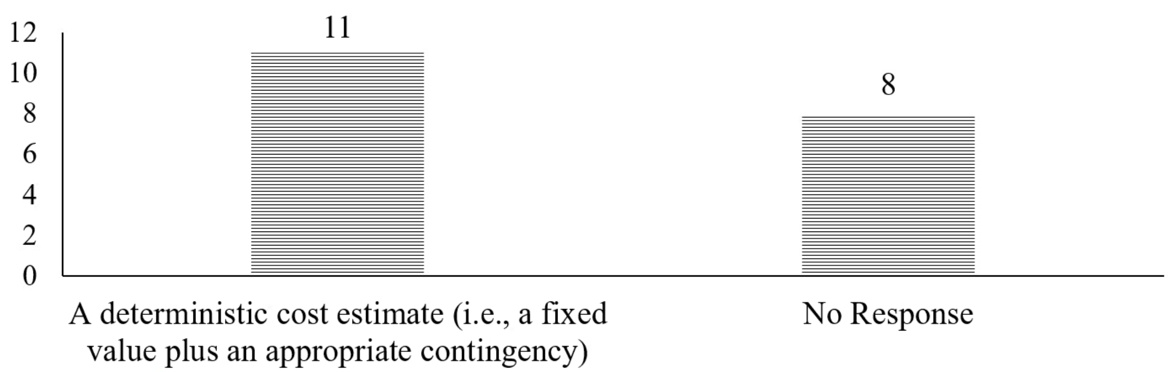

Figure 8. Type of Existence Preliminary Cost Estimate Method

Question Asked

Does your agency have a systematic process for developing unit costs for cost estimating purposes?

Responses

Diverse agency techniques for creating unit costs for cost estimation are depicted in Figure 9. Eleven organizations emphasized systematic methods and follow a methodical process. On the other hand, six agencies didn't have a systematic procedure, which suggests possible variability. Using their bidtabs.net, one agency employed a unit price based on previous data. One agency's unit cost development procedures were unclear because they did not reply. These showed that different examined agencies had other methods for creating unit costs in a systematic way for cost estimation.

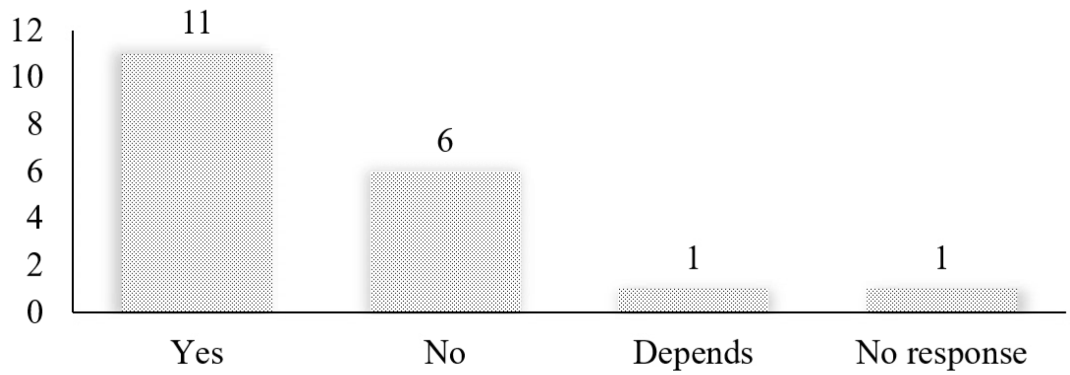

Figure 9. Systematic Process for Developing Unit Costs for Cost Estimating

Question Asked

Please describe the systematic process.

Responses

The bid history from comparable projects, which captures market trends for the present circumstances, was the first step in the systematic procedure. The expected cost per unit computation was derived from historical regression curves for uncommon items and recent data for often-used products. Construction amounts were added to all bid prices after the bidding, which were then sorted based on the project's specifications. Then, unit prices were determined through linear regression. In order to offer current average unit costs internally and externally, quality assurance teams monitored bid history. Furthermore, bid prices from the three lowest bidders over the last 24 months could be seen in the quarterly updated Bid History Catalog.

Question Asked

At what level are the historical unit costs maintained by your agency?

Responses

According to the survey, agencies' maintenanced levels of historical unit prices increased significantly. Ten agencies concentrated at the state level, four at the district level, and four use alternative approaches, like combining their own data with the state level, working on a specific project with a particular location, and paying attention to a specific pay item (Figure 10). There was ambiguity since one agency did not reply. These demonstrated how different survey agencies manage historical unit costs in different ways.

Question Asked

Does your agency have a systematic approach to account for inflation specific to the region/state for various project types?

Responses

According to the survey, agencies utilized different methods when estimating project costs to account for inflation in certain states or regions. Eleven agencies didn't have a structured strategy, which could lead to variability (Figure 11). On the other hand, five agencies used an organized approach for this. Two organizations pointed to a reliance on particular elements, such as the percent-based approach and the lack of a specific formula. Notably, confusion was introduced by one agency's lack of response. These demonstrated how different the investigated agencies' methods were when handling inflation issues in project cost estimation. The agency utilized tools like the Highway Construction Cost Index (HCCI) and a locally developed inflation calculator to account for inflation in the initial cost estimates. At the bottom of the forecast, inflation was included in and projected to the expected year of completion. A Composite Cost Index (CCI) was updated, and an on-staff economist ascertains the current inflation rate. In addition, they applied a percentage annually based on the project's delivery schedule, using suggestions from the statewide scoping manual during the yearly call for proposals.

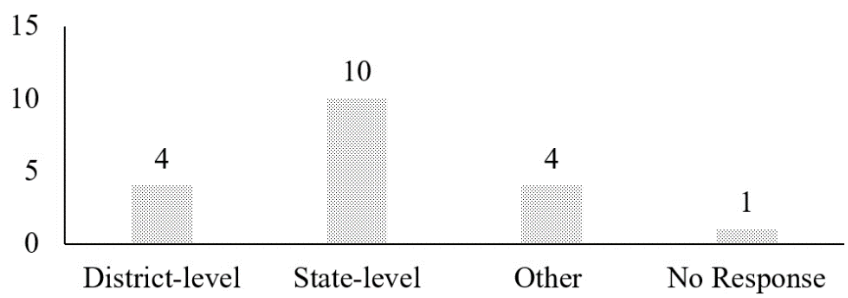

Figure 10. Level of Historical Unit Cost

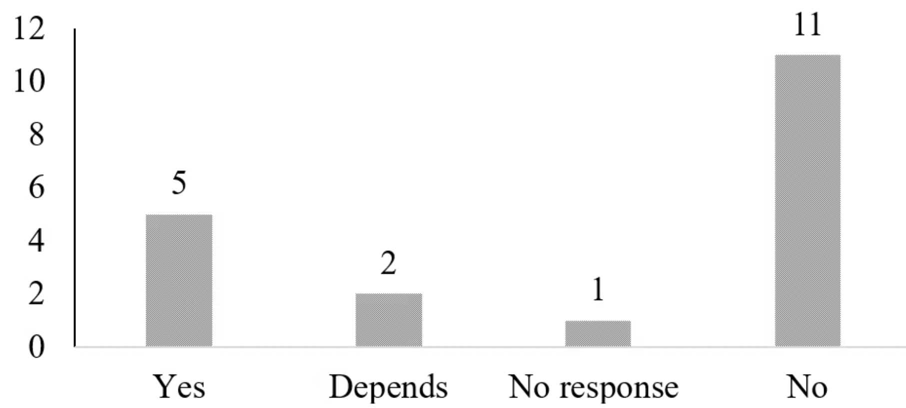

Figure 11. Systematic Approach to Account for Inflation Specific to the Region/State

Question Asked

Does your agency use a state-wide or region-wide highway construction cost index(HCCI) to account for inflation?

Responses

Figure 12 showed limitations on adopting the Highway Construction Cost Index (HCCI) for inflation adjustment across agencies at the state or regional levels. Two agencies were working to develop the tool to track actual bid data, while three agencies currently used HCCI. Interestingly, thirteen agencies chose not to reply, indicating a lack of understanding or participation regarding using HCCI for inflation adjustments. These showed that different surveyed agencies had different policies regarding using HCCI to account for inflation when determining the cost of constructing new highways.

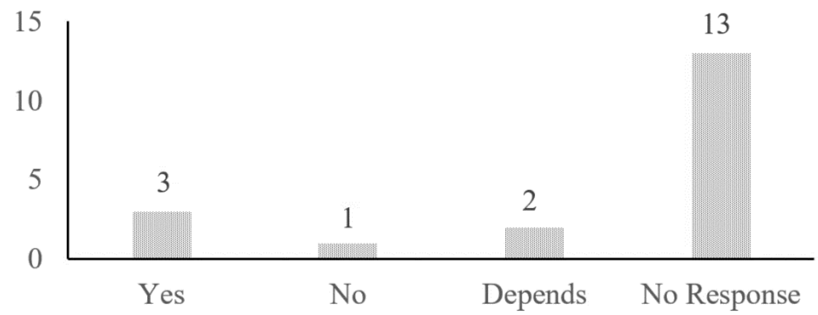

Figure 12. State-wide or Region-wide Highway Construction Cost Index (HCCI)

Question Asked

Are you able to share the preliminary cost estimating tool(s) along with other relevant tools and manuals with other state DOTs?

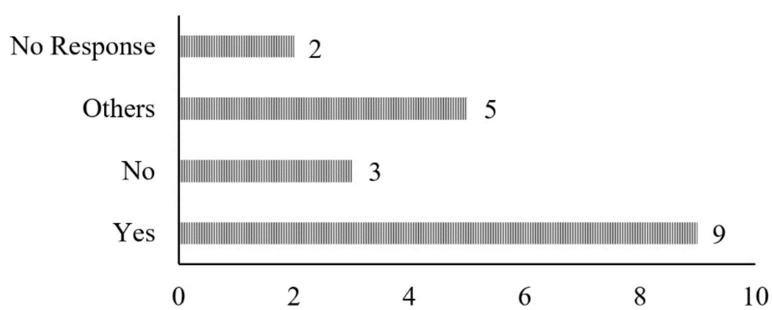

Figure 13. Distribution of Preliminary Cost Estimation Tools

Responses

According to the survey, agencies had differing opinions about exchanging preliminary cost estimation tools with other state Departments of Transportation (DOTs). Figure 13 showed that nine agencies were eager to contribute, three were reluctant, five offer an "other" response that suggests further considerations, and two remained silent, creating confusion. They employed AASHTOW software, which differs depending on state configurations, and the study still needed to be completed. There's no official statewide cost estimating tool, but they could share regional samples and non-sensitive information with verification. Every district managed its initial approximation. These highlighted the various strategies the agencies assessed used to share tools and resources with other state DOTs cooperatively.

CONCLUSIONS AND RECOMMENDATIONS

The survey, which included replies from 19 experts in 15 U.S. State DOTs and three unknown State DOTs, clarifies a diverse environment in preliminary cost estimation procedures. Even while excel tools and in-state development methodologies are widely used, non-responses in certain areas and the lack of standard methods indicate intrinsic diversity across the investigated organizations. Notably, different contingency estimating techniques demonstrate varied approaches, suggesting a sophisticated approach to risk management. Comparably, agency-wide practices vary in how unit cost development and inflation factors are handled. The research highlights the need to tackle these discrepancies to improve the effectiveness and uniformity of preliminary cost estimation procedures in transportation organizations. Standardization initiatives could lead to a more consistent and dependable framework, especially regarding tools and methods. The results also point to possible areas for development, including improved data-sharing procedures, more cooperation, and more precise rules. These insights provide helpful guidance for improving preliminary cost estimation procedures increasing the planning and development of infrastructure projects across various state agencies more efficiently and reliably.

The main recommendations of the survey are listed below:

- Stress the importance of defining project scope (90%) and managing risks and contingencies (10%) for accurate estimates.
- Use bid data from the last six months, prioritizing similar quantities, field districts, and project types for accurate analysis, and acknowledge reliance on historic prices, but emphasize the complexity of accounting for inflation.
- Use historical unit prices for similar work, adjusting based on current project specifics.
- Utilize recent project bids, consider cost indexes, inflation percentages, and contractor feedback for insights into market challenges, and seek perspectives from multiple subject matter experts.
- Recognize the simplicity in estimating construction costs versus challenges in estimating other expenses like Right of Way and Utilities, and be slightly conservative in estimates, rounding up for accuracy, especially for less frequently used items.
- Keep individuals engaged in bidding and estimation to anticipate changes and ensure an effective process, and utilize historical databases for research projects.
- Regularly update estimates for accuracy, referencing consistent guidelines, and considering various funding sources. Include risk evaluations for factors like complex construction, and use "composite bid items" for preliminary estimates, combining multiple bid items for 'per mile' costs, updating prices based on recent relevant project quantities.

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COVID-19 and Construction Industry: Workforce Challenges

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ABSTRACT

The coronavirus took toll on human lives and catalyzed a crippling economic recession that led to soaring unemployment rates. The construction industry, due in part to its labor-intensive nature, has a high incidence of COVID-19 cases that severely affected various aspects of project management, such as cost, schedule, contracts, finance, and occupational health and safety. To bridge a research gap, this study embarked on two primary objectives. First, it identified the key challenges that lead to construction cost and schedule overruns, contractual implications, and occupational health and safety issues by reviewing more than 131 articles. Second, it proposed strategies to mitigate or at least minimize the effects of the challenges during the pandemic. The study identified 26 unique challenges and provided respective mitigation strategies for each. Labor shortages, escalating material prices, and occupational health and safety issues were revealed as major factors contributing to cost overruns, and delays in material delivery, reductions in efficiency and productivity rates, and deferrals of ongoing projects for new ones also emerged as key issues. Contractual implications included a lack of guidance on the applicability of force majeure contract clauses, and health and safety concerns were primarily driven by the fear of job loss and reduced income in a volatile job market. This research provides invaluable insights for stakeholders and project managers in the construction sector, enabling them to understand and effectively manage the challenges induced by the pandemic.

Keywords: COVID-19; Construction; Challenges; Strategies

INTRODUCTION

The pandemic's public health impact was matched by economic fallout, leading to a U.S. recession from February 2020 (Arthi and Parman 2021). Unemployment surged from 3.8% to 14.7% within two months, impacting over 23 million Americans (Li et al. 2022). In addition, it had a wide-ranging effect on different sectors such as transport, finance, retail, and healthcare, with the transport sector being hit by a decrease in transportation and passenger traffic resulting from a reduced demand for transporting products and fuels (Adepu et al. 2022).

The pandemic significantly altered life and strained global health systems (Pamidmukkala et al. 2021). The construction industry, which has about 11.1 million employees who contribute to approximately 4% of the GDP of the United States, was notably impacted (Li et al. 2022; Karthick et al. 2022a). Reports indicate high COVID-19 incidence among construction workers, who registered more cases than employees' other sectors in a Los Angeles study and a five-fold increased hospitalization risk in another (Alsharef et al. 2021). Beyond health impacts, the pandemic has severely affected construction project management of costs, schedules, contracts, finance, and occupational health and safety (Adepu et al. 2023a; Nipa et al. 2023; Karthick et al. 2022b).

The objectives of this research are to address a research gap by,1) identifying challenges causing construction cost and schedule overruns, contractual implications, and occupational health and safety issues through reviewing over 131 articles, and 2) proposing strategies to mitigate these issues during a pandemic. The outcomes of this research will equip construction supervisors and personnel with a deeper understanding of the difficulties involved, enabling them to develop efficacious strategies to boost the success of their projects.

RESEARCH METHODOLOGY

The systematic research framework as depicted in Figure 1 was developed to meet the objectives of this study. In the first step, key words such as COVID-19, construction, cost, schedule, budget, timeline, contracts, insurance, and health and safety were developed. Later, search engines were employed to conduct extensive literature searches that produced relevant articles. In the third step, challenges were identified and in the final step strategies were outlined.

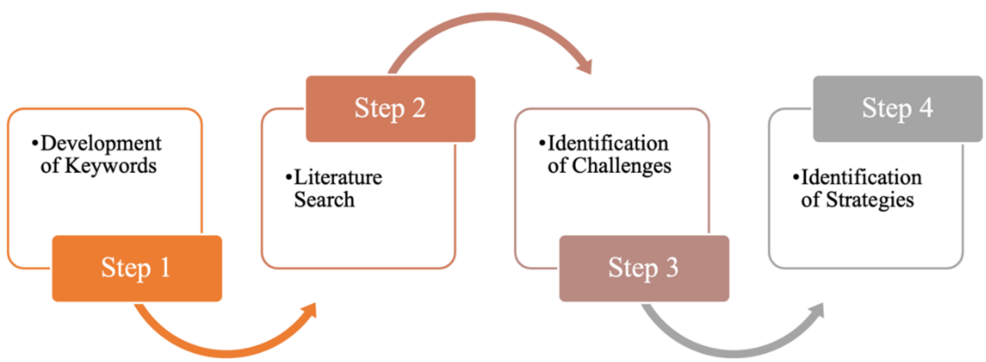

Figure 1. Research Methodology

IDENTIFICATION OF CHALLENGES RELATED TO CONSTRUCTION COST AND SCHEDULE OVERRUNS, CONTRACTUAL IMPLICATIONS, AND OCCUPATIONAL HEALTH AND SAFETY ISSUES.

The full texts of the gathered papers were evaluated to identify the challenges related to construction project management due to the COVID-19 pandemic. Table 1. Shows a list of the challenges that contributed to cost and schedule overruns, contractual implications and health and safety issues during the pandemic.

Construction cost overruns during the pandemic

Construction cost overruns, which were basically the final cost of projects more than the estimated cost, are common in construction (Kermanshachi and Pamidimukkala 2022) and are often attributed to factors like labor and material availability, provision of PPE, disinfectants, and sanitizers, and changes in project scope (Alsharef et al. 2021; Adepu et al. 2023a). The COVID-19 pandemic exacerbated these, causing project costs to surge (Hesna et al. 2021; Safapour et al. 2021; Subramanya et al. 2020). Labor shortages during the pandemic, due to health concerns and travel restrictions, reduced output and raised project costs (Ling et al. 2021; King et al. 2021), and the need to hire non-local laborers further strained resources (King and Lamontagne 2021). The scarcity of materials caused by lockdowns, disrupted trade and inflated prices (Barua 2020), and equipment shortages added to the challenges (Adepu et al. 2023a), while health and safety regulations also increased costs (Adepu et al. 2023b; Amoah and Simpeh 2021). Inaccurate cost estimations and design changes, also contributed to overruns during the pandemic (Ling et al. 2021; Ogunnusi 2020; Alhusban et al. 2022).

Construction schedule overruns during the pandemic

A schedule overrun, or schedule slippage, refers to the difference between actual and projected project execution time (Ansar et al., 2013). Larger and more complex projects, like megaprojects or those involving technical complexity, are more prone to overruns (Standish Group, 2004; Flyvbjerg et al. 2002; Sovacool et al., 2014). The COVID-19 pandemic amplified this issue, with 60% of respondents in an Associated General Contractors (AGC) of America study reporting project deferrals, often due to material or equipment shortages (AGC, 2020; Alsharef et al. 2021). Additionally, the shortage of skilled workforce, cash flow issues causing payment delays, and disparities in the essential service classification of construction activities across states contributed to schedule overruns during the pandemic (Adepu et al. 2023a; Assaad and El-adaway 2020). Challenges like adapting to remote work, team communication gaps, and enforcing social distancing protocols reduced worker productivity, further causing schedule overruns (Adepu et al. 2023c; Gammanage and Gunarathna 2022; Pamidimukkala and Kermanshachi 2021).

Contractual implications during the pandemic

Contractual implications and, the potential outcomes can influence various aspects of construction projects such as schedule, cost, risk distribution, and overall success (Assaad et al. 2022; Franzese 2020; Daniels et al. 2020). Delay penalties can increase contractor costs, while mandatory insurance types specified in contracts serve as risk management strategies (Assad and Abdul-Malak 2020; Laryea 2008). Indemnity clauses detail financial accountability for losses or damages, with insurance policies often providing the needed financial protection (Odeyinka 2000; D'arcy and Brogan 2001; Bunni 2003). During the COVID-19 pandemic, construction companies grappled with the applicability of force majeure clauses and other contractual challenges (Daniels et al. 2020; Franzese 2020), and uncertainties around insurance coverage and compliance with pandemic-induced health and safety regulations further exacerbated contractual implications (Haar et al. 2016; Adepu et al. 2023a; Assaad and El-adaway 2021).

Health and safety issues during the pandemic

The COVID-19 pandemic profoundly transformed work environments, impacting workers' sense of security, well-being, and the nature of the work itself (Pamidimukkala et al. 2021). Economic instability due to job losses and salary cuts led to increased worker insecurity, shifting the focus towards securing livelihoods (Chirumbolo et al. 2021). Mental health, as a critical component of occupational well-being, was severely impacted, as heightened stress levels stemmed from the threat of the virus, sustained work-from-home arrangements, and blurred personal-professional boundaries (Wickramasingha and Neve 2022; Vyas 2022; Adepu et al. 2023c), and isolation from social distancing protocols and remote work compounded the issue, inducing feelings of loneliness and anxiety (Williams et al. 2020; Nyashanu et al. 2020). The shift to remote work presented additional challenges, as it led to digital fatigue, a compromised work-life balance, and the need for remote management and communication tools (Pamidimukkala and Kermanshachi 2021; Mostafa 2021; Sokolic 2022).

Table 1. Workforce challenges during the COVID-19 pandemic.

Category	Challenges	Frequency
Cost Overruns	Shortage of labor	43
	Inflation or escalation of material prices	42
	Provision of PPE, disinfectants, and sanitizers	39
	Unavailability of heavy equipment	31
	Inaccuracy of cost estimation	29
	Lack of materials	28
	Specifications and scope changes	27
	Changes in design and engineering	21
Schedule Overruns	Delays in material delivery	35
	Deferral of ongoing projects	33
	Reduction in efficiency and productivity rates	28
	Shortage of skilled or experienced workforce	26
	Procurement of heavy equipment	23
	Payment delays due to cash flow problems	15
Contractual Implications	Differences among states in determining if construction activities are crucial or non-crucial	11
	Lack of guidance on the applicability of force majeure contact clause	15
	Health and safety compliance	11
	Inadequate regulatory direction for discerning the legitimacy of a pandemic-induced contract delay	9
	Uncertainty of insurance coverage	7
Health and Safety Issues	Fear of job loss and reduced income in a volatile job market	40
	Concerns about implementing effective health and safety measures for a safe transition back to physical workplaces	39
	The increased need for remote management and communication tools	38
	Decreased work-life balance	36
	Increased stress and anxiety due to the pandemic and isolation	24
	Lack of social interaction leading to feelings of loneliness	21
	Issues like digital fatigue due to the shift to remote work practices	18

IDENTIFICATION OF STRATEGIES RELATED TO CONSTRUCTION COST AND SCHEDULE OVERRUNS, CONTRACTUAL IMPLICATIONS, AND OCCUPATIONAL HEALTH AND SAFETY ISSUES.

Several strategies were identified that can decrease the impact of COVID-19 and similar pandemics in the future.

Strategies to mitigate construction cost overruns during the pandemic.

Managing construction cost overruns involved a myriad of strategies during crises such as the COVID-19 pandemic. Addressing labor shortages through automation, robotics, and enticing work conditions can alleviate workforce deficits (Ling et al. 2021). Enhancing supply chain resilience via diversified supplier networks and effective management can mitigate disruptions (Barua 2020; Adepu et al. 2023a). Rigorous health and safety measures, robust project management tools for accurate cost estimation, and contingency planning can help navigate the health crisis and market uncertainty (Adepu et al. 2023b; Amoah and Simpeh 2021; Ling et al. 2021). Inflation-triggered material price surges can be managed via bulk purchasing, contract clauses, and exploring alternative materials (Barua 2020). Unforeseen changes in project scope and design alterations can be handled through clear stakeholder communication and efficient change management (Ogunnusi 2020; Alhusban et al. 2022). Table 2 lists the strategies for mitigating construction cost overruns during the COVID-19 or a similar pandemic.

Strategies to mitigate construction schedule overruns during the pandemic.

The COVID-19 pandemic presented significant challenges to the construction industry, causing schedule overruns, including delayed material delivery, procurement problems, skilled workforce shortages, project delays, cash flow issues, regulatory discrepancies, and productivity reduction. Yet, effective strategies are available to address these issues. For instance, enhancing supply chain management techniques and diversifying supplier relationships can mitigate material delivery delays (Power 2005; Safa et al. 2014). Considering equipment leasing, sharing, or exploring alternative methods can optimize machinery procurement (Alsharef et al. 2021). Workforce shortages can be addressed by upgrading employee skills and, offering flexible schedules and competitive pay (Pamidimukkala and Kermanshachi 2021). Effective project and risk management methodologies, along with clear stakeholder communication, can keep projects on track (Alsharef et al. 2021). To deal with payment delays, firms can negotiate advanced or staggered payments and maintain a contingency fund (Adepu et al. 2023a; Alsharef et al. 2021). Understanding regulatory variations and seeking legal counsel can navigate discrepancies across states (Assaad and El-adaway 2020). Incorporating technology and upholding a healthy work environment can boost productivity (Gammanage and Gunarathna 2022; Pamidimukkala and Kermanshachi 2021; Adepu et al. 2023c). Table 3 lists the strategies for mitigating construction schedule overruns during the COVID-19 or a similar pandemic.

Strategies to mitigate construction contractual implications during the pandemic.

The COVID-19 pandemic introduced various contractual complexities in the construction industry, including uncertainties with force majeure clauses, unclear insurance coverage, and compliance with health and safety regulations. Fortunately, effective strategies can mitigate such issues. Consulting legal professionals can help clarify force majeure provisions and determine whether the pandemic is a permissible delay under contract terms (Daniels et al. 2020; Franzese 2020; Bunni 2003), and regularly reassessing and modifying insurance policies, along with advice from insurance professionals or legal advisors, can alleviate uncertainties around insurance coverage. Instituting COVID-19 safety measures, conducting regular safety training, and transparent communication can ensure compliance with health and safety regulations and prevent further contractual implications (Haar et al. 2016; Adepu et al. 2023a; Assaad and El-adaway 2021; Laryea 2008). Table 4. lists the strategies for construction contractual implications.

Table 2. Strategies to mitigate construction cost overruns during the COVID-19 pandemic.

#	Challenges	Strategies	Source
1	Shortage of labor	Investment in labor-saving technology, flexible work schedules and competitive compensation	Ling et al. (2021)
2	Lack of materials	Diversifying supplier networks, relying on local markets, strengthening supplier relationships, and anticipating disruptions and implementing effective supply chain management	Barua (2020)
3	Unavailability of heavy equipment	Diversifying supplier networks, relying on local markets, strengthening supplier relationships, and anticipating disruptions and implementing effective supply chain management	Adepu et al. (2023a)
4	Occupational health and safety issues	Implementing strict COVID-19 protocols, ensuring availability of PPE, conducting regular safety training	Adepu et al. (2023b); Amoah and Simpeh (2021)
5	Inaccuracy of cost estimation	Implementation of robust project management tools, using updated cost databases and including contingency planning	Ling et al. (2021)
6	Inflation or escalation of material prices	Bulk purchasing, price escalation clauses, and exploration of alternative materials	Barua (2020)
7	Specifications and scope changes	Strong project management, clear communication among stakeholders	Ogunnusi (2020)
8	Changes in design and engineering	Robust change management process, early contractor involvement	Alhusban et al. (2022)

Table 3. Strategies to mitigate construction schedule overruns during the COVID-19 pandemic

#	Challenges	Strategies	Source
1	Delays in material delivery	Diversifying suppliers, employing advanced supply chain management, maintaining regular supplier communication	Power (2005); Safa et al. (2014)
2	Procurement of heavy equipment	Leasing or sharing equipment, using alternative equipment, or adopting different construction methods	Alsharef et al. (2021)
3	Shortage of skilled or experienced workforce	Providing training programs and offering flexible scheduling and competitive remuneration	Adepu et al. (2023a). Pamidimukkala and Kermanshachi (2021)
4	Deferrals of ongoing projects	Implementing effective project and risk management strategies, ensuring clear stakeholder communication	Alsharef et al. (2021); Adepu et al. (2023a)
5	Payment delays due to cash flow problems	Negotiating advanced payments or installment plans, maintaining contingency fund	Assaad and El-adaway (2020).
6	Differences among states in determining if construction activities are crucial or non-crucial	Keeping updated on local and state guidelines, seeking legal advice	Assaad and El-adaway (2020).
7	Reduction in efficiency and productivity rates	Implementing productivity-enhancing technologies, streamlining operations, and ensuring a healthy and safe working environment	Pamidimukkala and Kermanshachi (2021); Adepu et al. (2023c).

Strategies to mitigate health and safety issues among construction workforce during the pandemic.

The COVID-19 pandemic imposed a range of occupational health and safety challenges in the construction industry, including job security fears, increased stress, loneliness, virtual work fatigue, work-life balance deterioration, the need for remote tools, concerns about a safe on-site return, vaccination reluctance, and difficulties in upholding COVID-19 protocols. Strategic planning and proactive management can help mitigate these issues (Pamidimukkala and Kermanshachi 2021), and transparent communication regarding job stability and wages can help alleviate employee fears (Chirumbolo et al. 2021). Resources such as mental health counselling and stress management workshops can support employees (Vyas 2022; Karthick et al. 2022d), and virtual team activities and frequent check-ins can foster a sense of community in remote teams (Sokolic 2022). Reducing non-essential virtual meetings, promoting breaks, and encouraging digital well-being can lessen screen time fatigue (Williams et al. 2020), and flexible work schedules can help balance personal and professional lives, thereby preventing burnout. Utilizing digital tools can enhance communication and project management in remote setups (Karthick et al. 2022c). Comprehensive guidelines on hygiene, social distancing, and the use of PPE use can ensure a safe return to physical workplaces (Mostafa 2021). Table 5 provides a list of strategies for mitigating these occupational health and safety challenges during a pandemic.

Table 4. Strategies to mitigate construction contractual implications during the COVID-19 pandemic.

#	Challenges	Strategies	Source
1	Lack of guidance on the applicability of force majeure contact clause	Engaging with legal professionals for advice based on specific contract conditions and legal norms	Daniels et al. (2020); Franzese (2020); Bunni (2003)
2	Inadequate regulatory direction for discerning the legitimacy of a pandemic-induced contract delay	Secure legal advice and scrutinize specific contractual terms	Daniels et al. (2020); Franzese (2020); Bunni 2003
3	Uncertainty of insurance coverage	Routinely reassessing and modifying insurance policies, consulting with insurance professionals or legal advisors	Haar et al. (2016); Assaad and El-adaway (2021); Laryea (2008).
4	Health and safety compliance	Implementing COVID-19 safety measures, conducting recurrent safety training, fostering transparent communication with workers	Haar et al. (2016); Assaad and El-adaway (2021);

Table 5. Strategies to mitigate the occupational health and safety issues of a construction workforce during the COVID-19 pandemic.

#	Challenges	Strategies	Source
1	Fear of job loss and reduced income in a volatile job market	Having a transparent communication regarding job stability and compensation	Chirumbolo et al. (2021)
2	Increased stress and anxiety due to the pandemic and isolation	Provision of mental health resources and stress management workshops	Vyas (2022); Karthick et al. (2022d)
3	Lack of social interaction leading to feelings of loneliness	Facilitation of virtual team bonding activities and frequent check-ins	Williams et al. (2020).

4	Issues like digital fatigue due to the shift to remote work practices	Promoting periodic breaks and reducing non-essential virtual meetings	Sokolic (2022)
5	Decreased work-life balance	Implementation of flexible work schedules	Pamidimukkala and Kermanshachi (2021)
6	The increased need for remote management and communication tools	Adoption of efficient digital communication and project management tools	Williams et al. (2020)
7	Concerns about implementing effective health and safety measures for a safe transition back to physical workplaces	Comprehensive guidelines on hygiene, social distancing, and PPE usage	Mostafa (2021)

CONCLUSIONS

The COVID-19 pandemic disrupted the construction industry and had posed serious challenges to the success of a multitude of projects. It has negatively affected the project costs and schedules, resulting in their overruns, and raised issues such as contractual implications and occupational health and safety. This current study aimed to identify the factors contributing to these challenges and outline the strategies that can help mitigate their impact. A total of 26 challenges were identified and their respective strategies were outlined, revealing that labor shortages, escalating material prices, and occupational health and safety issues were major factors contributing to cost overruns during the pandemic. Delays in material delivery, reductions in efficiency and productivity rates, and deferrals of ongoing projects also emerged as key issues. Contractual implications included a lack of guidance on the applicability of force majeure contract clauses. Health and safety concerns were primarily driven by the fear of job loss and reduced income in a volatile job market. The outcomes of this research will equip construction supervisors and personnel with a deeper understanding of the difficulties involved in sustaining a viable business amid a pandemic and will enable them to develop efficacious strategies to boost the success of their projects.

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Analyzing COVID-19 Mitigation Strategies in the Construction Industry

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ABSTRACT

The COVID-19 pandemic has brought about significant operational disruptions in the construction industry. While a wealth of literature suggests best practices, a discernible gap remains in gauging the consensus among industry professionals on these recommendations. Specifically, uncertainty arises regarding the degree to which construction engineers and managers align with these best practices during the pandemic. Additionally, there is a notable knowledge void concerning the real-world effectiveness and adaptability of these strategies. Addressing these concerns and aiming to fill the identified gaps, the primary objective of this research is to elucidate the favored mitigation strategies in the construction sector during the COVID-19 crisis. To achieve this objective, survey responses from 131 construction engineers and managers were analyzed using relative importance index (RII). The results revealed that establishing an effective communication system emerged as a top priority among industry professionals. Furthermore, restructuring, diversifying supply chains, and the inclusion of a force majeure clause specific to COVID-19-related delays were also highlighted by respondents. The study's contributions aim to enhance the construction sector's resilience, adaptability, and preparedness for both immediate and long-term challenges, such as the COVID-19 pandemic. It offers comprehensive guidelines and positions itself as a quintessential reference for engineers, managers, policymakers, and other industry stakeholders.

Keywords: COVID-19, construction sector, mitigation strategies, industry consensus, communication system, supply chain, contract clauses.

INTRODUCTION

The advent of the COVID-19 pandemic has exerted an unparalleled impact on global industries, with the construction sector standing at the forefront of this disruption (Allam et al. 2022). The industry's critical role in infrastructure development, juxtaposed with the on-site nature of work, has rendered social distancing measures and conventional health protocols challenging to implement (Naor et al. 2022; Rouhanizadeh et al. 2022). Consequently, operations within the construction industry have encountered significant hurdles, necessitating the formulation and application of robust mitigation strategies (Adepu et al. 2022; Safapour et al. 2017; Kermanshachi et al. 2023).

Literature in the realm of pandemic response within the construction industry has burgeoned, suggesting a plethora of best practices aimed at circumventing operational disruptions (Bozkurt et al. 2020; Rouhanizadeh and Kermanshachi 2019). Yet, despite this wealth of scholarly recommendations, a discernible chasm persists in the empirical assessment of industry alignment with these practices during such critical times (Adepu et al. 2023a). The nuances of industry acceptance and the pragmatic effectiveness of proposed strategies remain nebulous, with a glaring knowledge void in terms of adaptability and real-world applicability (Adepu et al. 2023b; Safapour et al. 2021). An integrated communication strategy has emerged as a cornerstone in maintaining project cohesion. Pandemic response training and inter-organizational synergy have been recognized as pivotal in fostering an agile response to the unfolding crisis (DiBella et al. 2023; Subramanya et al. 2020; Kermanshachi and Safapour 2019). The elucidation of key performance indicators (KPIs) and the bolstering of supply chain resilience have also been highlighted as vital measures (Hadi et al. 2023; Nipa and Kermanshachi, 2021). Furthermore, labor force analysis, project technological integration, and the adoption of a force majeure clause specific to COVID-19-related delays are among the measures scrutinized. The monitoring of regulatory compliance, coupled with contingency scheduling and contractual risk management, completes the ensemble of strategies assessed for their efficacy and practicality (Adepu et al. 2022; Pamidimukkala et al. 2022; Rad and Kermanshachi 2018).

Acknowledging a significant knowledge gap, several studies have identified various strategies to mitigate the effects of COVID-19 on the construction industry, yet there remains an unclear understanding of the practical application and effectiveness of these strategies. To address this deficiency, the goal of this study is to offer a detailed comprehension of how industry practitioners have formulated recommended practices into their operational frameworks. The objectives of this research are twofold: first, to identify the strategies employed by professionals within the construction sector during the COVID-19 pandemic; and second, to rank these strategies in terms of their practicality based on the insights provided by construction engineers and managers. The research aims to provide a detailed understanding of the extent to which professionals have integrated recommended practices into their operational paradigm.

This research is imperative for the identification and examination of key strategies that have proven critical in sustaining operational continuity. The import of this study extends beyond the immediate tactical responses to the pandemic, by examining the degree to which construction professionals have espoused and implemented these strategies, the research offers a navigational tool for current and future industry challenges. In addition, the outcomes of this inquiry are expected to reinforce the construction sector's resilience, adaptability, and preparedness, equipping it with the knowledge to thrive amid both present and future adversities.

LITERATURE REVIEW

The construction industry's response to the COVID-19 pandemic necessitates a comprehensive evaluation of various mitigation strategies. The importance of an integrated communication strategy has been particularly emphasized, given its role in ensuring the safety and continuity of construction operations. Research by Shahbazi et al. (2023) highlights the need for coherent communication to facilitate the dissemination of health guidelines and operational updates, while Plantes et al. (2021) have demonstrated the effectiveness of such strategies in reducing onsite transmission risks. Pandemic response training has been identified as a critical enabler of workforce safety. Chatigny (2022) discuss targeted training programs designed to equip workers with necessary health and safety knowledge, while Stiles et al. (2021) note the importance of training for ensuring regulatory compliance.

Collaborative efforts, termed inter-organizational synergy, are crucial for a robust pandemic response. Serenko and Bontis (2016) emphasize the benefits of resource sharing and knowledge exchange, while Scholten and Schilder (2015) highlight how such collaboration leads to flexible mitigation strategies. In assessing mitigation measures' effectiveness, key performance indicators (KPIs) are vital. Moreno et al. (2021) advocate for SMART indicators to monitor project health, and Rahman et al. (2022) provide frameworks for KPI identification that address challenges posed by the pandemic. The pandemic has tested the supply chain resilience of the construction sector. Adepu et al. (2022) emphasize diversifying supply sources, and also suggests strategies like strategic stockpiling and technology for supply chain visibility. Labor force analysis is pivotal in understanding workforce capacity impacts. Adepu et al. (2022) assess the workforce's adaptability to new health protocols, while Adepu et al. (2023a) focus on the implications for worker productivity and safety. Project technological integration has been accelerated by the pandemic. Adepu et al. (2023b) note an increase in the use of BIM and project management software and discuss drones for site inspection and VR for project walkthroughs.

The force majeure clause adoption in contracts is a legal consideration brought to the fore by the pandemic. Daniels et al. (2020) discusses the complexities of existing contracts, while Colak et al. (2023) advocate for renegotiation to include pandemic-specific clauses. Regulatory compliance monitoring is more critical than ever. Roy (2021) discusses the challenges of evolving regulations and the importance of maintaining compliance to ensure workforce safety. Contingency scheduling is essential for maintaining project timelines. Adepu et al. (2023b) propose dynamic scheduling techniques, while Adepu et al. (2023a) emphasize the need for flexibility in scheduling to mitigate financial impacts. Lastly, contractual risk management is crucial for navigating uncertainties. Karamoozian and Wu (2022) stress the importance of continuous risk assessment and highlighted the need for comprehensive risk mitigation plans. This literature review encapsulates the multi-faceted strategies the construction industry has employed to mitigate the impacts of the COVID-19 pandemic. The synthesis of scholarly discourse provides the groundwork for analyzing these strategies' effectiveness and developing a resilient industry framework. Table 1. List the strategies.

Table 1. List of Strategies

#	Strategy	Source
1	Integrated communication strategy	Shahbazi et al. (2023); Plantes et al. (2021)
2	Pandemic response training	Chatigny (2022); Stiles et al. (2021)
3	Inter-organizational synergy	Serenko and Bontis (2016); Scholten and Schilder (2015)
4	Key performance indicators (KPI) identification	Moreno et al. (2021); Rahman et al. (2022)
5	Supply chain resilience	Adepu et al. (2022)
6	Labor force analysis	Adepu et al. (2023a)
7	Project technological integration	Adepu et al. (2023b)
8	Force majeure clause adoption	Daniels et al. (2020); Colak et al. (2023)
9	Regulatory compliance monitoring	Roy (2021)
10	Contingency scheduling	Adepu et al. (2023b)
11	Contractual risk management	Karamoozian and Wu (2022)

RESEARCH METHODOLOGY

Figure 1 depicts the five-step research methodology adopted in this study. The initial step involved conducting a comprehensive literature review using various scholarly search engines to understand the impact of COVID-19 on the construction industry and to identify a set of key mitigation strategies. In the second step, an online survey was designed using QuestionPro and administered to gather the perceptions of industry professionals regarding their agreement with the identified best management strategies during the pandemic crisis. The third step consisted of collecting survey responses and analyzing them using the Relative Importance Index (RII) to evaluate the perceived importance of each strategy. In the fourth step, the strategies were ranked according to their RII scores, and the results were synthesized in preparation for discussion. The final step entailed a thorough discussion of the findings from the ranked strategies, culminating in the conclusion of the study.

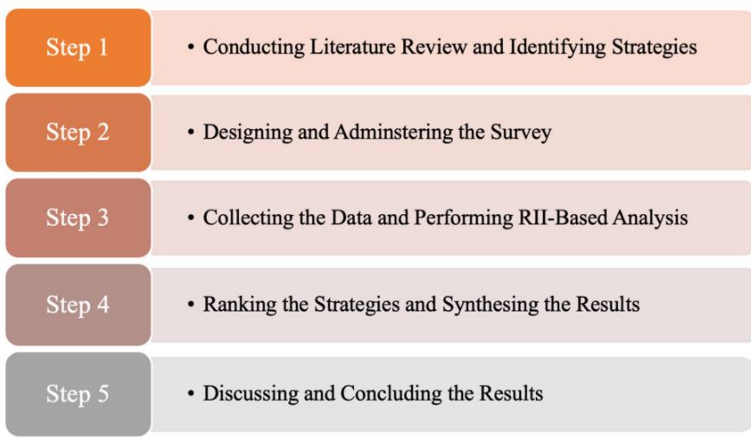

Figure 1. Research Methodology

Demographic Analysis

The demographic analysis of the 131 participants surveyed for this study presents a comprehensive view of the professional landscape within the construction sector during the COVID-19 pandemic are as shown in Figure 2. The data indicates that 53% of the respondents are at the management level, while 47% are at the engineering level, suggesting a balanced representation of both strategic decision-makers and technical experts. Work experience among the participants is diverse, with a plurality (30%) having between 5 to 10 years of experience, followed by 18% with 10 to 15 years, 15% with less than 5 years, 12% with 15 to 20 years, 11% with over 30 years, 8% with 20 to 25 years, and 6% with 25 to 30 years. This distribution indicates a wide range of insights from both relatively newer and highly experienced professionals.

When considering the scale of the organizations represented, the data is evenly split, with 34% of respondents from small, medium, and large organizations, respectively. This equitable distribution suggests that the findings of this research may be generalizable across various organizational sizes within the industry. Lastly, regarding the type of projects the participants are involved with, 39% are engaged with public projects, 36% with private projects, and 25% work on both public and private projects.

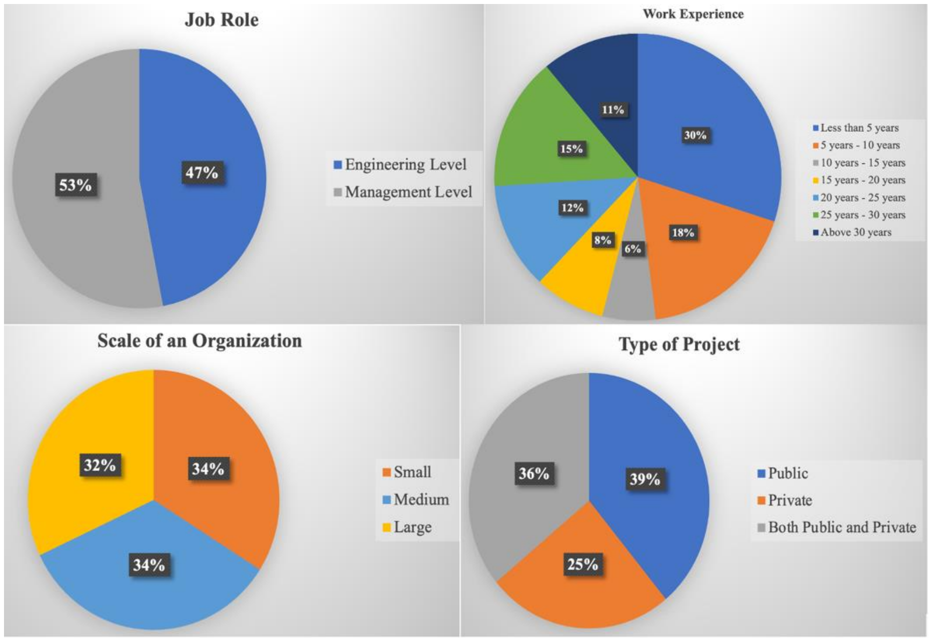

Figure 2. Demographic analysis

Relative Importance Index (RII)

The survey questionnaire was meticulously crafted to assess construction personnel's alignment with proposed best practices amidst the COVID-19 outbreak. Respondents were instructed to articulate their concurrence on a seven-point Likert scale, where '1' indicated 'strongly disagree' and '7' indicated 'strongly agree,' with the intervening figures reflecting a spectrum from 'disagree' to 'agree.' The Relative Importance Index (RII), a metric ranging from 0 to 1, was then employed to compute the degree of consensus based on these responses. The use of RII, as delineated by Chen et al. (2010), involves a transformation matrix that facilitates a nuanced interpretation of the data, allowing for the distillation of the practices' perceived significance into a quantifiable measure. This methodological approach ensures a rigorous analysis, providing valuable insights into the collective stance of the workforce regarding the efficacy of health and safety protocols during the pandemic.

$$RII=\sum W/(A\times N) \tag{1}$$

In this formula, 'W' denotes the weight assigned to each variable by participants. 'A' indicates the maximum possible weight (scale value), and 'N' represents the total number of respondents. The classification and corresponding ranges of the RII are taken from the study conducted by Chen et al. (2010) as illustrated in Table 2.

RESULTS

In the current study, the relative importance index (RII) has been utilized to ascertain the perceived priority of various mitigation strategies against COVID-19 challenges in the construction sector. As shown in Table 3, the results elucidate a hierarchy of strategies, with the integrated communication strategy attaining the highest RII of 0.815, thereby securing the first rank. This indicates a broad consensus on its criticality, aligning it within the high importance category. Such a strategy is paramount, as it underscores the significance of cohesive and transparent communication among project stakeholders, which is essential for agile response to pandemic-related disruptions. Following closely is the pandemic response training, with an RII of 0.811, reflecting its pivotal role in educating the workforce on COVID-19 policies and procedures. Although its importance is designated as high-medium, the marginal difference from the leading strategy suggests almost equivalent significance. The inter-organizational synergy and key performance indicators (KPI) identification strategies are ranked third and fourth, with RII values of 0.759 and 0.737, respectively, both categorized as high-medium. These findings imply a strong endorsement of cross-entity collaboration and the critical assessment of financial and operational metrics, reinforcing the need for a multi-faceted approach to project management during the pandemic.

Table 2. Range of Relative Importance Index (RII)

Category	Range
High	0.8 < RII < 1.0
High-Medium	0.6 < RII < 0.8
Medium	0.4 < RII < 0.6
Medium-Low	0.2 < RII < 0.4
Low	0.0 < RII < 0.2

Table 3. Ranking of Strategies

Variable	RII	Rank	Importance
Integrated communication strategy	0.815	1	High
Pandemic response training	0.811	2	High-Medium
Inter-organizational synergy	0.759	3	High-Medium
Key performance indicators (KPI) identification	0.737	4	High-Medium
Supply chain resilience	0.717	5	High-Medium
Labor force analysis	0.700	6	High-Medium
Project technological integration	0.603	7	Medium
Force majeure clause adoption	0.597	8	Medium
Regulatory compliance monitoring	0.583	9	Medium
Contingency scheduling	0.401	10	Medium-Low
Contractual risk management	0.397	11	Medium-Low

Supply chain resilience and labor force analysis are positioned in the fifth and sixth ranks with RII values of 0.717 and 0.700, respectively, which fall into the high-medium importance bracket. This highlights the industry's recognition of the need to adapt supply chain operations and safeguard skilled labor to maintain project viability. Medium importance is attributed to project technological integration, force majeure clause adoption, and regulatory Compliance monitoring, ranked seventh through ninth with RII values ranging from 0.603 to 0.583. These strategies, while not deemed as critical as the, are still acknowledged as significant contributors to project resilience. Lastly, contingency scheduling and contractual risk management, with RII values of 0.401 and 0.397 respectively, are considered medium-low in importance, occupying the tenth and eleventh ranks. These strategies are recognized as supportive rather than central, indicating a moderate influence on mitigating the pandemic's impact on construction projects. This stratification of mitigation strategies based on their RII values provides valuable insights into the industry's prioritization and paves the way for targeted implementation, ensuring that resources are allocated efficiently to address the most impactful areas. The rankings serve as a strategic blueprint for construction managers to navigate the pandemic-induced landscape, emphasizing the nuanced interplay between communication, training, collaboration, and risk management.

DISCUSSION

In discussing the implications of the presented results, it's crucial to contextualize the COVID-19 pandemic's impact on the construction industry. The pandemic introduced unprecedented challenges, necessitating rapid adaptation in project management and operations. Construction projects, known for their complexity and the intricate interplay of various stakeholders, were particularly vulnerable to the disruptions caused by the health crisis. This necessitated the identification and implementation of targeted mitigation strategies to sustain operations and ensure the safety of the workforce.

Turning to the specifics of the study, the use of the Relative Importance Index (RII) provides a data-driven understanding of the priority assigned to various mitigation strategies by industry professionals. The integrated communication strategy emerges as the most critical, evidenced by the highest RII value. This finding aligns with the sector's need for clear and effective communication to manage the dynamic and rapidly changing circumstances brought about by the pandemic. Effective communication is the lifeline of any construction project, more so in a crisis, ensuring that all parties are informed, aligned, and able to respond promptly to new information. The near-equivalent importance assigned to pandemic response training suggests an industry-wide consensus on the necessity of preparing the workforce to navigate the complexities of the pandemic. This involves understanding new health guidelines, adapting to changing work protocols, and ensuring that safety remains paramount. Inter-organizational synergy and KPI identification are also rated highly, reflecting an understanding that collaboration across different entities and a solid grasp of performance metrics are vital for strategic decision-making during the pandemic. These aspects are integral to maintaining project momentum and ensuring that the various moving parts of a construction project are coordinated and optimized for efficiency and effectiveness.

In the high-medium bracket, supply chain resilience and labor force analysis highlight an industry-wide recognition of the need to maintain a steady flow of materials and labor. These are the backbones of construction operations, and their disruption can have cascading effects on project timelines and costs. Strategies ranked as medium importance, such as technological integration, adapting contractual terms, and regulatory compliance, while crucial, are not seen as immediately impactful compared to the strategies ranked higher. They provide support and structure to the more direct actions taken in response to the pandemic. Lastly, strategies like contingency scheduling and contractual risk management, which fall into the medium-low category, are still valuable but are perceived as less immediate in their impact. These strategies may require a longer-term view and are part of the broader framework within which the industry operates. In conclusion, the RII values and corresponding rankings underscore the importance of a multi-tiered approach to managing the unique challenges posed by the pandemic. The insights drawn from these rankings provide a clear roadmap for construction managers, emphasizing a focused allocation of resources toward the areas of greatest impact, namely communication, training, and collaboration, to navigate the shifting landscape of the construction industry during the pandemic.

CONCLUSION

The inquiry into COVID-19 mitigation strategies within the construction sector has elucidated a hierarchical framework of interventions, as discerned from the professional consensus quantified by the Relative Importance Index (RII). At the apex of this hierarchy resides the integrated communication strategy, commanding the highest RII and thereby underscoring its criticality for operational cohesion in times of unprecedented disruption. Its preeminence, alongside the near-equivalent significance of pandemic response training, reflects a profound industry-wide accord on the indispensability of adept communication and workforce preparedness. These strategies are not mere stopgaps but essential cogs in the machinery of construction project management that enable nimble adaptation to the rapidly evolving pandemic scenario.

Further down the hierarchy, inter-organizational synergy, and the incisive identification of key performance indicators (KPIs) are affirmed as substantial, with their high-medium RIIs indicative of their robust role in steering through the crisis. While the strategies pertaining to supply chain resilience and labor force analysis are similarly positioned, they underscore the necessity to underpin the physical and human substrates of construction projects. Conversely, strategies like contingency scheduling and contractual risk management, despite their lower RII rankings, remain vital in the strategic matrix, offering a buffer of foresight and flexibility. Collectively, these findings articulate a nuanced stratification of strategic imperatives, guiding industry stakeholders towards a calibrated and targeted allocation of resources that fortifies the construction sector against the multi-dimensional impacts of the pandemic.

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Long-Term Physical and Mental Health Impacts of COVID-19 on Construction Workers

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ABSTRACT

The COVID-19 pandemic's profound effects on various sectors have been widely reported, yet the long-term physical and mental health ramifications for construction professionals remain underexplored. This study aimed to address this gap, drawing on data from 131 responses collected from construction engineers and managers to evaluate the enduring health implications of the pandemic on these professionals and ranked the impacts using mean score analysis. Preliminary findings indicate a notable increase in specific physical ailments such as fatigue, headache, and attention disorders. Concurrently, there was a marked rise in mental health challenges, with anxiety, depression, and fear being the predominant emotional states reported. These results underscore the pressing need for health interventions tailored to the construction sector, emphasizing both physical and psychological well-being. As the construction industry seeks to adapt and evolve in the pandemic's wake, these insights can prove invaluable. Understanding and addressing these health concerns can guide engineers, managers, policymakers, and decision-makers in crafting strategies and policies that ensure a healthier and more resilient workforce, paving the way for a more robust industry in future global crises.

Keywords: COVID-19; Construction Professionals; Physical Health; Mental Health; Health Strategies.

INTRODUCTION

The COVID-19 pandemic has left an indelible mark on global industries, with the construction sector standing at the forefront of continued economic activity during these tumultuous times (Sargent 2021; Safapour et al. 2021). The resilience of this sector has been paramount, yet the ramifications on the health of its workforce have sparked a growing concern (Niroshana et al. 2023; Subramanya et al. 2020). This study delves into the long-term physical and mental health impacts of the pandemic on construction workers, a topic that, until now, has remained underrepresented in research literature. Historically, the construction industry has been recognized for its contribution to infrastructure and its role in economic stability (Dang and Pheng 2015; Safapour et al. 2017). However, the health and safety of construction personnel often hinge on the industry's ability to navigate through crises (Ranasinghe et al. 2023). Existing research has extensively documented the immediate health effects of COVID-19 but has been less forthcoming on the chronic, long-term health consequences for those in the thick of essential operations (O'Donnell and Begg 2020; Pamidimukkala et al. 2020).

Studies have begun to surface, bringing attention to the acute onset of illness among the general population and various professional cohorts. Yet, there is a gap in literature specifically addressing the sustained health outcomes post-COVID-19 for construction professionals. Our goal is to fill this gap by presenting a comprehensive analysis of the enduring physical and mental health implications for construction workers. We posit that the long-term health effects of COVID-19 extend beyond the initial recovery period, significantly impacting the physical and mental well-being of construction personnel. This has implications for workplace safety, productivity, and the overall mental health climate within the sector. To achieve this goal, the objectives of the research search are 1) identifying the long term physical and mental health impacts in construction workers due to COVID-19 and 2) To analyze and rank them by employing a mean score analysis of survey data collected from construction engineers and managers.

This paper's contributions are significant; it provides empirical evidence of the long-term health impacts of COVID-19 on a key workforce within the construction industry. Furthermore, it highlights the necessity for industry-specific interventions and underscores the importance of ongoing support for mental health, which has emerged as a critical component of overall worker health and safety. In doing so, this research aims to guide industry stakeholders and policymakers in developing informed strategies to support a workforce.

LITERATURE REVIEW

The onset of the COVID-19 pandemic has precipitated unprecedented health challenges globally, with construction workers being uniquely affected due to the nature of their work. The construction industry, deemed essential in many regions, has required workers to maintain operations amidst potential health risks, leading to various direct and indirect health impacts (Adepu et al. 2022; Rouhanizadeh and Kermanshachi 2019; Kermanshachi et al. 2023). The literature has highlighted the vulnerability of this workforce to both the infection and its broader health ramifications due to factors like the difficulty of social distancing on job sites and inconsistent access to personal protective equipment (PPE) (Adepu et al. 2023a; Pamidimukkala and Kermanshachi 2021; Subramanya and Kermanshachi 2021). Studies have also pointed to the heightened risk of transmission in construction settings, given the close physical proximity required by many tasks, and the communal nature of workers' accommodations and transportation (Adepu et al. 2022; Pamidimukkala et al. 2021; Safapour et al. 2023). Furthermore, the industry's workforce demographics, often comprising older workers with pre-existing health conditions, increase susceptibility to severe outcomes following infection. In addition to the direct risk of viral infection, the pandemic has disrupted regular health services, leading to delays in treatment for non-COVID-related health issues among construction workers (Adepu et al. 2023b; Adepu et al. 2023c; Nipa and Kermanshachi 2021). This disruption is particularly concerning given the physically demanding nature of construction work, which necessitates ongoing health monitoring and care. The subsequent sections delve into specific physical and mental health impacts as evidenced by the current body of research, highlighting the multifaceted nature of COVID-19's implications for construction professionals.

Long-term Physical Impacts of COVID-19 on Construction Workers

Table 1. Lists the long-term physical health impacts. Fatigue has emerged as a predominant long-term symptom among individuals recovering from COVID-19, affecting various

occupational groups, including construction workers (Smallwood et al. 2022). The persistence of fatigue has been linked to the post-viral syndrome, which can severely affect work performance and quality of life (Salamanna et al. 2021). Headaches have been reported as a common post-infectious symptom, which may be related to the systemic inflammation caused by the virus or its impact on the vascular system (Caronna and Pozo-Rosich 2021). Cognitive impairments, including attention disorders, are increasingly recognized as part of the neurological sequelae of COVID-19, potentially impacting occupational safety and productivity (Meier et al. 2021).

Musculoskeletal complaints, such as joint pains, have been documented in individuals with long COVID, suggesting a lingering inflammatory response (Adepu et al., 2020). Cardiovascular symptoms, including chest pain, have been observed post-COVID, raising concerns about the potential chronic impact on cardiovascular health (Chilazi et al. 2021). Respiratory complications such as pulmonary disorders have also been noted, albeit with variable incidence and severity, reflecting the respiratory nature of SARS-CoV-2 and its potential for causing lasting lung damage (Halawa et al. 2022). Additionally, there is emerging evidence suggesting a link between COVID-19 and new-onset diabetes mellitus, indicating a complex interplay between the virus and glucose metabolism (Sabri et al. 2021).

Table 1. Long-term physical health impacts

#	Physical Challenge	Source
1	Fatigue	Smallwood et al. (2022); Salamanna et al. (2021)
2	Headache	Caronna and Pozo-Rosich (2021)
3	Attention Disorder	Meier et al. (2021)
4	Joint Pains	Adepu et al. (2020)
5	Chest Pain	Chilazi et al. (2021)
6	Pulmonary Disorders	Halawa et al. (2022)
7	Diabetes mellitus	Sabri et al. (2021)

Long-term Mental Health Impacts of COVID-19 on Construction Workers

Table 2. Lists the long-term mental health impacts. The mental health impacts of the COVID-19 pandemic are profound, with anxiety being a significant concern. The pervasive uncertainty and stress associated with the pandemic have been linked to heightened levels of anxiety across various populations, including construction workers (Bender et al. 2021). Fear, related to health risks and job security, has been widely reported, reflecting the broader psychological distress experienced during health emergencies (Gruber et al. 2021). Depression has been identified as a critical issue, with the pandemic exacerbating pre-existing mental health conditions and contributing to new instances of depressive disorders (Murphy et al. 2021). Furthermore, the emotional state of sadness, while less severe than clinical depression, is acknowledged as a widespread response to the pandemic's ongoing adversities, impacting individuals' well-being and work life (Prime et al. 2020).

RESEARCH METHODOLOGY

Figure 1 depicts the five-step research methodology adopted in this study. The initial step involved conducting a comprehensive literature review using various scholarly search engines to identify the long-term physical and mental health challenges on construction workers during the times of pandemic crisis. In the second step, an online survey was developed using QuestionPro and distributed to gather the perceptions of industry professionals regarding their agreement with the identified long-term physical and mental health impacts on construction workers due to COVID-19. The third step consisted of collecting survey responses and analyzing them using mean score analysis. In the fourth step, the impacts were ranked according to their mean scores, and the results were integrated in preparation for discussion. The final step entailed a thorough discussion of the findings from the ranked physical and mental challenges, formulating in the conclusion of the study.

Table 2. Ranking the long-term mental health impacts

#	Mental Challenge	Source
1	Anxiety	Bender et al. (2021)
2	Fear	Gruber et al. (2021)
3	Depression	Murphy et al. (2021).
4	Sadness	Prime et al. (2020).

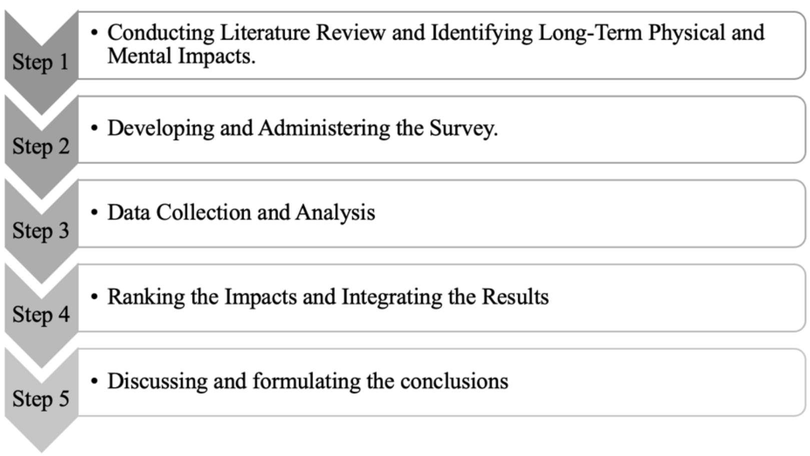

Figure 1. Research Methodology

Demographic Analysis

The demographic analysis of the 131 participants surveyed for this study presents a comprehensive view of the professional landscape within the construction sector during the COVID-19 pandemic are as shown in Figure 2. The data indicates that 53% of the respondents are at the management level, while 47% are at the engineering level, suggesting a balanced representation of both strategic decision-makers and technical experts. Work experience among the participants is diverse, with a plurality (30%) having between 5 to 10 years of experience, followed by 18% with 10 to 15 years, 15% with less than 5 years, 12% with 15 to 20 years, 11% with over 30 years, 8% with 20 to 25 years, and 6% with 25 to 30 years. This distribution indicates a wide range of insights from both relatively newer and highly experienced professionals.

When considering the scale of the organizations represented, the data is evenly split, with 34% of respondents from small, medium, and large organizations, respectively. This equitable distribution suggests that the findings of this research may be generalizable across various organizational sizes within the industry. Lastly, regarding the type of projects the participants are involved with, 39% are engaged with public projects, 36% with private projects, and 25% work on both public and private projects.

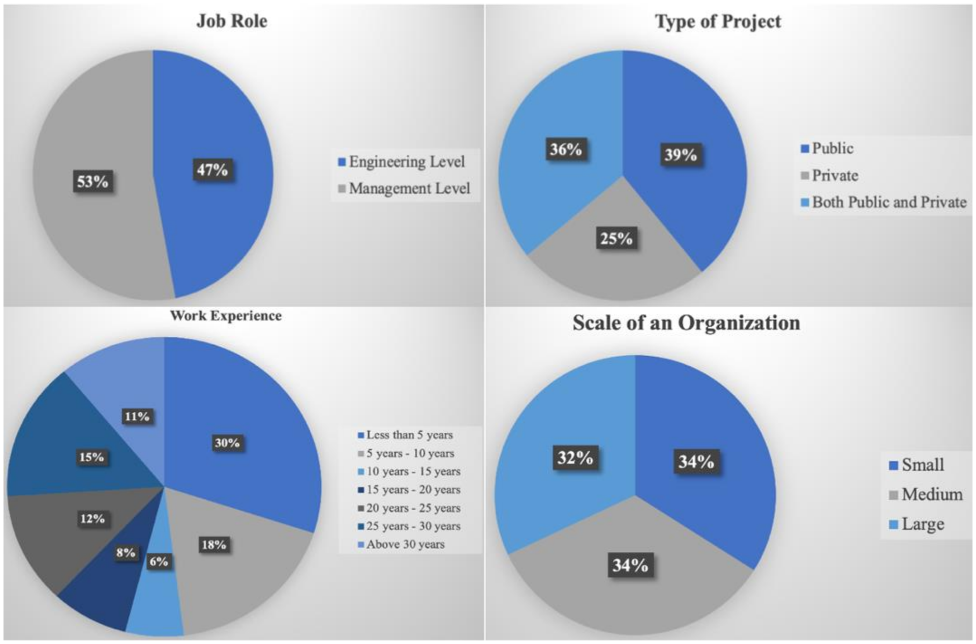

Figure 2. Demographic Analysis

RESULTS

Ranking the long-term physical health impacts

The study aimed to identify and rank the long-term physical health impacts of COVID-19 on construction personnel, a demographic that has been critical in maintaining infrastructure during the pandemic. The ranking was determined based on a mean score analysis derived from survey data. The physical challenges were listed in descending order of severity as per the mean scores calculated from the responses.

Table 3 presents the compiled ranking of long-term physical health impacts as reported by the surveyed construction personnel. Fatigue was reported as the most significant long-term health impact, with the highest mean score of 5.37, indicating that respondents experience this symptom 'usually' to 'always'. This is consistent with the literature, which identifies post-viral fatigue as a common long-term consequence of viral infections, including COVID-19. Headaches were the second most reported long-term impact, with a mean score of 4.93. This suggests that headaches are a frequent but slightly less pervasive issue compared to fatigue. Attention disorder, with a mean score of 4.52, ranked third, reflecting a significant cognitive impact that may affect the daily activities and work performance of the affected individuals.

Joint pains, with a mean score of 4.33, and chest pain, with a mean score of 3.91, were ranked fourth and fifth, respectively. These symptoms are indicative of the musculoskeletal and cardiovascular challenges experienced post-infection. Pulmonary disorders, understandably a concern with a respiratory virus such as SARS-CoV-2, were given a mean score of 3.45, ranking sixth among the health impacts. This lower ranking may reflect the nature of the construction workforce, which typically may have a lower incidence of severe respiratory issues or may underreport such symptoms. Lastly, diabetes mellitus, with a mean score of 3.23, was ranked seventh. The emergence of new-onset diabetes as a long-term impact of COVID-19 is a concerning development, potentially indicating a profound and systemic effect of the virus.

Table 3. Ranking the long-term physical health impacts

Physical Challenge	Mean-Score	Rank
Fatigue	5.37	1
Headache	4.93	2
Attention Disorder	4.52	3
Joint Pains	4.33	4
Chest Pain	3.91	5
Pulmonary Disorders	3.45	6
Diabetes mellitus	3.23	7

Ranking the long-term mental health impacts

In conjunction with the physical challenges posed by COVID-19, the mental health impacts on construction personnel have been of particular concern. The psychological well-being of these workers is paramount, as it directly influences their safety and productivity. This study quantitatively assessed the long-term mental health challenges using a mean score analysis based on the survey data collected from 131 construction engineers and managers.

As illustrated in Table 4, anxiety was reported as the most prevalent mental health challenge, with the highest mean score of 4.84, indicating that respondents experience this challenge 'frequently' to 'usually'. The nature of the pandemic, alongside the pressures of working in an essential sector, likely exacerbates feelings of anxiety among construction workers. Fear holds the second rank, with a mean score of 4.29, reflecting ongoing concerns about health risks, job security, and the potential for future waves of the pandemic. These fears may be compounded by the direct experience of the illness or through the impact on colleagues and the broader community. Depression was ranked third with a mean score of 3.76. As a more severe mental health condition, the presence of depression at this level is alarming and highlights the need for mental health support and resources for those in the construction industry. Sadness, with a mean score of 3.35, while less severe than depression, still represents a significant mental health challenge that affects a considerable portion of the surveyed personnel, ranking fourth.

Table 4. Ranking the long-term mental health impacts

Mental Challenge	Mean- Score	Rank
Anxiety	4.84	1
Fear	4.29	2
Depression	3.76	3
Sadness	3.35	4

DISCUSSION

In assessing the long-term health implications of COVID-19 among construction personnel, our study has unveiled a complex array of both physical and mental challenges, which are reflective of the broader symptomatology reported in post-COVID-19 syndrome. The predominance of fatigue as the primary long-term physical health impact underscores the profound and persistent nature of post-viral fatigue. Notably, the construction industry, characterized by physically demanding tasks, may exacerbate such symptoms, potentially leading to a reduced capacity for labor and impacting overall project timelines and safety. The significant reporting of headaches and attention disorders among participants can be interpreted as indicative of the neurological footprint of the SARS-CoV-2 virus, which has been documented to affect cognitive functions and exacerbate stress-related ailments. This has serious implications for safety on construction sites, where cognitive alertness is paramount for the prevention of accidents. The prevalence of musculoskeletal complaints, namely joint pains, and cardiovascular symptoms like chest pain, suggests a possible exacerbation of pre-existing conditions or the manifestation of the inflammatory responses associated with COVID-19. The construction workforce, often perceived as robust due to the physical nature of their occupation, may not typically prioritize reporting respiratory symptoms, which may explain the lower ranking of pulmonary disorders in our study.

Turning to mental health, the high incidence of anxiety and fear underscores the psychological toll of the pandemic. The construction industry has been under immense pressure to maintain infrastructure, often at the risk of personal health. This stress, compounded by the uncertainty surrounding job security and potential pandemic waves, amplifies anxiety levels, which could have long-standing effects on the mental well-being of the workforce. Depression and sadness, while ranked lower, are still of considerable concern. The presence of these more severe mental health challenges highlights the necessity for industry-wide mental health support and resources. It is imperative that construction companies and policymakers recognize the mental health repercussions and provide appropriate interventions. Furthermore, our findings suggest that the long-term health impacts of COVID-19 on construction personnel are significant and multifaceted, with considerable implications for occupational health management and safety protocols within the industry. Future research should aim to develop targeted strategies to address these challenges, emphasizing the need for comprehensive healthcare support, including mental health services, to ensure the well-being and productivity of this essential workforce.

CONCLUSION

The COVID-19 pandemic has disrupted lives and livelihoods across various sectors, but its enduring impact on the physical and mental health of construction workers has not been thoroughly explored until now. This study sought to bridge this knowledge gap by analyzing data from 131 construction engineers and managers, bringing to light the persistent health challenges faced by these professionals in the aftermath of the pandemic. Our findings revealed a significant prevalence of fatigue, headaches, and attention disorders, alongside a substantial rise in mental health issues such as anxiety, depression, and fear. These results not only reflect the immediate post-infection sequelae but also highlight the prolonged nature of COVID-19's impact on individuals in the construction industry. Practically, this study contributes to a deeper understanding of the post-pandemic landscape for construction professionals. The detailed explanation of long-term health impacts provides a foundation for policymakers, healthcare providers, and industry leaders to develop targeted interventions. The introduction of tailored health strategies, including mental health support and modified work practices, becomes imperative to safeguard the workforce's well-being and ensure the sector's resilience.

In considering the limitations of this study, it is important to note that while we have successfully identified and ranked the health impacts, we have not delineated strategies to mitigate these issues. The study's design was focused on the recognition of problems rather than the resolution, providing a platform for subsequent research to build upon. Future directions should include longitudinal studies to track the evolution of these health impacts over time, as well as the development of intervention programs to mitigate these effects. It is also crucial to examine the potential for these health challenges to influence work performance and safety on construction sites. As the industry continues to adapt to the new normal, the insights gained from this study will be invaluable in ensuring a healthier, more informed, and resilient construction workforce, capable of withstanding the challenges of future global health crises.

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Unconscious Bias in Self-Presentation: Exploring Gender Disparities in Leadership within the Transportation Industry

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ABSTRACT

This study examines the underrepresentation of women in leadership roles in the civil engineering industry, despite them having similar qualifications, experience, and degrees as men. It focuses on how unconscious biases may affect this disparity, especially in how female leaders present their skills and competencies on social platforms like LinkedIn. Analyzing 2,800 LinkedIn profiles of leaders from civil engineering companies, the study compares their self-presentation with colleagues' evaluations in the recommendation section. It finds that female leaders often align their skill and biography presentation with others' expectations, showing a 14% higher text similarity in received recommendations compared to male leaders. Despite being viewed as equally competent, female leaders are perceived as less likable, with a 28% likability score versus 51% for males. The study highlights the need to address these biases to enhance gender equality in leadership positions.

INTRODUCTION

Despite the well-documented advantages of gender diversity in senior management for organizational performance, as evidenced by studies like Baker et al. (2021), the civil engineering industry predominantly remains a male-dominated field. Previous studies, including Hickey and Cui's 2020, reveal that in the top 400 U.S. civil engineering firms, as ranked by Engineering News Record (ENR), women hold only 14.8% of leadership roles. This comprises 5.2% in engineering positions and 33.2% in non-engineering capacities (Hickey and Cui 2020). Numerous studies have explored why there is such a significant underrepresentation of women in leadership roles within civil engineering industry (Maurer et al. 2021). Earlier research shows that despite women acquiring advanced degrees more rapidly than men and having similar experience, titles (Hickey et al. 2022), and competencies (Erfani et al. 2023 a), they continue to face challenges in competing with their male counterparts.

Some socio-psychological theories attribute these challenges to concepts like social role theory (Eagly and Wood 2012) and gender role theory (Anglin et al. 2022). These theories propose that social roles, defined as sets of norms and expectations tied to specific societal positions, significantly influence individuals' behaviors, attitudes, and beliefs, as detailed by Eagly et al. in 2000. According to these theories, individuals in certain social roles, such as leadership, are expected to fulfill specific responsibilities, exhibit certain behaviors, and conform to the norms and values associated with that role. These roles are typically acquired and reinforced through socialization channels such as family, peers, and social media. The theory suggests that behavioral and attribute differences between genders are mainly a result of socially assigned roles to men and women, rather than innate biological distinctions. For instance, conventional gender roles might dictate that men should be assertive, independent, and competitive, whereas women should be nurturing, caring, and cooperative. Such expectations can shape an individual's self-view, ambitions, career decisions, self-presentation in social media, and social interactions (Tifferet and Vilnai-Yavetz 2018).

Our study employs a thorough, evidence-based analysis to show that female leaders, influenced by unconscious bias, tend to present themselves in a manner that aligns with their perceived expectations from others as leaders. Because traits commonly associated with successful leadership, like independence, assertiveness, self-reliance, and power, are often linked to masculinity and fall within the male behavioral domain, women in leadership positions feel compelled to exhibit and heavily emphasize these traits in a way that conforms to societal norms. We applied a data-driven text mining approach to simultaneously analyze and compare the LinkedIn biographies and skill sets of female and male leaders with the texts of recommendations they received from colleagues, friends, and former bosses. By contrasting how leaders present their skills and biographies with how others describe them, we gain the opportunity to assess unconscious biases in self-presentation. Furthermore, our analysis extends to comparing competencies and likability in the recommendations and skills listed by female and male leaders. The study contributes to the existing body of knowledge on gender disparity in civil engineering leadership by examining the influence of social theories in this context.

GENDER GAPS IN CIVIL ENGINEERING LEADERSHIP

Many studies have investigated the hurdles, difficulties, and challenges that women face in entering and advancing within the civil engineering industry (Hickey et al. 2022; Loosemore and Li 2016). Addressing the underrepresentation of women and other minorities in leadership positions is increasingly important due to both growing demand, companies' business outcome, and ethical reasons (Erfani and Cui 2023). Even in the absence of overt discrimination, many women feel the need to put in extra effort to gain respect when they reach leadership roles (Eagly 2005). Tackling diversity issues is a long-term endeavor, not a quick fix. It requires sustained efforts to change socio-psychological traits and cultural norms. This means going beyond mere policy changes to fostering a workplace where inclusivity is part of the culture. It's about challenging biases and reshaping interactions, a process that is gradual and intertwined with evolving societal values. Thus, it's important to analyze socio-psychological issues to identify, highlight, and address them effectively.

Eagly and Wood, in their social role theory (2000, 2012), suggest that gender-specific attitudes and behaviors are influenced by both biological and social factors. Koenig and Eagly (2014) explain that social roles, which give rise to gender role theory, develop from biological factors like men's physical size and strength, and women's reproductive roles, combined with historical and societal structures. For example, men are more commonly found in employment, particularly in positions of authority, while women are often seen in caretaking roles both in professional settings and at home. People's perceptions of leaders often align with agentic qualities like assertiveness and mastery, traits typically associated more with men than women.

This societal pressure leads to an unconscious bias among women, compelling them to conform to these prevailing leadership expectations. As a result, female leaders often feel the need to embody traits exactly as dictated by social norms for leadership, which predominantly reflect traditionally masculine qualities. This challenge highlights the struggle women face in balancing their authentic self-presentation with societal expectations of leadership. Research on the influence of social role and gender role theory on female leaders in civil engineering has been scarce. However, recent studies have begun to shed light on the gender biases prevalent within this field.

Poleacovschi's 2018 study revealed gender biases in the evaluation of expertise among civil engineers, with men often receiving higher ratings than women. Ling et al. (2020) discovered that gender stereotypes and related issues impede women's advancement in management roles, noting that women are often seen as less likely to acquire skills and technical knowledge, and to impact other work areas. Additionally, Norberg and Johansson (2021) identified a bias in the construction industry's culture, where women are expected to perform beyond their designated job responsibilities.

DATA AND METHODS

To create a representative dataset, our first step was to identify leading civil engineering companies in the United States using the Engineering News Record (ENR) top 400 reports. We then examined the websites of these top firms, specifically under the “Leadership” or “Meet Our Team” sections, to compile a list of their publicly available leadership teams. The subsequent manual process involved matching each leader's LinkedIn profile with their names, titles, and, where available, photos. This effort resulted in a comprehensive list of LinkedIn URLs for over 2,850 leaders from these top civil engineering firms. For data collection, we developed a Python-based web scraper to automate the extraction of the recommendations, skills, and biography sections from each LinkedIn profile. The scraping script was coded using the “Urllib” and “BeautifulSoup” libraries, enabling the capture of recommendations received by each profile. The data collection process was finalized in September 2023.

The biography and skill sections on LinkedIn offer individuals a platform to showcase their key skills and competencies, allowing them to highlight their primary strengths and experiences. These sections serve as a personal showcase, where professionals can not only detail their professional journey and achievements but also emphasize specific areas of expertise and experience. This opportunity for self-representation is crucial in building a professional identity online, giving others a comprehensive view of one's abilities, accomplishments, and areas of specialization. On the flip side, professional recommendations act as endorsements that detail an individual's contributions, qualities, and character traits. These testimonials, provided by colleagues, supervisors, or clients who have worked directly or indirectly with the person, offer valuable insights. They serve as an external perspective on the leader's competencies and likability. The final collected recommendation dataset includes more than 1,277 recommendations written for almost 400 leaders among collected profiles. Among collected data, 352 recommendations received by the 105 females (3.35 average) and 925 by 295 men (3.15 average). The final dataset consists of female and male leaders who have included biographies and skills in their profiles. This provides a foundation for comparing how they represent themselves versus how others perceive them.

Semantic Text Similarity Calculation.

Semantic text similarity calculation is an advanced technique in natural language processing (NLP) that seeks to understand and quantify the degree of similarity between textual entities, such as sentences or documents (Erfani and Cui 2021; Erfani et al. 2023 c). Among the various methods developed for this purpose, SBERT (Sentence-BERT) and Word2Vec stand out for their effectiveness and efficiency. SBERT (Reimers and Gurevych 2019), an innovative adaptation of the renowned BERT (Bidirectional Encoder Representations from Transformers) model, is specifically tailored for capturing sentence-level semantic information. BERT, known for its deep understanding of language context and nuance, primarily focuses on word-level embeddings. SBERT modifies this approach to generate sentence embeddings, allowing for more direct and meaningful comparisons between sentences (Erfani et al. 2023 b). This adaptation makes SBERT particularly useful for tasks requiring a deep semantic understanding of complete sentences, rather than just isolated words. Word2Vec (Mikolov et al. 2013) is a group of models that map words into a high-dimensional vector space. This method involves training a neural network model to reconstruct linguistic contexts of words. Word2Vec learns word associations from the training corpus and represents words as dense vectors that capture semantic meanings and relationships. Words used in similar contexts are positioned closer together in the vector space, allowing the model to infer a level of semantic similarity (Erfani and Cui 2022).

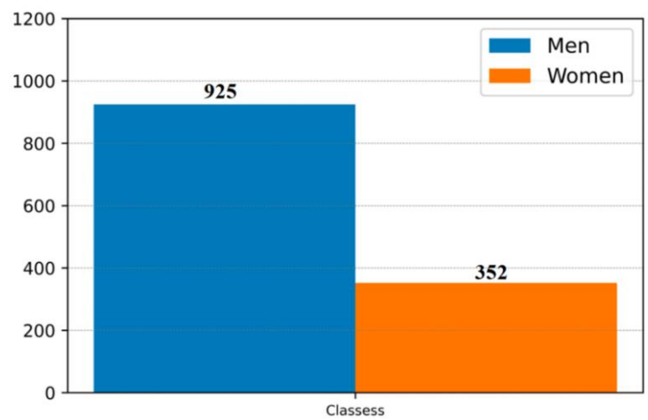

Figure 1. Number of Recommendations.

We employed two popular semantic similarity calculation methods, SBERT and Word2Vec, to evaluate the text similarity between 'Received Recommendations'—the descriptions of a leader by others on their LinkedIn profile—and a text compilation of the individual's own biography and skills as listed on LinkedIn. This comparison aims to analyze the difference between how leaders present themselves and how they are perceived by others on professional social media. Table 1 showcases examples of how this calculation process is executed.

Extraction of Keywords Related to Likability and Competency.

We created a text mining method to identify key competency categories in LinkedIn endorsements, utilizing an extensive competency lexicon. Pariafsai and Behzadan (2021) undertook an exhaustive examination of over 31 pertinent sources to pinpoint terms and expressions linked to core competencies for civil engineering leaders. The initial list of inputs was derived from their analysis, and the WordNet Python package was employed to automatically generate a list of word synonyms (Farkiya et al. 2015). Table 2 presents the definitive compilation of phrases connected to each competency category. Using a python script, authors matched each recommendation with the list of terms and phrases to identify each category of competencies from text.

Table 1. Similarity calculation example

Bio and skills: Kristin works with small to midsize companies as a fractional CHRO, interim HR leader, executive coach, consultant, and/or search partner. She has successfully worked with start-up organizations & private equity owned companies as a fractional or interim HR leader, as a search partner to bring in the best talent, and as an executive coach to assist in the successful onboarding of key leaders. Kristin is an experienced HR executive that brings a wealth of knowledge and has a proven track record of being a key leader in completing multiple mergers, acquisitions, and divestitures. Her expertise is in the following areas: - Contingent recruiting for all levels of roles, primarily in the areas of sales, marketing, finance, HR, operations, and executive assistants - Retained Executive Recruiting for C-level, VP, and key strategic leadership roles - Fractional CHRO or Interim CHRO leadership roles - Merger, acquisition, and divestiture activities, such as, HR due diligence, integration, and project work. - Coaching & onboarding of new leaders and key talent - Coaching of executives and high potential leaders - HR Transformation projects	
Recommendation: Kristin played an integral role in helping grow a new business at our Group. Kristin was able to partner with senior executives to facilitate and jointly develop the Human Capital strategy for this new business. Kristin has a breadth of experience and has an amicable style that makes her easy to work with. Kristin worked for me in a fast paced, growing company that was very entrepreneur in spirit. She was amazing. Kristin has a keen sense of process and human relation skill sets to get the job done. She brought quality systems and strong hires to our recruiting efforts. Most importantly, Kristin is a great team player, consistent in performance and attitude, and I would be thrilled to have the opportunity to work with her again.	
SBERT similarity: 0.83	**Word2Vec similarity:** 0.85

On the other hand, a person's likeability can be understood as the extent to which they are perceived by others as amiable and agreeable. Within a work setting, colleagues are more inclined to collaborate with individuals who exhibit these traits. Certain terms and expressions in a recommendation serve as indicators of likeability. We have compiled a comprehensive dictionary of these markers to gauge the recommended individual's likeability, focusing on their personality traits and the extent to which they are favored as collaborators (Leising et al. 2012). Mirroring our earlier approach, we employed the WordNet Python package for automatic synonym identification. Our objective was to compile an exhaustive inventory of words and phrases applicable for detecting likeability. However, we acknowledged the constraints in encompassing every possible word. Table 3 showcases the dictionary of likeability signals, encompassing both phrases and terms that describe a person's likeability from both personality and coworking perspectives.

RESULTS

A comparison of the average similarities in received recommendations, biographies, and skills between female and male leaders reveals a significantly higher degree of similarity within the female group. Regardless of the semantic similarity technique employed, whether SBERT or Word2Vec, females consistently exhibit a higher degree of similarity (0.63 vs 0.49 and 0.68 vs 0.59) in their skills and biographies compared to the recognition of their skills and competencies by friends, colleagues, and employers (Figure 2).

Table 2. Competency categories and terms and phrases used in each category (Pariafsai and Behzadan (2021))

Competency Category	Terms and phrases grouped as same category.
Communication	‘communication’; ‘public relations’; ‘ability to understand people’; ‘developing client relations’; ‘interpersonal skills’; ‘master communications techniques’; ‘relationships’; ‘networking’; 'interaction relaxation'; 'interactant respect'; 'interaction management'; 'sociability'; 'social competencies'; 'approachable'; 'social skills'; 'listens to others'; 'fluency of speech'; 'speaking'; 'writing'; 'communication management'; 'ability to work with others'; 'communicating'; 'accessible'; 'reachable'; 'public speaking'
Technical	'technical'; 'estimating'; 'scheduling'; 'knowledgeable'; 'technical knowledge'; 'standards and specifications'; 'relevant engineering principles'; 'urban planning'; 'building architecture'; 'building structure'; 'civil engineering’; ‘construction'; 'construction equipment'; 'construction materials'; 'construction operations'; 'constructability'; 'plans interpretation'; 'project management concepts'; 'disciplinary understanding '; 'construction technology'; 'technology and software'; 'computational tools'; 'accounting'; 'computer skills'; 'BIM model '; 'software skills'; 'ability to model '; 'technical expertise'; 'expertise'; 'field experience'; 'professional practice'; 'proficient'; 'technological'; 'expert'; 'approximate'; 'calculate'; 'figure'; 'forecast'; 'programming'; 'knowing'; 'learned'; 'lettered'; 'well-educated'; 'well-read'; 'versed'; 'accountancy'; 'expertness'
Creativity	'creativity'; 'initiative'; 'innovation'; 'diverse thinking'; 'imaginative'; 'motivate creativity'; 'creativeness'; 'creative thinking'; 'enterprise'; 'inaugural'; 'initiatory'; 'invention'; 'excogitation'; 'creation'; 'inventive'
Leadership	'leadership'; 'team leadership'; 'leadership competencies'; 'multidisciplinary'; 'persistent optimism'; 'politics'; 'diplomacy'; 'systems thinking'; 'managerial support'; 'directing'; 'directiveness'; 'give instructions'; 'ability to coach'; 'ability to train'; 'mentor'; 'enable others to act'; 'handle others'; 'manage people'; 'dominance'; 'handling complexity'; 'project controls'; 'authority'; 'direct'; 'lead'; 'guide'; 'head'; 'directive'; 'guiding'; 'authorization'
Teamwork	'team management'; 'team building'; 'team development'; 'teamwork'; 'collaboration'; 'cooperation'; ' build coalitions within project team'; 'recognize other skill'; 'knowledge network'; 'empathy'; 'unselfishness'; 'dedication to the organizational '; 'effective team'; 'collaborationism'
Motivation	'motivating'; 'motivation'; 'ability to encourage'; 'ability to motivate'; 'ability to inspire'; 'promoting change'; 'willingness'; 'motivate', 'actuate', 'propel', 'move', 'prompt', 'incite'
Problem solving	'problem solving’; ‘handling problems'; 'identify problem'; 'solve problem'; 'effective solution'; 'solving problem'

Decision making	'decision making'; 'decision'; 'timely decision'; 'decision making skills'; 'decision'; 'determination'; 'conclusion'; 'decisiveness'
Stakeholder	‘stakeholder’; ‘client’; ‘deal with owner’
Resource	'human resources'; 'organizing project'; 'organizational structure '; 'key personnel'; 'labor management'; 'resource management'; 'resource allocation'; 'allocation skill'; 'materials management'
Legal	'legal issues'; 'legal aspects'; 'building codes'; 'regulations'; 'construction law '; 'economic law'; 'engineering contract '; 'administrative regulation'; 'contract documents'; 'conflict management'; 'issues management'; 'contract negotiations'; 'regulation'; 'regulating'; 'government'; 'governing'
Integration	'integration management'; 'integration'; 'integrating'; 'consolidation'
Scope	'scope'; 'scope management' 'range'; 'compass'
Managing	'management'; 'managing organizational effectiveness'; 'management competencies'; 'management theory'; 'organizational theory'; 'management skill'; 'personal management'; 'goal setting'; 'structuring work'; 'strategic thinking'; 'direction'
Risk	'risk'; 'risk management'; 'risk planning'; 'risk assessment'
Reasoning	‘reasoning’; ‘critical thinking'; 'personal vision'; 'analytical thinking'; 'Intellectual property'; 'intellectual leader'; 'good judgment'; 'conceptual thinking'; 'broad perspective'; 'having vision'; 'constructive thinker'; 'resourceful'; 'information processing'
Trustworthy	'building trust'; 'honest'; 'truthful'; 'loyalty'; 'moral reasoning'; 'justice'; 'accountable'; 'responsible'; 'reliable'; 'dependability'; 'commitment'; 'dependable'; 'dedication'; 'creditworthy'; 'authentic'; 'dependableness', 'committal'
Curiosity	'curiosity', 'knowledge networks'; 'information seeking'; 'ability to obtain information'; 'awareness'; 'learning orientation'; 'wonder'; 'curio'; 'oddity'; 'oddment'; 'peculiarity'; 'rarity'; 'consciousness'
Maturity	'mature'; 'professional'; 'emotional self-control'; 'remain calm under pressure'; 'stress management'; 'self-awareness'; 'realistic expectations'; 'emotional balance'; 'identity maintenance'; 'maturate', 'matured'; 'master'
Flexibility	'flexibility'; 'behavioral flexibility'; 'adaptability'; 'flexibleness'; 'tractability'
Administration	‘administration'; 'administrative skill'; 'public administration'; 'governance'
Ethical and Cultural	‘ethical’; ‘ethic’; ‘cultural differences’
Determination	'decisiveness'; 'tolerance and respect'; 'serious personalities'; 'persistence'; 'consistency'; 'focus'; 'endurance'; 'resilience'; 'courage', 'risk taking'; 'self-motivation'; 'willingness'; 'excellence'; 'enthusiasm'; 'energetic'; 'interest in work'; 'willingness to work'; 'working hard '; 'decisiveness'; 'tenacity'; 'tenaciousness'; 'pertinacity'; 'perseveration'; 'consistence'; ‘hard working’

Table 3. Likeability signals and terms and phrases used in each category.

Likeability category	Likeability signals
Personality	Loved, liked, well-liked, enjoyable, great friend, friendly, admired, very likeable, always be a joy, favorite people, nice, cheerful, lovable, adorable, sweet, charming, pleasant.
Working pleasure	like to be around, like to be on team, want to be on team, work with again, great person to work, welcome on team, recommend to any team, go to person, looking forward next project, looking forward next contract. {Please, honor, happy, enjoy, pleasure, good, great, best, privilege, wish, benefit, lucky, fortunate, not hesitate, hope, continue, opportunity, welcome, looking forward, proud} + {to work with / of working / collaboration / collaborating}

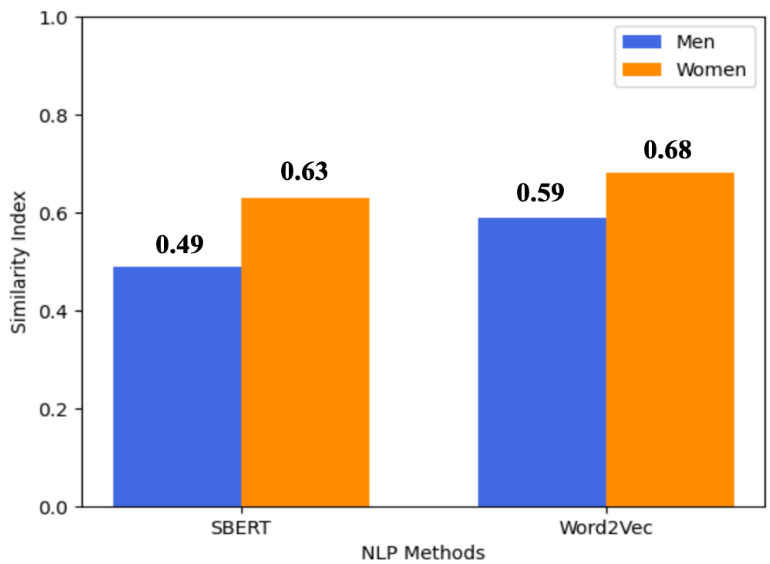

Figure 2. Similarity of received recommendation vs self-presentation in LinkedIn.

The findings support our initial hypothesis that due to cultural pressures; female leaders exhibit self-presentation biases in their LinkedIn profiles, shaping their portrayal (how they present their biography and skills) to align closely with external expectations of leadership (how other provided them with recommendations).

Analyzing LinkedIn recommendations reveals gender-based competency trends: male leaders are more often praised for leadership (53.5%) and technical skills (40.8%), whereas female leaders excel in maturity (34.9%), creativity (32.1%), and communication (30.4%). These findings reflect societal norms associating leadership and technical prowess with masculinity. In summary, while female leaders are on par with males in overall competencies, the areas of expertise recognized differ by gender. Table 4 details the competency levels of female and male leaders, highlighting gender-specific trends in recognized areas of expertise. The comparison of likeability signals in recommendations for female and male leaders indicates that male leaders are perceived as more likeable. As illustrated in Figure 3, likeability signals are present in 51% of recommendations for male leaders, compared to only 28% for female leaders. This trend of higher likeability scores for male leaders is consistent across recommendations written by both male and female professionals.

Table 4. Competency level by gender

Competency Category	Men (%)	Women (%)
Leadership	53.5	40.1
Technical	40.8	32.7
Managing	33.4	28.4
Trustworthy	32.4	25.3
Maturity	27.9	34.9
Communication	27.8	30.4
Creativity	19.9	32.1
Problem Solving	17.3	18.8
Teamwork	14.5	11.9
Determination	11.7	11.1
Administration	11.1	6.8
Motivation	7.1	10.2
Ethical and Cultural	6.4	3.7
Integration	6.2	5.7
Stakeholder	5.2	3.1
Decision Making	3.6	4.3
Risk	2.6	1.1
Legal	2.5	2.8
Flexibility	1.3	1.1
Scope	1.2	0.4
Resource	0.9	0.9
Curiosity	0.6	0.3
Reasoning	0.4	0.9

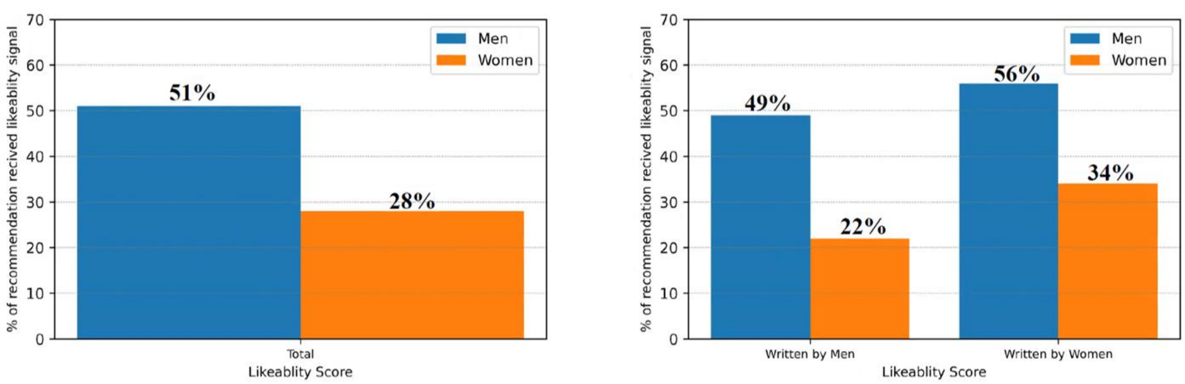

Figure 3. Likeability comparison results

The findings indicate that women in male-dominated fields like construction encounter a paradox of success: as they gain competency and succeed, they often face increased social rejection, including dislike and personal attacks. This situation is not only distressing but also impedes their career advancement and fair reward distribution. Understanding where and why this occurs, its implications, and strategies to mitigate its effects is crucial.

CONCLUSION

The results suggest that female leaders, influenced by societal expectations, tend to craft their biographies, and list their skills on LinkedIn in a manner that aligns more closely with what others anticipate or expect from a leader. This indicates a conformity to perceived norms or standards in their professional self-presentation. In the civil engineering sector, female leaders exhibit competencies on par with their male counterparts, yet displaying these traits often results in a penalty, manifesting as a decrease in their perceived likeability. Our research underscores the significance of sociopsychological aspects related to diversity and biases in the perception, description, and evaluation of female leaders compared to male leaders. The influence of social and cultural norms on gender role expectations is notably important and warrants focused attention. Supporting underserved communities through efforts to promote diversity is indeed valuable, yet it's crucial to recognize that understanding and addressing the psychology and cultural norms of these communities plays a significant role in achieving long-term solutions. Our findings are limited by the nature of the collected data from LinkedIn, companies, and the civil engineering industry within the USA. The level of user activity on social media and the purpose and structure of providing recommendations also play an important role. Future studies could delve into additional areas of bias in social presentation beyond gender roles, exploring other factors contributing to social media persistence and examining their significance in career progression.

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Analyzing Post-Pandemic Remote Work Accessibility for Equity through Machine Learning Analysis

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ABSTRACT

The COVID-19 pandemic has significantly impacted people's travel behavior, leading to a surge in remote work adoption, a trend many companies continue to embrace. This shift toward working from home has not only directly influenced travel demand, traffic congestion, and emissions but also yielded benefits, such as increased productivity and improved work-life balance for individuals. However, as the pandemic recedes, it becomes crucial to investigate whether the opportunity to work from home is equitably distributed among diverse population groups. In this paper, we delve into identifying which population segments have better access to remote work in the post-pandemic era. We analyze survey data collected from individuals in the United States between July and October 2020, employing machine learning techniques such as neural networks, gradient boosting, and logistic regression to model people's expectations regarding working from home post-pandemic. Through permutation importance analysis, we unveil the significant factors influencing these expectations. Notably, we find that less educated individuals, low-income individuals, and females are less likely to work from home in the post-pandemic era. The results of this study hold the potential to guide policymakers in addressing gender and income disparities in access to remote work opportunities. By developing targeted strategies, policymakers and employers can foster a more inclusive and equitable workforce, ultimately benefiting individuals, communities, and the economy.

INTRODUCTION

The COVID-19 pandemic has undeniably reshaped numerous facets of human behavior, with a pronounced impact on travel patterns. A notable outcome of this transformation is a substantial surge in the adoption of remote work, a phenomenon that persists even in the post-pandemic era (Zheng et al., 2023). This paradigm shifts towards working from home (WFH) has not only engendered significant alterations in travel patterns, including traffic congestion, and emissions but has also yielded individual benefits, such as heightened productivity and an improved work-life balance (Alipour et al., 2021). However, as the pandemic gradually subsides, a pivotal question arises: does the newfound opportunity for remote work extend uniformly across different socio-demographic segments? This study endeavors to explore inequities in accessing the WFH option based on individuals' anticipation of the future.

Previous studies have extensively delved into various facets of WFH in the pre-pandemic era. Notable investigations encompass the adoption of telecommuting(Bernardino & Ben-Akiva, 1996; Yagi & Mohammadian, 2008), the impacts of WFH on individuals' activity schedules (Asgari et al., 2019), and the environmental impacts of teleworking (Shabanpour et al., 2018). Early studies predominantly concentrated on individuals' preferences and choices regarding WFH. For example, utilizing a logistic regression model, discovered a positive correlation between a higher level of education and a propensity to prefer WFH in San Diego(Huang et al., 2023). Subsequent studies have also focused on the frequency of teleworking. In this context, Mannering and Mokhtarian's examination of work behavior in California revealed that higher-income groups choose WFH more frequently compared to lower-income groups(Mannering & Mokhtarian, 1995).

The COVID-19 pandemic has engendered significant challenges to achieving equitable access to social services, for instance, the gender gap observed in accessing job opportunities during the pandemic(Dunatchik et al., 2021), racial disparities in access to healthcare services (Quinn et al., 2011), and income inequalities affecting access to educational services (Sahlberg, 2021). Despite a substantial body of research on the equity implications of the pandemic, there remains a notable gap in understanding equity in post-pandemic remote working opportunities. Emerging evidence indicates that telecommuting continues beyond the pandemic (Mohammadi et al., 2023), emphasizing the need to comprehensively address telecommuting inequities in the post-pandemic era. This underscores the importance of characterizing and addressing telecommuting disparities as we navigate the evolving landscape.

This study is fundamentally centered on understanding the disparities in accessing WFH opportunities associated with demographic segments. To achieve this, we analyze the survey data collected from a representative cross-section of individuals in the United States during the pandemic, spanning from July to October 2020. Employing Machine Learning techniques, including neural networks, gradient boosting, and logistic regression, we develop descriptive models that unveil individuals' anticipation towards adopting WFH in the post-pandemic era.

The insights derived from our study shed light on the obstacles faced by vulnerable groups in accessing WFH, providing important policy implications for more equitable access to working from home among disadvantages people. By implementing these meticulously designed policy interventions, policymakers and employers can work hand in hand to cultivate an environment conducive to the growth of an inclusive and fair workforce. This collaborative effort carries the potential to yield far-reaching advantages, benefiting not only individuals and communities but also contributing to the overall resilient performance of the wider economy.

DATA

In our investigation, we utilize the COVID Future Wave 1 survey data. This dataset signifies the findings from the initial stage of a nationwide longitudinal survey that captures information on travel-related behaviours and attitudes before, during, and after the COVID-19 pandemic (Mohammadi et al., 2023). Comprising 8,723 responses, the dataset encompasses various topics such as commuting, daily travel, air travel, working from home, online learning, shopping, and risk perception. Additionally, it includes attitudinal, socioeconomic, and demographic details. Our study specifically focuses on features related to working from home, socioeconomic factors, and demographic information. The dependent categorical features are detailed in Table 1; furthermore, the independent feature is the expectation of working from home, indicating the anticipation of being able to work remotely at least some of the time after COVID-19.

Table 1. Categorical variables in the dataset

Variable/Parameter		Count	Mean
WFH_pre	Were you able to work from home prior to the COVID-19 pandemic?	Yes = 3077 No = 2382	0.436
WFH_now	In the last week, were you able to work from home?	Yes = 3225 No = 1597	0.668
Sex	**Male** **Female**	**5456** **3267**	**0.581**
Education level (Resident)	high school or completed	1414	0.163
	College	2521	0.290
	Above College	4758	0.547
Income Level (Household)	Less than 15K	769	0.088
	15k to 35k	1334	0.153
	35k to 50k	983	0.113
	50k to 75K	1574	0.180
	More than 75K	4063	0.466

METHODOLOGY

Data Preprocessing

To prepare the data for a machine learning algorithm, our initial step involved data preprocessing. Initially, we used a weighting technique to reduce the bias due to missing data (Asgharpour, Javadinasr, et al., 2023), resulting in 4733 datapoints. Subsequently, we addressed categorical variables; apart from age, all variables fell into this category. Thus, we transformed these variables into dummy variables, expanding the dataset to a size of 4733 rows and 20 columns. Following the dataset cleansing process, within the pool of 4733 instances, 2741 instances (58%) are categorized as "Yes," while 1992 instances (42%) are labeled as "No." This distribution implies a balanced dataset, indicating no significant imbalance in the data. Additionally, prior to running the model, we conducted a correlation analysis among variables, revealing no significant correlations that might indicate multicollinearity issues.

Machine Learning Models

In this research, aimed at assessing the equitable distribution of teleworking access post-pandemic, we employed three machine learning algorithms including Logistic regression, gradient boosting, and BackPropagation Neural Network. These models are widely utilized to study individuals' travel behavior (Javadinasr et al., 2023; Koushik et al., 2020). Our initial algorithm of choice is logistic regression, a classification method falling under the supervised learning category. Logistic regression is specifically designed for predicting categorical target variables. In this method, we model the probability of instances belonging to a particular class. The fundamental concept behind logistic regression is an extension of the linear regression model tailored for classification problems. In its basic form, it addresses a binary outcome (0 and

1) for the target variable y. Utilizing this algorithm facilitates classification in supervised learning. An additional advantage of the logistic regression model lies in its ability to analyze both positive and negative coefficients of variables within the model. This analysis provides valuable insights into the factors influencing the classification outcomes. We leverage this feature to gain a deeper understanding of the nuanced relationships between variables and their impact on the classification process.

The second algorithm in our study is the gradient boosting machine (GBM), a model rooted in decision trees within the category of supervised learning, adept at addressing both classification and regression problems. This approach relies on constructing an ensemble of multiple decision trees to enhance the predictive performance of the model. The collective strength of the ensemble surpasses that of individual models. The methodology involves the sequential construction of decisions, followed by the use of a loss function to identify residuals (or misclassified instances in the case of classification). Subsequently, a new tree is trained to refine the errors of the preceding tree. Notably, instances with higher errors carry greater weight than those with lower errors during this iterative process. This sequence continues until the error term is minimized. We selected this algorithm due to its potency in tackling classification problems, and our analysis extend to examining data through the lens of permutation importance. This technique allows us to discern the significance of variables in the model by evaluating their impact on the classification outcomes.

The final model incorporated into our research is the Backpropagation Neural Network. Neural Networks, widely employed in supervised learning for both regression and classification tasks, draw inspiration from the intricate functioning of neurons in the human brain, following the principles of connectionism. Neural networks typically consist of structured networks with nodes and edges. Specifically, the BackPropagation Neural Network (BPNN) is the algorithm we utilize to train neural networks, executing a weight adjustment process in a backward direction. Following the traversal of the network for each data point, backpropagation undertakes a backward pass to iteratively adjust the parameters, including weights and biases. This adjustment is guided by a comparison between the predicted and observed values of the target variable. The backpropagation algorithm strategically modifies the weights of parameters to minimize the error term, optimizing the network's predictive accuracy. In alignment with our methodology, we employ permutation importance analysis for this algorithm. This analytical approach assist us in comprehending the individual impact of each feature on the model's performance, contributing to a comprehensive understanding of the neural network's dynamics.

As mentioned previously, we employ permutation importance to analyze each model. Permutation Feature Importance serves as a model inspection technique for evaluating the significance of a feature or variable within a fitted model. Using common methods for assessing the importance of a feature involves fitting two models under different scenarios: one with the feature of interest and another without it. Comparing these two models provides insights into the overall significance of the feature. However, this approach is computationally intensive, requiring the training of two distinct models. As a more efficient alternative, Permutation Feature Importance avoids the need for re-training a model. Instead, it utilizes a single model to gauge the general significance of a specific feature. The methodology involves measuring the decrease in model scores between the original dataset and a dataset in which the feature of interest is randomly shuffled. In another word, Permutation Feature Importance demonstrates the decline in model performance when the feature of interest is transformed into meaningless noise. A higher model score in this context indicates greater significance of the feature.

RESULTS AND DISCUSSION

In this study, our objective is to forecast whether individuals anticipate working from home in the future. The initial model employed for this task is logistic regression. Notably, logistic regression lacks hyperparameters for tuning; nevertheless, we execute cross-validation to evaluate training stability within the training set. Following this approach, the model exhibits stability, with mean and variance values of 0.83 and 0.02, respectively. Furthermore, both train and test accuracies for the model stand at 0.84 and 0.85, indicating commendable performance on unseen data akin to the training dataset. To delve deeper into the analysis, we utilize permutation importance. Figure 1 depicts the Permutation Importance, averaged over 30 shuffling iterations, for the logistic regression model estimates. In this assessment, we consider accuracy as the model score, reflecting changes in accuracy. Notably, wfh_now (i.e., working from home after the pandemic) and wfh_pre (i.e., working from home before the pandemic) emerge with the highest Permutation Importance among various model scores. These findings underscore the significance of these variables in influencing the accuracy of our logistic regression model. We use imputation importance to identify important features in the model and interpret their impact based on the sign of their coefficients. To delve deeper into model interpretation and understand the impact of each feature, we analyze the coefficients of each variable in the logistic regression model. The results are summarized in Table 2. It is evident from the analysis that individuals currently or previously engaged in working from home exhibit a higher expectation to continue doing so in the future. Moreover, individuals with higher income and greater education levels also have more expectations toward future remote work. Gender differences also play a role, with men expressing a higher expectation of working from home in the future.

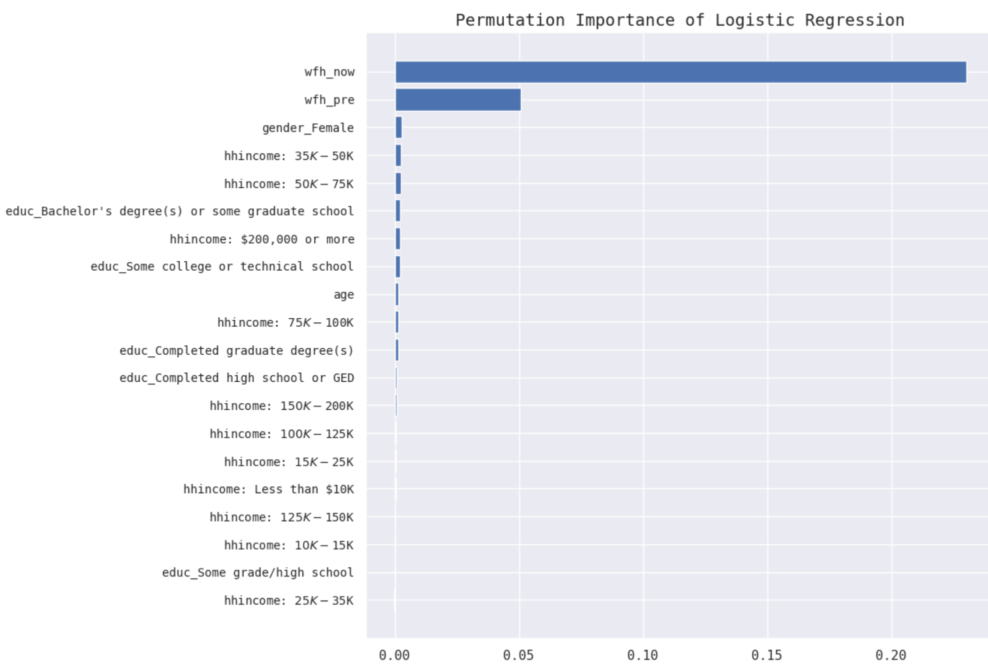

Figure 1. Permutation Feature Importance Mean for Logistic Regression Model

Table 2. Estimated Coefficients of the LR Model

Variable/Parameter		Value
Constant		0.467
age		-0.038
WFH	In the past	1.177
	Now	1.401
Gender	Female	-0.157
Education	Bachelor's degree(s) or some graduate school	0.103
	Completed graduate degree(s)	-0.046
	Completed high school or GED	-0.099
	Some college or technical school	0.001
	Some grade/high school	-0.001
Household income	Less than $10,000	0.094
	$10,000 to $14,999	-0.007
	$15,000 to $24,999	0.054
	$25,000 to $34,999	-0.041
	$35,000 to $49,999	-0.089
	$50,000 to $74,999	-0.128
	$75,000 to $94,999	-0.060
	$100,000 to $124,999	0.032
	$125,000 to $149,999	0.009
	$150,000 to $199,999	0.096
	$200,000 or more	0.129

The second model employed in our study is the GBM. Unlike logistic regression, GBM entails tuning several hyperparameters prior to implementation. This process is vital to maintain the individual trees' weakness, enhance overall model accuracy, and prevent overfitting. Some critical hyperparameters include:

- Learning rate: Governs the contribution of each tree to prevent overfitting.
- N Estimators: Signifies the number of decision trees utilized in the model. Increasing trees can enhance learning but might slow down the process significantly.
- Max depth: Determines the depth of the trees, influencing prediction accuracy.

To optimize these hyperparameters in GBM, we employed the Grid Search method. This approach systematically explores various parameter combinations through cross-validated searches, selecting the most effective set. In our case, we evaluated 100 combinations via random selection, focusing on specific hyperparameters within defined search ranges. Following this process, the optimal values were identified among the 100 combinations n_estimators: 200, max_leaf_nodes: 5, learning_rate: 0.05, max_depth: 6.

Following cross-validation, the model demonstrated accuracy with a mean of 0.84 and a variance of 0.02. These metrics are indicative of stability within the model, highlighting its consistent performance across multiple iterations of the training data. Additionally, we conducted permutation importance analysis based on accuracy for this model. Figure 2 illustrates that the most crucial feature in the GBM model is the current engagement in working from home (WFH_now).

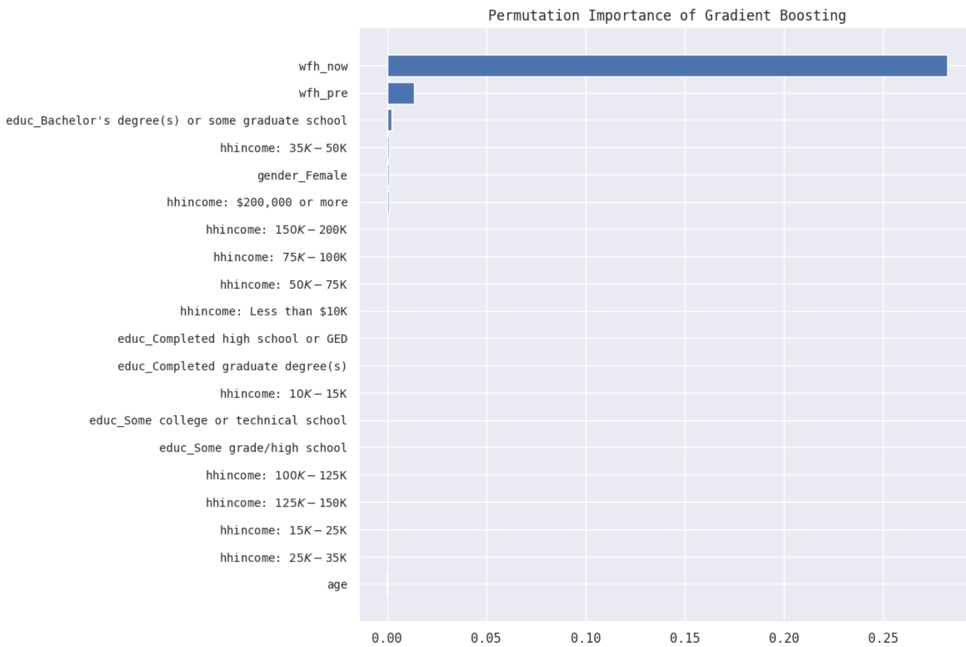

Figure 2. Permutation Importance Results for Gradient Boosting Model

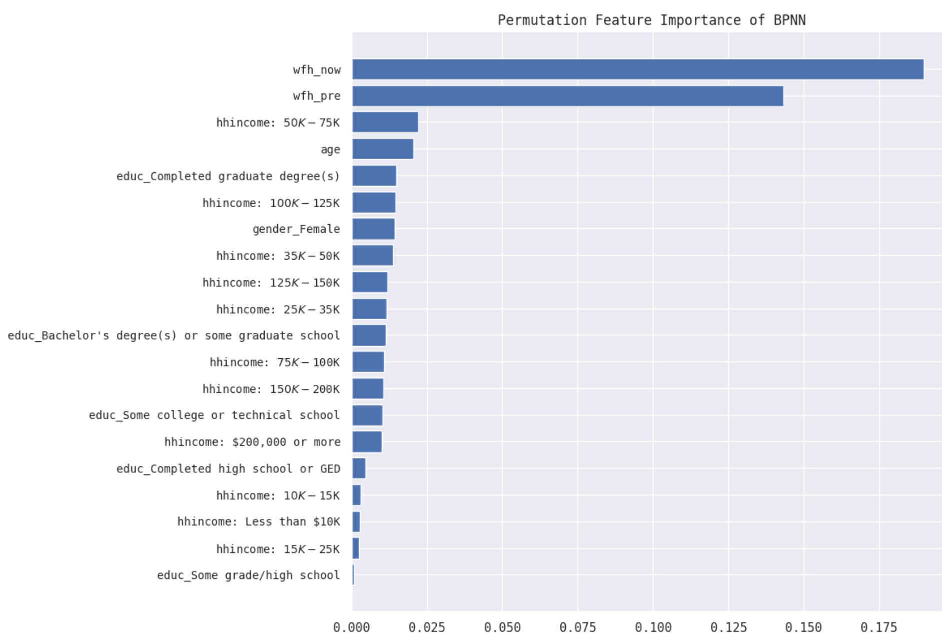

Figure 3. Results of Permutation Importance for BPNN

Finally, we employed the Backpropagation Neural Network (BPNN) model to classify our dataset and make predictions about future work-from-home expectations. Similar to the GBM model, we applied the Grid Search method to fine-tune the hyperparameters of BPNN. This method optimizes specified parameters through a cross-validated search over sets of parameter values. We explored 100 combinations through random selection and focused on specific hyperparameters within predefined search ranges. Among the 100 combinations, we identified the following values: activation='logistic', max_iter=100, and hidden_layer_sizes=9. Upon conducting cross-validation, the model exhibited an accuracy of 0.81 with a variance of 0.02. These results affirm the stability of the model's performance, providing confidence in its ability to make accurate predictions.

Furthermore, we conducted permutation importance analysis for this model, the result as it is shown in Figure 3 revealed that "wfh_now" and "wfh_pre " are the variables with the highest permutation importance among the explanatory variables. This underscores the significance of these features in influencing the model's predictions regarding future work-from-home expectations.

CONCLUSION

In this study, we conducted an analysis of survey data collected from individuals in the United States spanning the period between July and October 2020. Our primary objective was to identify factors related to people's inclination toward working from home (WFH) in the future. To achieve this, we employed three distinct machine learning models: logistic regression (LR), Gradient Boosting Machine (GBM), and Backpropagation Neural Network (BPNN). The accuracy scores for these models were found to be 0.83, 0.84, and 0.81, respectively. Through permutation importance analysis across these models, we determined that "wfh_pre" (working from home before the pandemic) and "wfh_now" (working from home during the pandemic) carry the highest Permutation Importance among the independent variables. This suggests that an individual's history of WFH both before and during the pandemic significantly influences their attitude toward WFH post-pandemic.

Upon comparing the models, LR emerges as a preferable option for this problem for several reasons. Firstly, it boasts good prediction accuracy, comparable to BPNN and superior to GBM. Secondly, LR features fewer significant factors in comparison to BPNN, contributing to a simpler model that mitigates the risk of overfitting. Thirdly, LR does not require the tuning of hyperparameters, unlike the complex and time-consuming task associated with GBM. Additionally, the sign of estimated coefficients in LR aids in understanding the nature of the association between explanatory and target variables. In contrast, this association is less clear in GBM and BPNN.

Based on the LR model, our analysis indicates that individuals presently or previously engaged in WFH are more likely to anticipate continuing this practice in the future. Furthermore, individuals with higher income and greater education levels exhibit a stronger inclination to have future remote work. Gender differences also come into play, with men expressing a higher expectation of working from home in the future.

In light of our research findings, we propose a set of policy recommendations aimed at promoting inclusivity and equitable access to remote work opportunities. Firstly, there is a need to encourage companies to establish inclusive practices that support work-from-home arrangements for all employees, irrespective of gender. This cultural shift toward inclusivity should extend particularly to disadvantaged individuals, ensuring that they are not excluded from the benefits of remote work. To bridge socioeconomic gaps, policymakers should implement initiatives that guarantee equal access to remote work opportunities for individuals across various income levels. Targeted support and incentives are essential to create an environment where remote work is not only accessible but also beneficial for those facing economic challenges. By prioritizing inclusivity, these policies can contribute to a fair and supportive remote work landscape, addressing the specific needs of disadvantaged individuals and fostering a more equitable future of work for all.

In this study, our focus has been on examining equity in future access to remote work, with a particular emphasis on education, income, and gender as key determinants. However, it is imperative to broaden the scope of our equity analysis to encompass additional critical factors. Considering factors such as ethnicity, disability status, and spatial features including built-environment variables can contribute to a better understanding of equity in remote work dynamics (Asgharpour, Allahyari, et al., 2023; Asgharpour, Davatgari, et al., 2023). Furthermore, extending our inquiry to include environmental considerations, such as safety and pollution levels in remote work environments, is essential. By incorporating a more comprehensive set of equity indicators, we can better understand the multifaceted nature of remote work accessibility and formulate inclusive policies that address a wider range of societal needs and challenges.

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Promoting Workforce Development Using CAVe-in-a-Box and Computer Vision Based Vulnerable Road User Detection

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ABSTRACT

This paper presents lessons learned through intensive workforce development projects with the USDOT ITSJPO PCB initiative connected and automated vehicle education (CAVe). With the support of Ohio Department of Transportation (ODOT) and DriveOhio Student Transportation Advancement Research (STAR) program, the University of Cincinnati Infrastructure Institute (UCII) team has assembled CAVe-in-a-Box and CAVe-Lite Infrastructure and Mobile kits. In this project, CAVe-in-a-Box assembly integrated with latest computer vision based detection technology has been utilized as a demonstration tool to showcase real-world benefits such as the vulnerable road user (VRU) safety at intersections. Furthermore, CAVe-Lite module has been utilized to actively engage 5–12 grade students in a scaled, hands-on desktop level smart mobility technology deployment.

INTRODUCTION

As CAV technologies move from research to deployment phase, the FHWA and USDOT Intelligent Transportation Systems Joint Program Office (ITSJPO) Professional Capacity Building (PCB) program have identified the need to educate the workforce that will be needed to deploy, operate, and maintain these technologies. Based on this need, the Connected and Automated Vehicle Education (CAVe) series of educational tools (USDOT 2022) were developed. This series of tools focus on teaching users the data flows that exist in an ITS environment and how each equipment generates, handles, or processes CAV data. With the desire to educate a wide audience, the educational material that accompanies the hardware can be used to help users learn how to operate the equipment or be used as supplementary material to a greater topic, such as computer networking or wireless communications.

Previously, the FHWA (USDOT 2014) has sponsored Nanosonic, Inc., through small business innovation research (SBIR) award. The company worked with local middle school and high school STEM teachers in Giles County, Virginia, to develop 60+ STEM lesson plans. The team also created a mobile game app and board game that engage students in ITS and connected vehicle concepts. In the latest addition to the training suite, the FHWA and PCB program developed and offer free of cost CAVe-in-a-Box workshops. The hands-on workshop is a mixture of lectures and exercises that begins with an introduction to CAVe-in-a-Box. The session progresses to an examination of use-cases and applications, providing real-world examples to highlight the tool's versatility and adaptability. A significant portion of the workshop is dedicated to hands-on training, where participants learn to configure CAVe-in-a-Box and use key plugins. Following each workshop, attendees are invited to provide feedback through a post-training survey. The feedback serves as a measure of the effectiveness and impact of the CAVe-in-a-Box training.

With strong local, state, and federal level partnerships, the University of Cincinnati Infrastructure Institute (UCII) team has organized four workforce development projects (Bonthu et. al., 2024) throughout 2023, as highlighted in this paper: 1) demonstration with CAVe-In-A-Box at Aiken New Tech high school (8th grade students), Cincinnati Public Schools, 2) engagement with CAVe-Lite at UC College of Engineering and Applied Sciences (CEAS) summer camp (5-12 grade students from different states in the US), 3) demonstration of CAVe-Lite and simulation of traffic lights at The Gaskins Foundation (TGF) STEMulates program, and 4) CAVe-Lite engagement at the TGF STEAM day and Girl Scouts camp. With lessons learned from above-mentioned workforce development projects, the team utilized CAVe tools to develop: 1) smart mobility lesson plans and case-based learning approaches to engage young learners (i.e., 5-12 grade students); and 2) discuss potential pre- and post-assessment methods from engagement sessions to test the approach.

CONNECTED AND AUTOMATED VEHICLE EDUCATION (CAVE) TOOLS

CAVe-In-A-Box. The CAVe-In-A-Box Infrastructure kit, as shown in Figure 1a, consists of a traffic signal controller (TSC), road side unit (RSU), network switch, and vehicle-to-everything (V2X-Hub) computer. In this project, the UCII team integrated a Bosch Autodome Inteox 7000i camera to detect pedestrians in real-time and send SDLC ped detection calls to the signal controller while transmitting personal safety messages (PSM) to the RSU. PSM messages are further broadcasted to on-board units (OBU) which is part of the CAVe-In-A-Box Mobile kit, shown in Figure 1b. The CAVe-In-A-Box can be primarily utilized to demonstrate real-world smart mobility advancements to high school (8-12 grade students), undergraduate, and graduate students.

CAVe-Lite. The CAVe-Lite Infrastructure and Mobile kits are small, scaled desktop CAV STEM kit, as shown in Figure 2, to actively engage young learners such as 5-12 grade middle and high school students in smart mobility advancements using basic V2X communications between traffic lights and CAV operations. The LED signal head can be replaced with a simple breadboard-based LED circuit directly connected to controlled Raspberry Pi output pins.

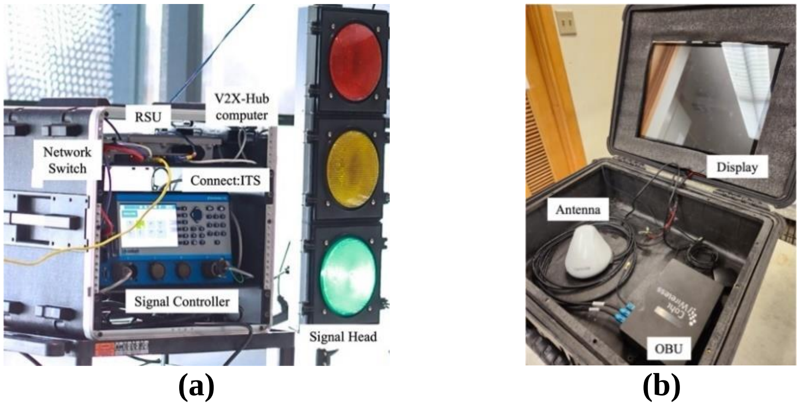


Figure 1. CAVe-In-A-Box (a) Infrastructure kit and (b) Mobile kit.

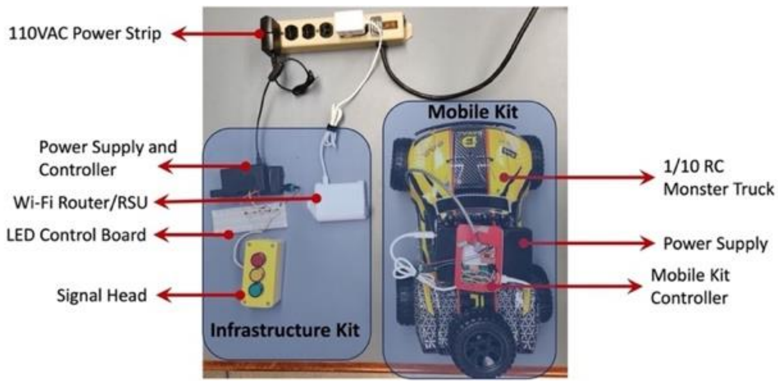


Figure 2. CAVe-Lite STEM kit.

Paper circuit & traffic light simulation. In this segment, students (e.g., 5-8 grade middle school) are instructed to play "Red light, green light with a twist". This involves active participation and role play in a real-world traffic light simulation with a mockup of traffic light using paper circuit, copper tape, and LEDs, as shown in Figure 3.

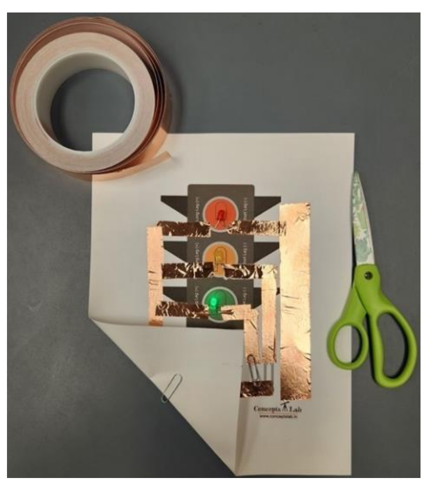


Figure 3. Paper circuit traffic light setup.

ENGAGEMENT

DriveOhio, an initiative of Ohio Department of Transportation (ODOT) to manage and accelerate smart mobility, is preparing Ohio's talent for the future with a portfolio of workforce development programs. Key programs include smart mobility ambassador, equipment grants, and workforce credentials. Recently, DriveOhio published an educator toolkit (DriveOhio 2023) that provides a summary of resource for K-12 and career technical educators, employers, and other workforce stakeholders to facility smart mobility education (Figure 4).

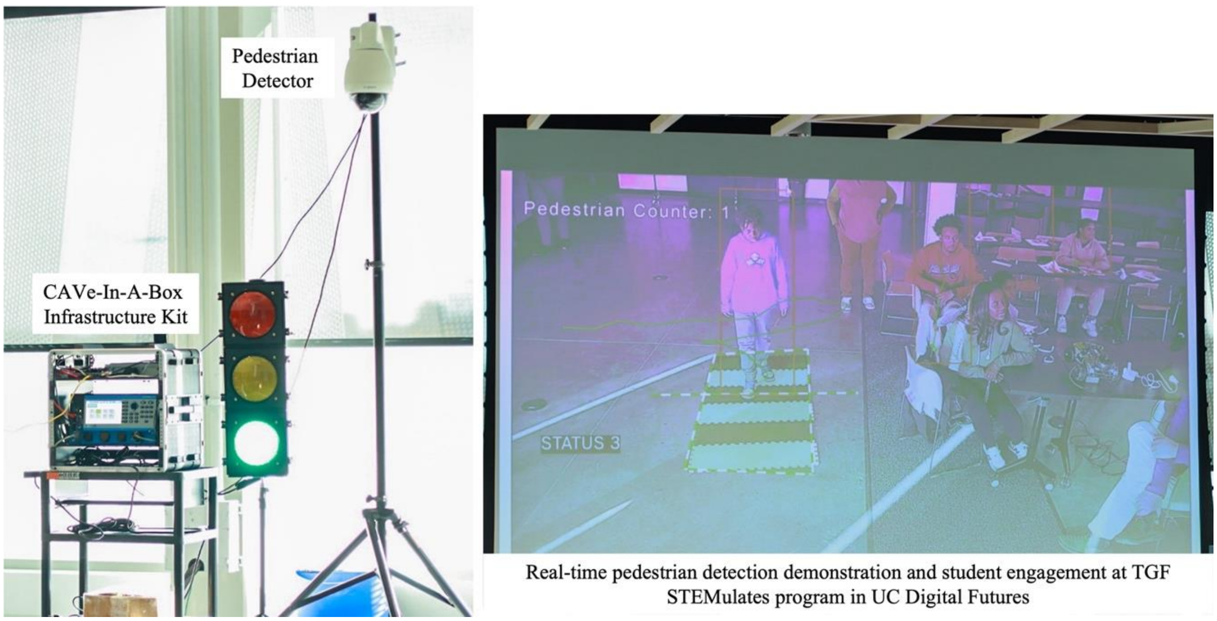
Figure 4. DriveOhio Educator Toolkit.

The Partnership for Innovation in Education (https://piemedia.org) offers case-based curriculum that is experiential, immersive, engaging and offers "real world" solutions to today's challenges. Originally used as the teaching pedagogy in medical, law, business and engineering schools, PIE uses the case method to present K-16 students with modern, open-ended, incomplete scenarios requiring complex solutions, with particular attention to content featuring Science, Technology, Engineering, and Mathematics (STEM) scenarios. Each case is an account of events and facts particular to the problem, with intriguing decision points designed to encourage critical thinking and student discussion. Cases are solved through the dynamic process of exchanging information, countering and defending varying points of view, and building on the ideas of others. The environment is filled with energy, excitement and ongoing interaction between teachers and students. As a result, students develop skills ranging from high-level thinking and creative problem solving to project planning and solution communicating.

Learners who participate in case-based learning develop lifelong learning and career readiness skills. They learn to assess situations based upon a set of facts and circumstances; they discuss the relevance and value of information, with the development of evidence-based arguments. Learners tackle the process of problem-identification and decision-making, by weighing the value and relevance of information, taking sides in discussions and explaining their reasoning.

Continuing with lessons learned from the engagement at Aiken New Tech High School, Cincinnati Public Schools and UC CEAS summer camp, the UCII team collaborated with The Gaskins Foundation (TGF) to engage several 8th grade girl students at the TGF STEAM Day and Girl Scouts camp conducted at UC Digital Futures on November 11, 2023. It is important to note that the traffic module was co-developed with parents based on how parent participants in TGF

Empowering Parents in Community Churches (EPICC) saw STEM their everyday life. Each element of the module was co - developed for maximum engagement for the family and contextualized for real world connection. The engagement sessions for November 11 were split into three phases. In the initial stage, students engaged with each other to replicate a traffic environment, assuming roles as a counter counting down from 20, a traffic signal head, or a vehicle. Going through the simulation builds up a basic knowledge of how the underlying logic of traffic signals and their phasing is controlled. This is followed by session building the paper circuit shown in Figure 3 providing them a hands-on exploration of circuitry. After these a demo of cave-lite is provided informing about what is cave and why it's important and how it works, building up a foundational knowledge. Figure 5 and Figure 6 depict a few engagement sessions with CAVe tools.



Real-time pedestrian detection demonstration and student engagement at TGF STEMulates program in UC Digital Futures

Figure 5. CAVe-In-A-Box Infrastructure kit demonstration and young learner engagement through VRU detection and intersection safety use case.

Figure 6. Young learner engagement at UC CEAS summer camp with CAVe-Lite module.

ASSESSMENT METHODS AND RESULTS

Continuing with lessons learned from above mentioned experiential smart mobility workforce development engagement projects, a few assessment questions, as listed in Table 1, have received good responses. Assessment questions are refined and selected as they would provide quantified feedback on student's level of understanding.

Table 1. Assessment questions to gauge participants knowledge before and after demonstration and engagement with CAVe tools

How would you describe your current knowledge of connected and automated vehicle (CAV)?	Have you seen a traffic camera before?
How familiar are you with Raspberry Pi?	How would you rate your programming or coding?
Have you considered a career pathway in transportation?	What is the full form of V2X?
Year in school?	

Results

1. Pre- and post-assessment results from UC CEAS summer camp

As shown in results (Figure 7), 50% of all participated high school students who have indicated that they are not familiar with CAVs have demonstrated an understanding of CAVs and smart mobility advancements with an experiential demonstration of VRU detection use case and hands-on engagement with CAVe-Lite module. Towards the end of the engagement, almost 50% students have shown interest in considering transportation as a career pathway.

2. Post-assessment results from TGF Girls STEAM day and Girl Scout camp at UC Digital Futures

Results from TGF STEAM day and Girl Scout camp at UC Digital Futures are shown in Figure 8. As results indicate, a diverse group of girl students have demonstrated an understanding of CAVs and smart mobility technologies. More than 2/3rd of participated students indicated that they are 'somewhat familiar' with CAVs and smart mobility due to an experiential demonstration of traffic and engagement with CAVe-Lite.

1. Due to the wide age range of participants, it was clear that a glossary of terms was necessary to help students understand the different elements of the traffic simulation. The goal of all TGF curriculum is to provide contextualized STEAM curriculum to students/families. As part of the glossary terms, students would need to have examples that allow them to understand the words/terms not just by definition, but how it may appear in their everyday life.
2. The activities were appropriate for the wide age range. Starting the unit using red light. Green light allowed students to have fun, understand the traffic simulation and engage in a physical way. The movement and simulation of traffic allowed for students to visualize

the flow. After the simulation, there were multiple questions about sensors, technology, signals, and circuits

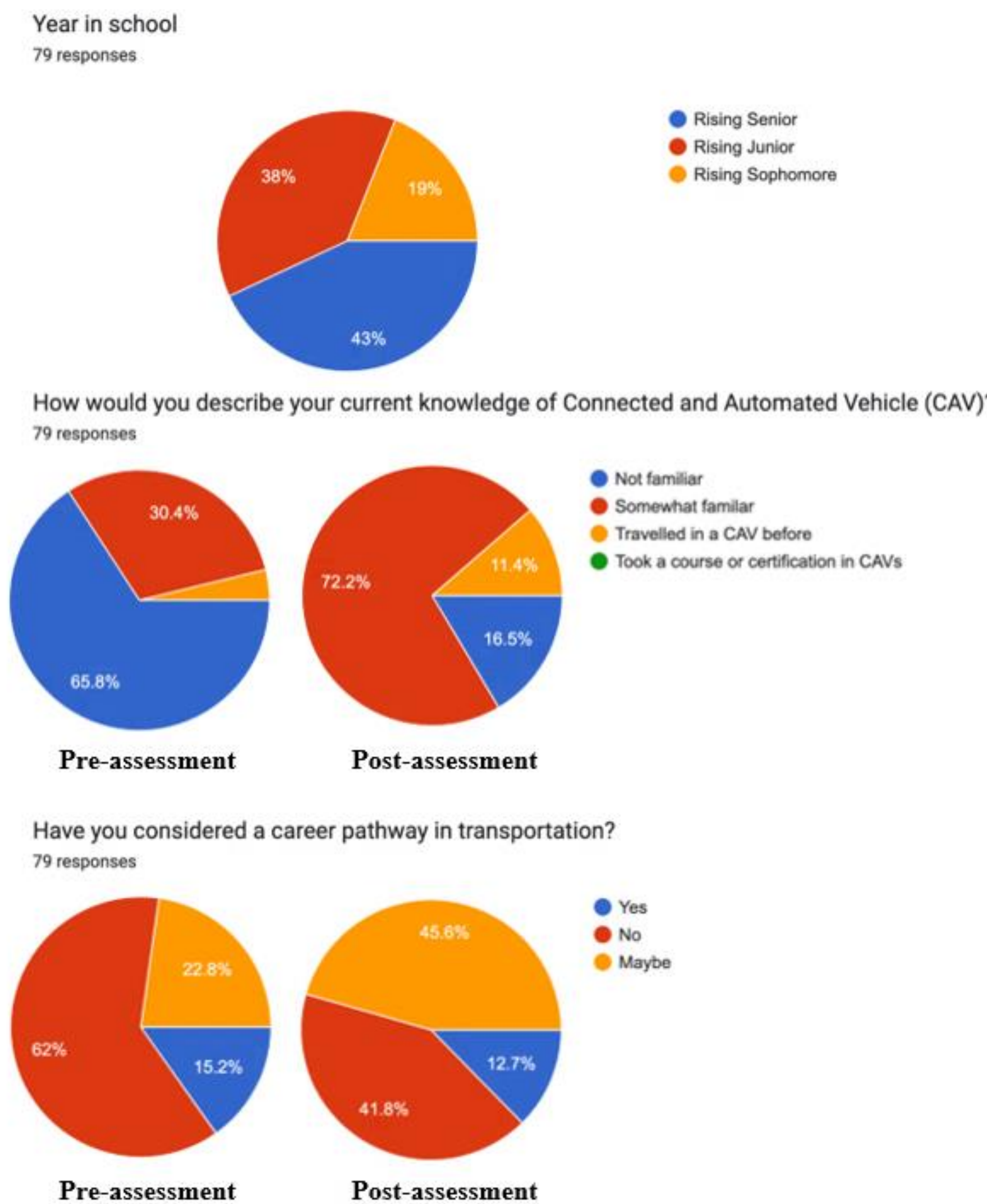


Figure 7. Comparison of assessment results at UC CEAS summer camp.

3. Due to time constraints, students were unable to construct a circuit using the Raspberry Pi, bread boards, wires and LED lights (which would be the next phase of the curriculum and project). Students would benefit from building a circuit with more sophisticated tools instead of using only paper circuits.
4. Adding challenge elements for older students like coding and building with more sophisticated tools could also help facilitate conversations to career connection. Students

noted throughout the workshop that they had no idea that traffic is developed by a variety of STEM professionals. When asked what professions they thought, were part of transportation some students noted civil engineers. All the students were surprised by the added the connection of computer science or electrical engineering.

5. The future technology of traffic was a highlight to the students. Understanding that a camera can sense and categorize objects excited students and sparked curiosity.
6. Although parents weren't direct participants in the module. They were engaged and asked follow-up questions with their children.

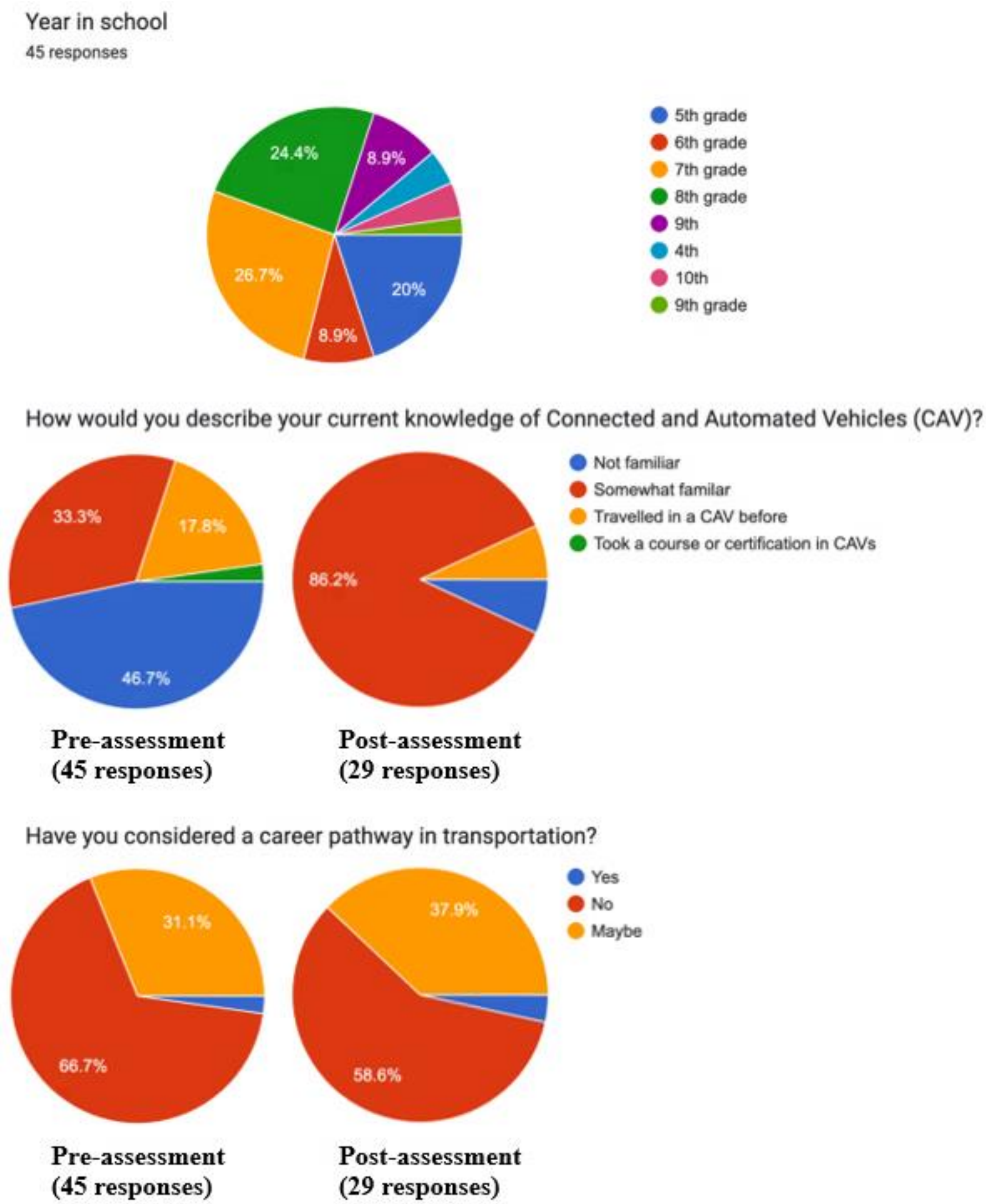


Figure 8. Comparison of assessment results at TGF and Girl Scout student camps.

LESSON PLANS

Based on the feedback received from educators and students, lesson plans are drafted for CAVe-Lite module as shown in Figure 9.

Introduction

In this activity, students will assemble and test a connected and automated vehicle education kit (CAVe-Lite). CAVe-Lite module is a small-scale light-weight module developed by the Federal Highway Administration (FHWA) Saxton Lab. Students will utilize the bill of materials shown in **Table 1** to assemble 1) infrastructure kit; and 2) mobile kit.

1. CAVe-Lite Infrastructure kit consists of a digital signal controller for a LED traffic signal circuit with the Raspberry Pi GPIO pin programming and basic circuit controls.
2. CAVe-Lite Mobile kit consists of a script to decode SPaT messages received from the signal controller via a Wi-Fi router and controls a 1/10 scale RC vehicle (**Figure 1**).

Figure 1: CAVe-Lite Infrastructure and Mobile kits used for young learner engagement.

TABLE 1 CAVe-Lite Required Materials

Qty.	Item	Vendor
3	Red/Yellow/Green Red, Yellow, Green Diode 3.3V LEDs	Any 3.3V color LEDs
2	Mini Breadboard and Dupont cables	Mini breadboard
1	20 AWG wire	Remington 20UL1007 or DuPont female to female and male to female breadboard cables
6	2N2222A NPN Transistors	ON Semiconductor P2N2222A
1	Wireless Router	GL-iNet SFT1200
2	Infrastructure/Mobile Kit Computer	Raspberry Pi 4
2	Motor Driver	HiLetgo BTS7960
1	1/10 Vehicle	DEERC 9201E Or any 1/16 truck
2	Monitor, keyboard and mouse	Bluetooth recommended
2	HDMI cable	HDMI to Micro HDMI (Raspberry Pi 4)

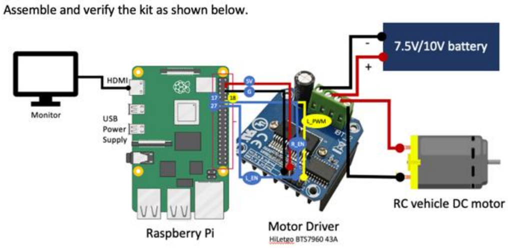
Mobile Kit Assembly and Test Procedure

Pre-requisites: What You Need

- Acquire Raspberry Pi (Model 3 or higher), 12V DC power supply, DC motor driver, 1/10 scale RC vehicle, USB mini cable and some circuit board connector cables.
- Install V2X-Hub and copy CAVe-Lite files into the Raspberry Pi.
- Verify SPaT Plugin, Immediate Forward Plugin are enabled and configured as per manual.
- Connect to GL-SFT1200-xxx Wi-Fi network with static IP address of **192.168.0.110**.

Assembly procedure:

- Assemble and verify the kit as shown below.



Test procedure:

1. Turn ON the switch on 12V power supply to power up the kit.
2. When the Pi powered up, open a Terminal window (follow the demonstration).
3. Type '*cd cave-mobile*' command to enter into the CAVe-mobile folder.
4. Type '*bash mobile.sh*' to startup the script to receive and decode SPaT messages from Infrastructure kit.
5. Terminal should respond '*Enter distance to signal head*'. Ensure you see this on the screen. **WARNING!!! STAY AWAY FROM THE RC VEHICHE WHEELS, THEY WILL SPIN IMMEDIATELY**
6. Type '*25*' to input the distance in feet. The script converts it to meters.
7. Terminal should respond '*vehicle listening*'.
8. Terminal reports changes of states as they are received and decoded until the target distance is reached.
9. Only when '*protected-movement-allowed*' state (green signal) is received, the outputs to the motor drivers are set high and the RC vehicle wheels spin in forward direction. The vehicle halts in other states (*stop-and-remain* – red signal and *protected-clearance* – yellow signal).

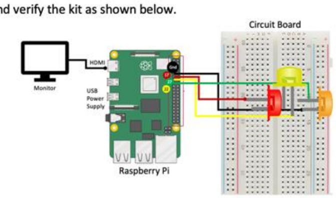
Infrastructure Kit Assembly and Test Procedure

Pre-requisites: What You Need

- Acquire Raspberry Pi (Model 3 or higher), 12V DC power supply, circuit board, 3 NPN transistors, 3 LEDs (red, yellow, green) for signal head, 3 330-ohm resistors, 1 171-ohm resistor, USB mini cable and some circuit board connector cables.
- Install V2X-Hub and copy CAVe-Lite files into the Raspberry Pi.
- Verify SPaT Plugin, Immediate Forward Plugin are enabled and configured as per manual.
- Setup Raspberry Pi static IP address to **192.168.0.146**.

Assembly procedure:

- Assemble and verify the kit as shown below.



Wi-Fi router setup:

- From your phone or computer, connect to GL-SFT1200-xxx router and change the router's IP address to 192.168.0.1.
- Connect both Infrastructure and Mobile kits to this Wi-Fi network with static IP addresses.
  - Password: **goodlife**
- When both kits are connected to the Wi-Fi router, you should be able to ssh login to test.
  - Passwords for ssh log in:
    - Infrastructure kit – **cave**
    - Mobile kit - **cavelite**

Test procedure:

1. Turn ON the switch on the 12V power supply to power up the kit.
2. When the Pi is powered up, open a Terminal window (follow the demonstration).
3. Type '*sudo docker ps*'. This opens up three containers, php, v2xhub and mysql, and sets them running. Ensure you see these on the screen.
4. Type '*cd cave-lite*' command to enter into the CAVe-Lite folder.
5. Enter '*./rc.local start*' to start up the digital signal head. You should be able to see the traffic signals on the screen.
6. Step 5 should also fire the GPIO pins 17, 27, and 22 to cycle physical signal head with a pre-programmed signal control script (verify connections as shown in Assembly procedure)

Figure 9. Sample CAVe-Lite lesson plans developed for educators.

CONCLUSIONS

With an experiential learning of CAVs through real-time pedestrian detection with computer vision and AI, high school students participated in the summer camp have demonstrated enhanced knowledge in smart mobility. Specifically, as post assessment results indicated, about 20% more students expressed their interest in pursuing a career in transportation. Majority of students indicated increased level of knowledge in smart mobility due to their experiential learning with Raspberry Pi, python programming, CAVs, AVs, EVs, and V2X technologies. From the results, it is important to note that definitions of words used in smart mobility such as 'connected', 'automated', and 'autonomous' need more example-based learning methods for students to understand their real-world applications.

ACKNOWLEDGEMENT

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Automatic Feedback Cruising Control of the Aeromovel Automated People Mover

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ABSTRACT

Aeromovel consists of a new concept of steel-wheel steel-rail automated people mover (APM). The operation procedure depends on a propulsion system based upon the use of pneumatic power systems that insufflate pressured air inside a duct where a rodless piston connected to the vehicle is driven. In the traditional configuration of the Aeromovel, the power system is designed and adjusted for operating with open loop control strategies. In recent years, Aeromovel application have significantly expanded, resulting in new challenges to be overcome, especially that associated with different trajectories that the vehicles must be performed due to geometric restriction imposed by existent airports' architectural configurations. Aiming at overcoming these difficulties, a novel automatic driving strategy, based on feedback control, is being developed for the vehicle cruising control. This article deals with this new challenge and the design of the feedback cruising control algorithms that are being developed, including numerical results achieved by simulation performed with a suitable physical model of the system. The closed loop strategy is based on the definition of a desired velocity trajectory that is tracked by driving the blower based pneumatic power system to increase or decrease the effective force applied to the vehicle, forcing the trajectory to converge to the desired one. In this work, the design of the closed loop algorithm and the simulation results using a comprehensive model are addressed, showing the effectiveness of the proposed cruising control strategy. The new line that is being developed to operate in GRU Airport—São Paulo-BR main's airport—is used as a case-study for availing the analysis strategy.

INTRODUCTION

The Aeromovel System is a proprietary technology characterized by the use of pneumatically propelled passive vehicles. The working principle is similar to the standard rodless pneumatic cylinders, where a moving part - the vehicle, in the case of Aeromovel - is connected to a piston that is displaced due to the application of an appropriate pressure difference. One of the main advantages of this arrangement is a reduction of the vehicle deadweight by a factor of two to three times when compared to traditional APMs and/or light rail transit technologies. Fundamentally, less weight means less energy required to move the same number of passengers. The result is a sizeable reduction of capital and operational costs to move the same number of passengers relative to conventional modes of transportation.

The Aeromovel System is a unique technology system characterized by the use of pneumatic propulsion vehicles made externally to the vehicles (Abs, 2016). The functioning principle is similar to that of commercial pneumatic cylinders without rods. In the case of Aeromovel, a piston that travels in a large duct is connected to the vehicle by means of a rod. The vehicle travels on a road built over this pipeline. For the movement of the vehicle, an appropriate pressure difference is applied on both sides of the piston that is achieved through the use of industrial blowers working stationarily in strategic positions on the runway. Due to the fact that there is no need to carry engine and fuel, one of the main advantages of this technology is the reduction of the dead weight of the vehicle by a factor of two to three times when compared to light rail technologies, or even compared to traditional APMs. Essentially, a lower weight implies in less energy required to carry the same number of passengers, resulting in a considerable reduction in capital and operating costs to carry the same number of passengers compared to conventional transport systems. Aeromovel completed nine years of successful revenue service in Porto Alegre, Brazil, as a 1-km long landside shuttle system at Salgado Filho International Airport (Figure 1) connecting it to the local suburban commuter train station.

Figure 1. Aeromovel Salgado Filho Airport System.

Currently, a new line is being developed to operate in São Paulo-BR main's airport (GRU). As the new trajectory of the vehicle, which will connect the three terminals of the airport among them and one of then to the subway line, must pass through existing constructions that are allocated without prior planning to foresee such a solution for the transport of passengers, it will be imperative to overcome several challenges imposed by the topology necessary to carry out suitable travels by the vehicles. Thus, each line section, in addition to the straight sections, will contain curves with different radius and uphill/downhill sections. In addition, there are some turnout accessories on some line ducts, like a sealing system between the propulsion plate and the driving duct. The line under study presents 3 distinct sections, totaling a length of 2647.2 m. The sections are described below:

Subway Station (CPTM) to Airport Terminal 1 (TPS1): 618.2-metre-long section, composed of three smooth horizontal curves, where the smallest radius of curvature is 60 m, sinuous layout with part of it on a slight slope of 0.45% (red line in Figure 2). Airport Terminal 1 (TPS1) to Airport Terminal 2 (TPS2): 1354.1 meters long, composed of a straight initial section, after smooth horizontal curves, where the smallest radius of curvature is 60m, practically straight with part of it on a 2.75% slope. This stretch has the implementation of an intersection of vehicles through the duplication of the road (Bypass). This intersection will have its beginning and end through the implementation of Turnouts, with a radius of 27 m. The double-track section will be flat, and after its completion, towards Section 3, an ascending ramp with a slope of 2.5% will begin to overlap the access roads to TPS2 (blue line in Figure 2). Due to its most challenging route, the section Airport Terminal 2 (TPS2) to Airport Terminal 1 (TPS1) is used in the case-study of present work. Airport Terminal 2 (TPS2) to Airport Terminal 3 (TPS3): 674.9-meter-long stretch, composed of a practically straight line with only two horizontal curves where the smallest radius is 60m, with a steep slope of up to -4.07% (green line in Figure 2).

Aeromovel technology is based on the vehicle movement caused by a pressure difference applied to a piston. The vehicle has pistons that divide the duct inside the beams into two chambers, as can be seen in the schematic drawing of Figure 3.

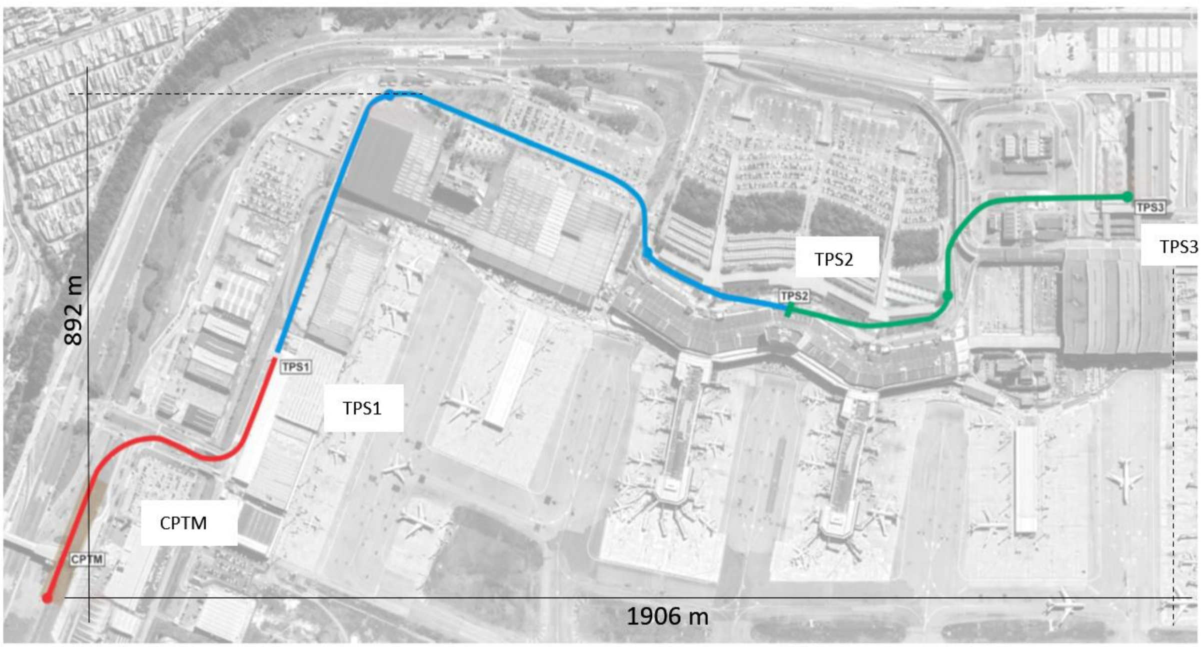

Figure 2. GRU Airport System.

The propulsion system (PPU) consists of the electric drive system and the fluidic power generation system. The latter consists of an industrial centrifugal fan, equipped with a speed converter, and a set of four flow-directing valves (valves 1 to 4). Due to the centrifugal operation of the fan, the appropriate opening or closing of valves 1 to 4 allows to alternate the effect of the fan on the duct, inflating or exhausting it according to the desired direction of movement for the vehicle. In present work, the trajectory control of the vehicle is performed by means accelerating and decelerating the blower through increasing or decreasing the power delivered by the electric AC motor coupled to the blower, allowing the mass flow rates entering or leaving each duct chamber to be regulated continuously, controlling the dynamics of the pressures that drive the vehicle.

In Figure 3, Atmospheric Valves (AV) are dampers opened or closed to connect or disconnect the inner guideway duct to the atmosphere in response to command signals from the Automatic Train Control, thus allowing the intake and outtake of air flow generated by heavy-duty high-efficiency stationary blowers arranged in each Power Propulsion Units.

The complete transport system is divided into sections comprised between 2 stations. In standard application, each section consists of 2 GMPs, 2 VA and one vehicle. This configuration allows for three types of system operation: i) Push Operation: in this case, the vehicle is "pushed" by the action of the GMP upstream of the vehicle. In the vehicle's downstream chamber, the AV is open, communicating the duct to the atmosphere; ii) Pull Operation: in this situation, the vehicle is "pulled" by the action of the GMP downstream of the vehicle. In the chamber upstream of the vehicle, the AV is open, communicating the duct to the atmosphere; iii) Push-Pull Operation: in this case, both GMP are operating, and the two atmospheric valves are closed. Thus, the vehicle moves by the combined action of the upstream pression and the downstream depression, which results in the development of higher power transmitted to the vehicle. Disc brakes with ABS control are installed on each wheel, which ensures that the vehicle stops at the station without locking the wheels. Vehicle pneumatic braking is also available and does not rely on wheel-rail adhesion, having the same performance either with dry or wet rails, even when their heads are covered by thick layer of snow or ice, which are still considered extremely harsh conditions for conventional rail technologies or even for most of self-propelled rubber-tired APM. The primary (disk) and secondary (pneumatic) braking systems are fully redundant and complementary at the same time, normally functioning in blending, resulting in an effect of overlap, with a deliberate predominance of the former.

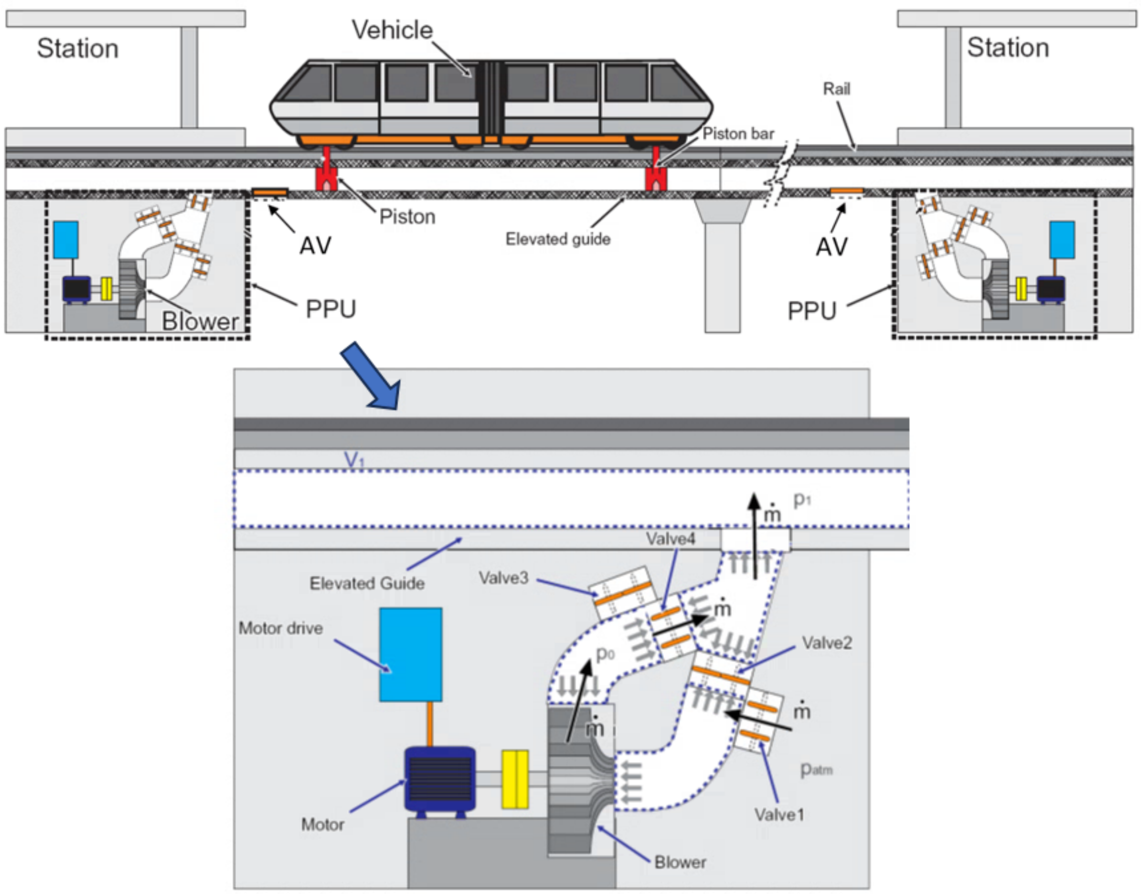

Figure 3. Typical configuration of Aeromovel's propulsion system (adapted from Britto et al., 2014).

In standard applications, the control is performed in open loop, being the power system "calibrated" for using in standard shuttle applications. In this paper, the researchers propose an alternative closed-loop control strategy for the vehicle propulsion system aiming at surpassing the new challenges imposed by novel applications, in which new lines topology introduce hindrances that are difficult to overcome by the present control strategy.

DYNAMIC MODEL OF THE VEHICLE

In order to ease the study of all the main aspects of the system operation, especially with regard to the design of the new control system, a suitable computational model of its dynamic behavior has been developed. Britto et al. (2014) developed an analytical model to describe the dynamic behavior of the Aeromovel System and computationally implemented it on the Matlab-Simulink®, inputting parameters obtained from real measurements in the Aeromovel private test track located in Porto Alegre downtown, Brazil. The model is able to represent most of the nonlinear phenomena affecting the system behavior, such as variations on the dynamic of pressures inside the propulsion duct due to the compressibility of air, head loss and overall leakages. The traditional model considers important effects that are not usually taken into account in simplified analysis, like air compressibility and air leakages, wheels-rail contact friction forces (allowing the simulation of braking conditions), fan blower behavior and gravity effects due to climbs along the line. Current model has increased the capabilities when compared with original one, incorporating, for instance pneumatic braking capability and motor + blower dynamics.

Vehicle dynamic model. The mathematical modelling of the system dynamic uses the coordinates shown on Figure 3, where x is the direction of the vehicle translational displacement, and y is the displacement on the perpendicular axis to x. The variables $\dot{x}$ and $\ddot{x}$ represent, respectively, the vehicle velocity and acceleration. The study of vehicle dynamics has the purpose of modelling the net force which determines the resulting movement. According to Britto et al. (2014), from Newton's Second Law, the vehicle dynamics can be given by Equation (1):

$$M\ddot{x} = A_{al}(p_{1al} - p_{2al}) - \left(F_{ved} + c_{ved}(\dot{x})\right) - F_{aero} - F_{ades} - F_{cur} - gmsen(\varphi) - F_{brake} \quad (1)$$

In this equation, x is the coordinate associated to the vehicle displacement, A_{al} is the propulsion plate surface, M is the mass of the vehicle, p_{1al} and p_{2al} are the pressures applied to the vehicle propulsion plates, F_{ved} is the friction force between the propulsion plate pylon and the duct slot sealing, c_{ved} is the linear dynamic coefficient of friction between the sealing and the pylon, F_{aero} is the aerodynamic drag force e F_{ades} is the steel-wheel steel-rail adhesion force, F_{cur} is the force associated to the curved trajectory parts, F_{brake} is the braking force and $gmsen(\varphi)$ is the term that takes into account uphill effects, where g is the acceleration of gravity and φ is the angle with respect to the horizontal plane.

For the determination of the sealing translational friction force, static Coulomb friction model is applied (Armstrong-Hélouvry, 1994) considering the normal force given by $A_{bor}(p - p_{atm})$. The sealing friction F_{ved} is expressed by $F_{ved} = f_{bor}A_{bor}(p - p_{atm})$, while the aerodynamics drag force is calculated by the standard aerodynamical drag force equation (Gillespie, 1992) $F_{aero} = 0{,}5c_D A_{eq}\rho(v_{ar} + \dot{x})^2$, where c_D is the vehicle drag coefficient, A_{eq} is the vehicle equivalent cross-section area, v_{ar} is the wind speed and ρ is the air specific mass, calculate by means the perfect gas equation as $\rho = p_{atm} / (RT)$.

The steel-wheel steel-rail contact model is modeled based on Hertz contact theory for elastic bodies and in according to Polach (2005), where the tangential stress gradient in the adhesion region ε in the adhesion region is expressed as $\varepsilon = 0{,}25 Slip G \pi a b c_{11} W_{wl} \mu^{-1}$, being a and b the half-axes of the elliptic contact region, c_{11} is a fixed coefficient given by the theory of Kalker (1982), G is the material shear module, and $Slip$ is the creep in the longitudinal direction, given by $Slip = (\dot{x} - \omega_{wl} r_{wl})\text{abs}(max(\dot{x}, \omega_{wl} r_{wl}))^{-1}$, where r_{wl} is the wheel effective radius and ω_{wl} is the wheel angular velocity. In this approach, the tangential stress τ_{adh} in the adhesion region presents a crescent linear behaviour up to a maximum value. In the slip part of the contact region, which has an elliptic shape, τ_{adh} is assumed to be proportional to the normal stress σ. Then, the adhesion force F_{adh} can be obtained by integrating τ_{adh} along the surface of the contact region, which results in the equation $F_{adh} = 2 W_{wl} \mu \left(arctan(\varepsilon) + \frac{\varepsilon}{1+\varepsilon^2} \right) / \pi$, where W_{wl} is the load on the wheel and μ_{soil} is calculated based on a set of experimental parameters related to the contact conditions. To model the effect of the curves of the lines, the influences of the resistive force due to the contact between wheel flange and in the rail head a Coulomb model of friction is used, which is expressed by equation $F_{cur} = \mu_{cur} M r_{cur} \dot{x}^2$, where μ_{cur} is the friction coefficient on each curve and r_{cur} is the curve radius.

Wheel/brake dynamics. The dynamic interaction between the brake system and the wheel of the vehicle is presented in Figure 4.

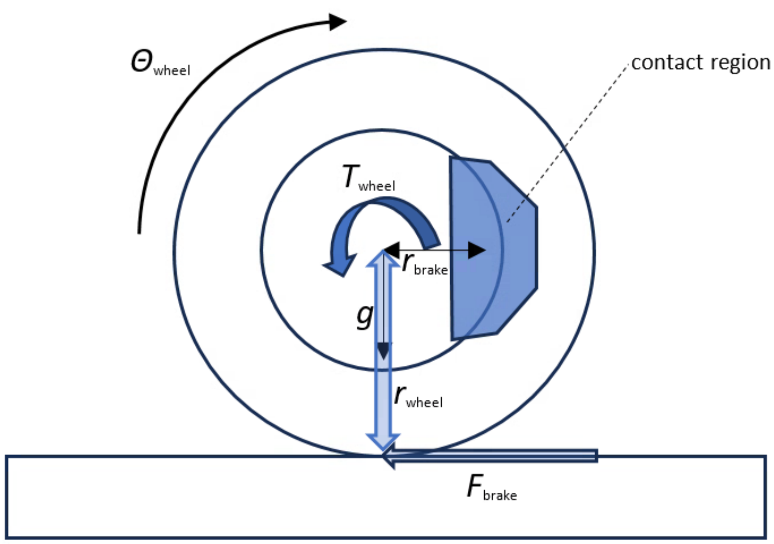

Figure 4. Wheel dynamic *equilibrium* (adapted from Britto et al., 2014).

According to Britto et al. (2014), the equation of motion applied to the wheel is:

$$J_{wheel} \ddot{\theta}_{wheel} = T_{brake} + (c_{wheel} \dot{\theta}_{wheel} + T_{wheel}) - F_{ades} r_{wheel} \quad (2)$$

where J_{wheel} is the mass moment of inertia of the wheel, θ_{wheel}, $\dot{\theta}_{wheel}$ and $\ddot{\theta}_{wheel}$ are respectively wheel angular displacement, velocity and acceleration, F_{ades} is the force adhesion to the rail, r_{brake}

is the average radius of the caliper action on the brake disc, c_{wheel} is the angular viscous coefficient of friction of the wheel connection shaft to the vehicle, T_{wheel} is the torque due to the static friction of the wheel connection shaft to the vehicle, r_{wheel} is the wheel radius and $T_{brake} = F_{disc} r_{brake}$ is the braking torque correspondent to the F_{disc} force that results from the actuation of the braking system on the brake disc surface. This force applied on the brake disc is a consequence of the hydraulic pressure imposed on the brake piston. According to Dal Ponte, 2007, this force can be calculated by means:

$$F_{disc} = \left(\mu_{brakeS} + \mu_{brakeV} \dot{\theta}_{wheel}\right) A_{brake} p_{brake} \tag{3}$$

where A_{brake} is the elastic membrane area, μ_{brakeS} is the Coulomb static friction coefficient of the brake pad, μ_{brakeV} is the viscous coefficient of friction of the brake pad as a function of angular velocity, and p_{brake} is the pressure of the hydraulic system actuating the brake system. The coefficients of friction between brake pads and disc are functions of multiple variables, such as temperature, pressure, humidity and sliding speed. These coefficients are represented by curves surveyed through dynamometer tests.

The current Aeromovel brake actuation system consists of a system that transforms an electrical control signal into an actuation pressure on the brake piston. The pressure p_{brake} is dependent on the actuation of the braking signal. The physical component responsible for increasing the pneumatic pressure is an elastic membrane actuator. The dynamics of this system can be approximated by a first-order transfer function, as proposed by Sarmanho et al. (2012). A first order with transport delay transfer function (Equation 4) is used to represent the relationship between the hydraulic pressure of actuation on the brakes p_{brake} and the pneumatic pressure of actuation on the brake disc p_{disc}.

$$\frac{p_{brake}}{p_{disc}} = K_t \frac{e^{-Ls}}{T_v s + 1} \tag{4}$$

where K_t is the amplifying gain of the pressure, L represents the time transport delay, T_v is the time constant of the brake drive system. To model the dynamics of the brake system, it is also necessary to consider the behavior of the pneumatic proportional valve. According to Sarmanho et al. (2012) the proportional valve can be mathematically modeled through a second-order transfer function expressed by:

$$\frac{p_{disc}}{u_{brake}} = K_v \frac{{w_n}^2}{s^2 + \zeta w_n s + {w_n}^2} \tag{5}$$

where u_{brake} is the control signal input applied to the control valve, K_v is the valve static gain, ζ is the damping factor of the valve and w_n is the natural frequency of the valve. Hence, the transfer function that relates the control signal to the hydraulic pressure can expressed by:

$$\frac{p_{brake}}{u_{brake}} = K_t K_v \frac{{w_n}^2 e^{-Ls}}{T_v s^3 + \left(T_v \zeta w_n + 1\right) s^2 + \left(\zeta w_n + T_v {w_n}^2\right) s + {w_n}^2} \tag{6}$$

This transfer function is used to obtain p_{brake} regarding any brake control input u_{brake}. Hence, using Equation (3), it becomes possible to calculate F_{disc} and thus the braking torque T_{brake}.

Pneumatic Subsystem. In the next subsections, the researchers briefly describe the physical phenomena that occur in the duct chambers, presenting the correspondent mathematical equations, taking into account, for example, the energy losses caused by air movement and the leakage distributed along the system structure. Britto et al. (2014) provide a complete pneumatic system model, with detailed data information.

Pressure Dynamics. The analysis of the dynamics of the pressures in the chambers is based on the approach used, for instance, by Virvalo and Koskinen (1988), for the case of standard pneumatic cylinders. It is based on the energy balance and the continuity of flow in a control volume. The equation set thus obtained is supplemented by a complementary study, which incorporate air leaks and pressure loss along the line. According to these authors, considering the air as a perfect gas and the thermodynamics process as isentropic (adiabatic and reversible), a suitable manipulation of the energy equation (Fox and McDonald, 2006) in a variable control volume that represents a pneumatic piston allows to obtain the dynamics of the vehicle upstream p_{1al} and downstream p_{2al} pressures:

$$\dot{p}_{1al} = -\frac{p_{1al}kA}{V_{o1}+Ax}\dot{x} + \frac{RkT}{V_{o1}+Ax}\dot{m}_1, \dot{p}_{2al} = -\frac{p_{2al}kA}{V_{o2}+A(L-x)}\dot{x} + \frac{RkT}{V_{o2}+A(L-x)}\dot{m}_2 \tag{7}$$

where p_{1al} is the upstream and p_{2al} is downstream pression (on the respective surfaces of the piston), x is the piston position, V_{o1} is the dead volume of the chamber 1 control volume, A is the duct area, k is the ratio of specific heats c_p/c_v (constant pressure and volume specific heats respectively), R is the gas constant, T is the air temperature, $\dot{m}_1$ and $\dot{m}_1$ are mass flow rates in each side of the piston and L is the length of the duct. The sub-indexes 1 and 2 refer to the upstream and downstream chamber, respectively. Energy losses are mainly originated by the air friction against the internal duct surface and by the continuous alteration of the air volume while travelling in the control volume. The usual approach for the pressure reduction related to the head losses is based on a practical formulation for turbulent flows (Darcy-Weisbach Equation) that consists in the empirical term $h_{lt} = fL_0\bar{v}^2/(2D)$ multiplied by the density of the fluid, where $\bar{v}$ is the average velocity (velocity of the vehicle in present case) along a duct with a length L_0 and an equivalent diameter D, and f is the friction factor for turbulent flows. The pressures closed to both PPU, described as p_1 and p_2, can, therefore, be written as:

$$p_1 = p_{1al} + f\frac{x}{D}\frac{\dot{x}^2}{2}\frac{p_{1al}}{RT}sgn(\dot{x}),\ p_2 = p_{2al} - f\frac{(L-x)}{D}\frac{\dot{x}^2}{2}\frac{p_{2al}}{RT}sgn(\dot{x}) \tag{8}$$

Power Propulsion Unit System Model. The pressure dynamics in the PPU is modeled taking into account the control volumes delimited by the system actuator, the blower and the valves, viewed in Figure 2. Appling the energy conservation equations it can be evidenced the pressure variation rates in each control volume. The pressure rate in the downstream volume of the upstream blower can be calculated by $\dot{p}_0 = RkT(\dot{m}_{blow} - \dot{m}_3 - \dot{m}_4)V_0$, where p_0 is the pressure in the downstream (related to the blower) chamber, V_0 is the downstream volume,

$\dot{m}_{blow}$ is the mass flow rate of the blower, $\dot{m}_1$ and $\dot{m}_2$ are mass flows rate through the PPU valves 3 and 4. The other cases of pressures inside both the PPU are modeled analogously to this one.

Blower Model. The blower used is a centrifugal backward-curved-blade type, whose characteristic curve was informed by the supplier, containing experimental data that, multiplied by the normalized blower rotational speed, approximates the output mass flow rate from the input given in terms of outlet pressure. The curves are dependent on the specific blower considered.

Valve Model. The butterfly-like air valves cause the flow obstruction by angular movements. The angular movement is produced by the action of pneumatic actuators. The mass flow rate value is function of the downstream pressure difference, p_u, upstream pressure, p_d, and of the actual area of passage. The value is obtained using an empiric correlation for constricted flow (Boulter, 1999) given by $\dot{m}_i = K_{qm} e^{u_{val}} \sqrt{max(p_u, p_d) - min(p_u, p_d)}\, sgn(\, p_u - p_d)/2$, where i references the valve number, K_{qm} is a mass flow rate gain, u_{val} is the normalized input control signal and *max*, *min* and *sgn* are standard mathematical functions (maximum, minimum and signal, respectively).

Leakages. Leakages to the atmosphere occur mainly due to the deformation of the flexible rubber elements of the sealings of the piston axis that transmit force to the vehicle from the intern part of the pneumatic actuator. In current approach, the modelling of the leakage flow rate $\dot{m}_l$ is based on the description of the constricted gas flow rate (Fox and McDonald, 2006), which, for an orifice with passage area $A_{leak} = d_y x$, under upstream and downstream pressures p_u and p_d actions, is given by Equation (12):

$$\dot{m}_l = d_y x \sqrt{\frac{2k}{RT(k-1)}}\, b\, sgn(p_d - p_u) \sqrt{\left(\frac{a}{b}\right)^{\frac{2}{k}} - \left(\frac{a}{b}\right)^{\frac{k+1}{k}}}, \tag{9}$$

where $a = min(p_d, p_u)$, $b = max(p_d, p_u)$, d_y is defined as the transversal propulsion plate leakage orifice width, and x is the vehicle propulsion plate pylon distance from de station. The pressures p_u and p_d are suitably chosen aiming to contemplate all the leakage situations of the system operation.

Fan + electrical motor dynamics. Based on the technical data furnished by the vendor of the electrical machine, a 1st order dynamic was considered. The time constant T was identified through analysis of available experimental results, resulting in $T = 9{,}877$ s, while the motor constant K_{motor} that relates the regimen rotation velocity with the input voltage to the motor driver was also identified, resulting in a value of $K_{motor} = 0{,}74$ (rot/min)/V. Therefore, the motor + fan dynamics model was defined by the following 1st order transfer function:

$$\frac{\omega_{fan}}{u_{control}} = K_{motor} \frac{1/T}{s + 1/T} \tag{10}$$

where $u_{control}$ is the control input of the motor + blower set and ω_{fan} is the angular velocity of the blower. This information and that of the pressure in the downstream volume inside the PPU allow to calculate the mass flow rate of the blower through the use empirical information about the blower behavior.

DESIGN OF THE CRUSING CONTROLLER

PID-type controllers (with proportional, integral and derivative control actions, Dorf and Bishop, (2008)) consist of traditional controllers that are applied to most physical system control and were designed to control the trajectory of the Aeromovel vehicle. In this context, three versions were proposed and tested. One of them with fixed gains, another, based on a discrete scheduling strategy of the controller (Gain Schedule Controller - GSC) based on ranges of values total mass transported (passengers + vehicle) and, finally, a third, based on a continuous parameterization of the values of gains (Continuous Gain Schedule Controller - CGSC) as a function of the value of the total mass transported. The main idea of the gain schedule scheme is to define previously to each travel a set of gains perform a suitable tracking of the desired trajectory based on one (or more) important parameter that does not vary significantly during the vehicle translation. In current approach the total transported mass (vehicle + passengers) is used as a switching criterion for changing the values of the gains set of the PID controller. This switching can be continuously or not continuously executed. In the case of fixed gains PID controller, the gains are defined as fixed for all mass conditions. In this case, despite obtaining acceptable performance for some cases in relation to which the gains are suitably adjusted, its performance degrades as the mass varies depending on the number of passengers. The fixed PID controller can be implanted by means the following expression:

$$u_{control} = K_p\left[(e(t) + K_d\dot{e}(t) + K_i\int e(t)dt\right] \tag{11}$$

Therefore, by changing the value of K_p, modify proportionally the effective gains of the integral (K_pK_i) and derivative (K_pK_d) control actions. This structure can also be used in the case of discrete or continuous gain scheduling, being suitable to choose or calculate the value of K_p in terms of the total mass transported. In current approach, 3 set of gains were defined for a 4 mass values chosen identically spaced from the minimum value (empty vehicle) to the maximum (full vehicle). In the continuous case, an equation that considers the maximum and minimum values admissible for the gains in relation to the range of possible mass values was constructed:

$$K_p = (K_{p\min}M_{\max} - K_{p\max}M_{\min} + (K_{p\max} - K_{p\min})M))/(M_{\max} - M_{\min}) \tag{12}$$

where the subindexes max and min are related to the maximum and minimum values suitable for the parameters. It is important to remark that for standard stability conditions, all gains must be strictly positive, implying that the condition $(K_{p\min}M_{\max} + K_{p\max}M > K_{p\max}M_{\min} + K_{p\min}M$ where M is the measured mass of the vehicle just before departing from the station. The pneumatic braking is performed by means the use of the controller introduced in Perondi et al. (2018), where the opening and closing action of the atmosphere valves implies in and effective control action capable of following a desired stopping trajectory, while the standard ABS braking action is performed in function of the velocity error with relation to the velocity set-point for each part of the line. The starting position for pneumatic braking is calculated based on knowledge of the desired deceleration and the current speed. This calculates the point at which braking, if started, at a constant and predetermined deceleration reaches the station at zero speed according to the equation: $v^2 + 2ad \geq 0$ where v is the actual velocity, a the desired acceleration and d the distance to the next station. Once the pneumatic brake is activated, to each controller cycle a new s = $v^2 - v_0^2 - 2ad$ is calculated and is the result is bigger than the *boundary layer configurated* the *boolean* signal u_{brake} is updated to close or open the atmospheric limiting the vehicle movement.

SIMULATIONS

In the Aeromovel technology, the velocity tracking closed-loop control system is divided into 3 actuators: GMP control, pneumatic brake, and friction (disc) brake. The propulsion system controls the fan speed by means a signal adjusted between '0' and '1'. Zero (0) refers to zero speed and one (1) to maximum fan speed. Currently, this control strategy is carried out via a PID (proportional + integral + derivative control actions) controller. Adjusting the PID gains aims to minimize the difference between the speed setpoint and the resulting vehicle speed along the time. The PID controller was designed to be adjustable to different loads in vehicle, in a strategy known as gains schedule. The PID gains were optimized using multithread optimization library based in Julia programming environment. The controller was programmed in Simulink/Matlab System and exported to the open standard functional mock-up interface (FMI). The simulations were performed with the system parameter values given in Britto et al. (2014). Figure 5 presents simulation results the section between TPS2 and TPS1 stations (in a journey from Terminal 2 toward Terminal 1. In Figure 5-a) we present the speed setpoint (*sp*) and the controlled speed response along the displacement trajectory. Figure 5-b) present the values of curve radius (*dir*) and of the inclination (*inc*) of the section line chosen for the tests, while Figure 5-c) present the difference of pressure in Pascal (also along displacement trajectory). Among the different stations, this segment was selected because it includes the characteristics where it is most difficult to control the vehicle due to the more significant line trajectory variation. In Figure 5, the trajectory tracking is divided into 2 steps: the first part involves the combined actuation of the PPU control and the disc brake. The second stage is related to the approach to the destination station, when the air brake control is activated by the actuation of the atmospheric valves while the power system is left in an idle situation. In deceleration situations followed by a resumption of speed, can occur long delays when resuming the setpoint as is possible to observe in Figure 5 between 750 meters and the full stop of the vehicle. When occur a decrease in speed at the setpoint or an approach that could indicate the possibility of exceeding the setpoint, the control signal can present signal with negative values. The controller is defined in a way that positive values are related to speed control, while negative values are related to the percentage of application of the friction braking system. Where '1' is full disc brake actuation and '0' or positive is the full release of the braking system. The friction brake is only applied when necessary. As can be seen in Figure 6, the main differences in the use of the brake (when using non-optimized PID values) are in the deceleration steps. Comparing the trajectories with the optimized PID gains, as we can see in Figure 6, a best trajectory tracking when we add the active brake together with the PID control especially when decelerating followed to a regaining speed as can we see between 750 m and the full stop of the vehicle. It is possible to observe that the combination of the disc brake action with the pneumatic braking action soften the slowing response.

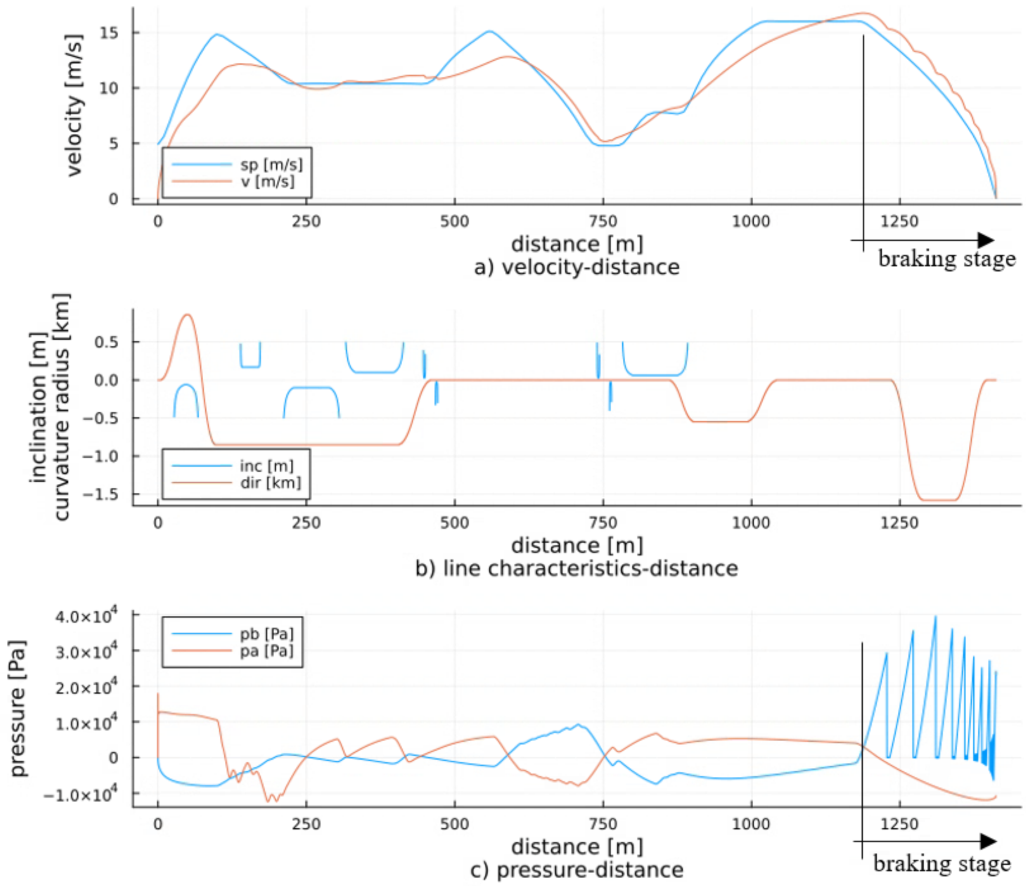

Figure 5. Simulation results of Optimized PID Gains.

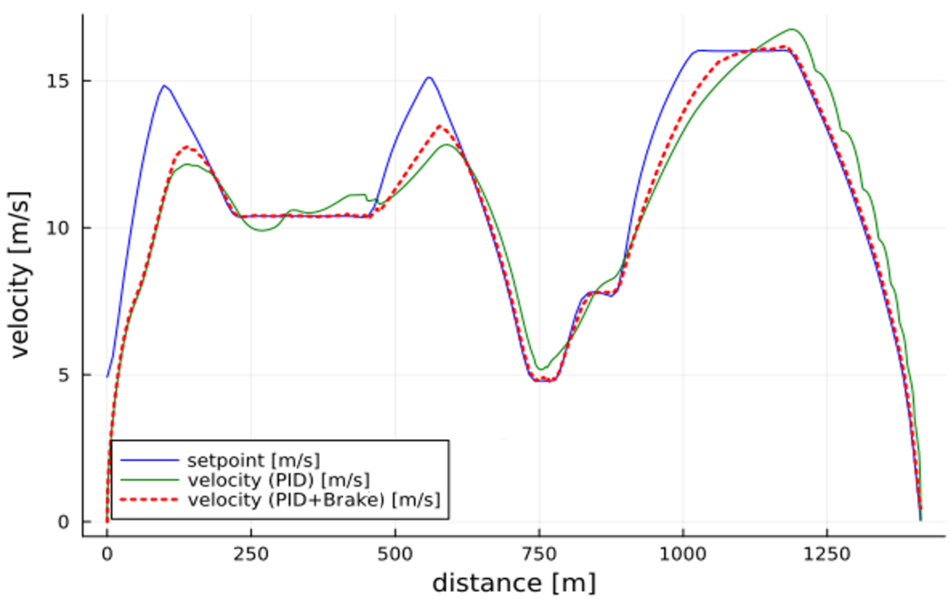

Figure 6. Simulation results of Optimized PID Gains with and without Friction Brake.

CONCLUSIONS

Simulations consist in important tool for a prior evaluation of the performance of control systems, allowing to evaluate the feasibility or not of a given proposed solution. The results of the simulations presented in the current work provide information of great importance for decision-making in the design of dynamical systems. Based on the results of the simulations, some points must be highlighted aiming to improve the system under development. Initially, it can be noticed that the blower acceleration curve may not be sufficient to provide the power needed to precisely follow the trajectory of the reference speed when it is most demanding, as shown in Figure 5(a). Another point that should be highlighted is the need to perform the actuation of the disc brake together with the PID speed control through the acceleration and deceleration of the fan. Speed path tracking is significantly improved when disc braking is integrated into the control. This is mainly due to the difficulty that the system encounters in braking the vehicle in more challenging line sections using only the control by the fan drive motor. As the pneumatic braking is programmed only closed to the stations, even reducing the speed of the fan motors as much as possible, the energy losses due to dissipative effect are not sufficient to guarantee a suitable performance in reducing acceleration. Thus, the contribution of auxiliary braking by means of the disc brake is very important to adequately reduce vehicle speeds in these circumstances. Therefore, considering a challenging route involving curves and variations in altitude, a control strategy including a friction brake system becomes necessary. Based on the results of the study, we can finally conclude that the proposed Aeromovel system vehicle trajectory control strategy is feasible for experimental testing when the plant is operational.

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Seismic Analysis of Protected Elements in Monorail Guideway Structures

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ABSTRACT

Monorail guideway structures (MGWS) exhibit distinct performance characteristics compared to traditional bridges due to the flexibility of their guideway beams. Therefore, a comprehensive study of the seismic behavior of MGWS is imperative to ensure their ductility and flexibility through seismic events. Shear and torsion failures are brittle modes of structural failure, necessitating that elements designed for seismic protection possess sufficient resistance capacity to ensure safety and integrity during extreme ground motions. While design codes have addressed shear over-strength ratios for bridges, they do not offer specific guidance for determining the over-strength ratio necessary to safeguard the shear and torsion capacity of MGWS elements. This paper presents a methodology for establishing the shear and torsion over-strength ratio required to protect MGWS elements from brittle failure and to achieve ductile failure. This in research was developed using displacement-controlled pushover analysis (PA) conducted with SAP2000 software. The finite element model created for this study was calibrated based on experimental test results from the existing literature. Shear and torsion over-strength ratios were determined according to the 2022 publication of *AASHTO Guide Specifications for LRFD Seismic Bridge Design* and were compared to the values calculated from the SAP2000 model. This comparison was conducted in both longitudinal and transverse directions, considering various parameters such as span length, pier height, pier cross-section, reinforcement ratio, confining stirrups, and concrete compressive strength. Ultimately, proposed over-strength ratios for structural members of the MGWS are provided to maintain ductility and prevent brittle failures, both in terms of shear and torsion.

INTRODUCTION

Seismic performance of roadway/railway bridges differs from monorail guideway structures as such bridges have large deck sections. The large deck sizes significantly decrease the probability of plastic hinge occurrence in the deck, therefore, these bridges are designed based on strong beam-weak column concept, where the plastic hinges occur in columns under seismic effect. Consequently, the performance of the monorail bridge under seismic effect differs from the performance of ordinary bridges and needs significant evaluation.

Flexural failure is ductile and passes through many propagative stages before complete failure, contrary, the shear and torsional failure is brittle (Lee et al. 2004) and (Park et al. 1991). Therefore, when designing the monorail guideway structures, the shear and torsional capacity of the sections must be greater than the moment capacity in order to develop sufficient ductility of the structure under seismic loads -shear protected element-.

The importance of the research is that there are no studies that investigate the effect of shear force and torsional moment on monorail guideway structures under the effect of seismic load. Also, the design codes do not provide any guidance for the over-strength ratio needed for a protected shear and torsion capacity of monorail guideway structural elements including (AASHTO 2020), (AASHTO 2022) and (CALTRANS 2019).

STRUCTURE CONFIGURATION

The hypothetical case study considered in the analysis is based on Cairo Monorail Projects. Cairo Monorail Projects consist of two monorail lines in Greater Cairo metropolitan area, one between the New Capital City and Nasr City – Cairo (56.5 km route length), and the other from the 6th of October City into Wadi Al Neel Street – Giza (42.5 km route length). Each frame consists of four-spans 26m, 30m, 30m, and 26m spans length, respectively with two post-tensioned guideway beams in each span, which are connected to pier caps and supported on circular intermediate with different heights (ranging from 6 to 22 m). The foundation system for the guideway structures was monopile pile foundation. The 3D model of the structure was developed using SAP2000. Extruded view of the developed model is shown in Figure 1 illustrating the element definitions and notations.

Pushover Analysis of Monolithic Monorail Guideway Structures research was conducted on seismic performance for flexural behavior on monorail guideway system under seismic load (Sayed et al. 2022). Based on the recommendation of this research, bearings were implemented at the end pier caps to improve ductility and enhance the system.

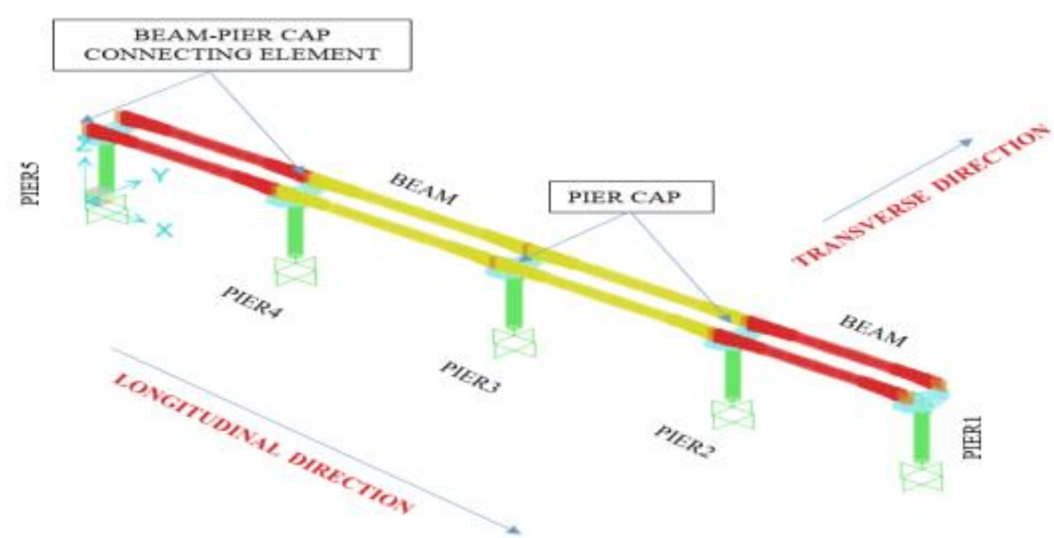

Figure 1. Case study extruded shape of a typical guideway structure 3D model

Material Properties

The mechanical properties of reinforcement and concrete used in the design and the construction phase are shown in Table1 including concrete, steel, and prestressing tendon properties.

Table 1: Material Properties for Structural Elements.

Properties	Value	Units
Concrete		
Concrete compressive strength, F_{cu}	60	MPa
Modulus of elasticity of concrete, Ec	34082.25	MPa
Steel*		
Yield strength of rebar, F_y	600	MPa
Ultimate strength of rebar, F_u	800	MPa
Modulus of elasticity of steel, E_s	200000	MPa
Tendon		
Strands 15.7mm area	150	mm^2
Ultimate strength of strands (F_{pu})	1860	MPa
Strands yield stress (F_{py})	1580	MPa
Jacking stress (F_{pj})	1395	MPa

(*) Steel properties used in this research is A706 Gr 60 based on AASHTO Guide Specifications for LRFD Seismic Bridge Design (AASHTO 2022) Table 8.4.2-1 and CALTRANS Seismic design criteria version 2.0 (CALTRANS 2019) Table 3.3.3-1

Structure Base Geometry

Structure details and section dimensions used for MGWS are shown in Table 2, which includes frame configurations, beams, pier cap and piers dimensions.

Table 2: Structure details and section dimensions for Cairo Monorail case study.

MGWS Configurations	Value and Description	Units
Number of bays along longitudinal direction	4	
Spacing along longitudinal direction	26-30-30-26	m
Columns		
Pier	Circle 1600	mm
Beam-Pier Cap Connecting Element	690x1500	mm
Beams		
Beam	690 x 2200/1600	mm
Pier Cap	2000x 2281/1000	mm

FINITE ELEMENT MODEL DEVELOPMENT AND VERIFICATION

Moment curvature relation is a basic tool used to model plastic hinges flexural performance for reinforced concrete members in non-linear analysis (C.S.I. 2020). The Moment curvature relation was calculated using SAP2000 for all sections.

Model Definition in SAP 2000

Guideway beams, pier caps, and piers were modelled in SAP 2000 as frame elements. SAP 2000 frame element has six degrees of freedom at its ends with local axes. Moreover, the connection between guideway beams and pier cap was modelled as a vertical frame element connecting those elements together. All members were rigidly connected in the analysis model. The six degrees of freedom of the column base were restrained forming a total fixation support.

Pushover analysis (PA) is a static nonlinear procedure in which the magnitude of the lateral load is increased monotonically maintaining a predefined distribution pattern along with the height of the structure. The structure is displaced till the -control node- reaches -target displacement- or structure collapses. The sequence of cracking, plastic hinging, and failure of the structural components throughout the procedure is observed.

Plastic hinges were defined using Caltrans moment curvature relation after idealization. Furthermore, performance levels of hinge plastic capacity were identified according to the acceptance criteria of the AASHTO guide specifications for LRFD Seismic Bridge Design (AASHTO 2022).

MC was used for modelling the user defined hinges for monorail guideway sections. Moment (M3) is used for Beams and Pier Cap at its ends and at the middle, while interacting (P-M2-M3) was used for Piers and Beam-Pier Cap Connecting element at ends.

Pushover analysis (PA) was executed till plastic hinges formation. Plastic hinges are formed at the bottom of (pier 2 and 4) due to flexural. Then, shear force and torsional moment are calculated corresponding to the maximum moment.

Load Cases and Seismic Assessment

Few design loads were included in the assessment of seismic behaviour of the MGWS including gravity loads, train loads and seismic loads. Gravity loads were defined by assigning the unit weight for each element. The train loads were obtained from the project design criteria based on the operating loads for the trains according to the Egyptian Code of Practice 207-2015 Part 4: Loads and Forces on Bridges and Intersections (ECP 2015). The structure is assumed to be in Cairo, Egypt and a response reduction factor of 1 with 30% of live loads according to the Egyptian Code of Practice 207-2015 Part 4: Loads and Forces on Bridges and Intersections (ECP 2015).

Model Verification

The verification process for our developed model using SAP2000 involved a comprehensive comparison with experimental studies sourced from literature, specifically referencing the insightful work by Moehle in 2014 where a detailed investigation into moment curvature was conducted. This section outlines the methodology and key findings of this verification process.

Our developed model, which addresses nonlinear pushover analysis for plastic hinges, was subjected to verification to ensure its accuracy and reliability. The experimental results obtained by (Moehle 2014) served as a benchmark for our verification efforts. The moments and curvature values derived from our model using SAP2000 were compared with those reported by Moehle.

Furthermore, Figure 2 visually encapsulates the outcomes of this comparison. The figure graphically illustrates the correlation between our model's results and the moment curvature relationship obtained from Moehle's study.

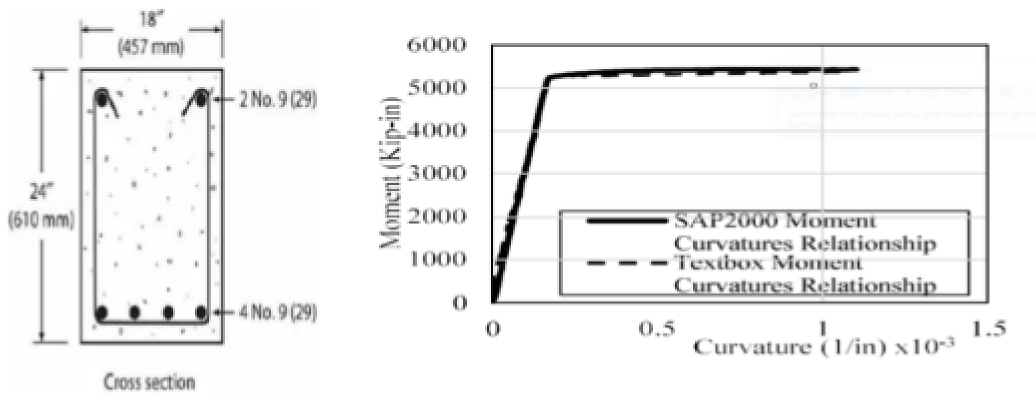

Figure 2. Moment-Curvature Relationships of Experimental Work (Moehle 2014) compared to SAP2000 verification model.

SHEAR AND TORSION PROTECTED ELEMENT

The capacity design philosophy - shear and torsion capacity protected elements - in bridges inhibits brittle and premature shear and torsion failure. The highest shear force that the column can expect is designed to be larger than its flexural capacity under seismic load, by using an over strength ratio (AASHTO 2022), (CALTRANS 2019) (Marsh 2014) and (Priestley et al. 1996).

AASHTO Guide Specifications for LRFD Seismic Bridge Design (AASHTO 2022), as well as, CALTRANS Seismic design criteria version 2.0 (CALTRANS 2019) defined shear over strength ratio for bridges equals 1.2 for Reinforcing Steel Grade A706 60. The shear capacity shall be calculated by dividing the over-strength moment capacity of column by the Length (H), where (H) is the length of the column from point of maximum moment in the pile to the point of contraflexure in the column (AASHTO 2022).

The flexural failure of a structure is characterized by ductility, progressing through multiple stages before eventual collapse. In contrast, shear and torsional failure tend to be brittle. Consequently, when embarking on the design of monorail guideway structures, it becomes imperative to ensure that the shear and torsional capacities of the sections surpass the moment capacity. This approach is vital for instilling sufficient ductility in the structure, particularly when subjected to seismic loads, thereby creating a shear-protected element.

The significance of this research lies in the absence of comprehensive studies exploring the impact of shear force and torsional moment on monorail guideway structures under seismic loads. Equally noteworthy is the dearth of guidance within current design codes regarding the necessary over-strength ratio required to ensure a protected shear and torsion capacity for the structural elements of monorail guideways. This gap in knowledge persists even in widely referenced design codes such as (AASHTO 2020), (AASHTO 2022), and (CALTRANS 2019).

Consequently, addressing these knowledge gaps is vital for advancing the understanding and safety of monorail guideway structures, especially in seismic-prone regions.

PARAMETRIC STUDY

Investigated Parameters

A parametric study was done varying several parameters as shown in Table 3 for studying Shear and Torsion over-strength ratio using nonlinear PA in longitudinal and transverse directions. The investigated parameters include pier height, span length, pier reinforcement ratio and pier cross-section.

Table 3: Investigated Parameters.

Parameter	Variation	Unit
Pier height	5-8-10-12-15	m
Span lengths	(20-24-24-20)-(22-26-26-22) (24-28-28-24)-(26-30-30-26) -(28-32-32-28)	m
Pier reinforcement ratio	1.5-2-2.5-3	%
Pier cross section diameter	1500-1600-1700-1800-1900	mm

Based on the performed analysis for monorail guideway system, pier was selected as a main source for ductility and energy dissipation. The other elements (pier cap and beam-pier cap connecting element) are protected from shear and torsion compared to pier flexural capacity.

Over strength ratios for shear and torsion were calculated varying each of the parameters mentioned above. The **Shear over-strength ratio of a section** is defined as the ratio between maximum shear forces from pushover analysis model at certain section due to flexural failure, over pier moment capacity divided over height calculated from AASHTO Guide Specifications for LRFD Seismic Bridge Design (AASHTO 2022) equation 8.5.1. as shown in Figure 3. However, the **Torsion over-strength ratio of a section** is defined as the ratio between Torsional Moment from pushover analysis model at certain section due to flexural failure divided over the top of pier flexural capacity as shown in Figure 4.

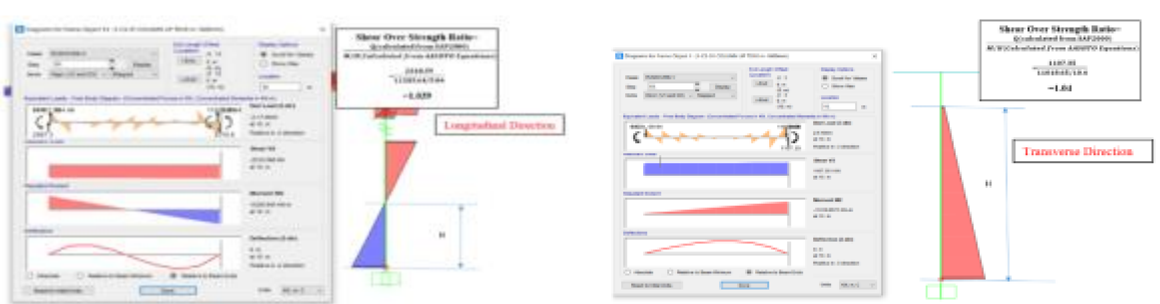

Figure 3. Excerpts from SAP 2000 illustrating shear over-strength ratio calculation for pier in longitudinal and transverse direction respectively.

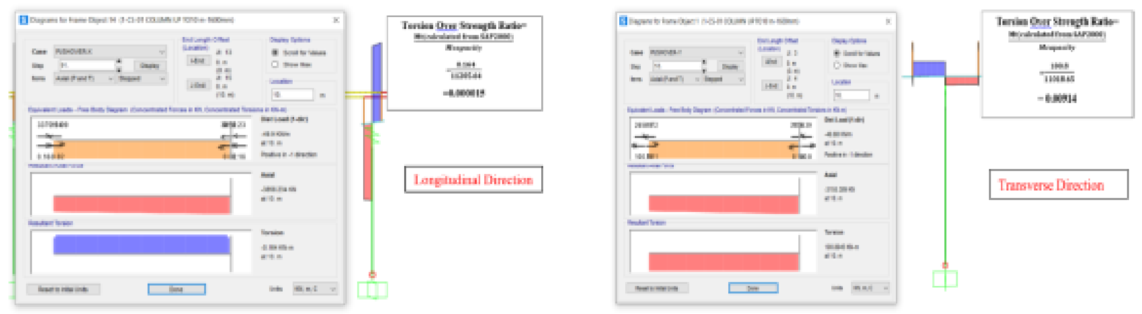

Figure 4. Excerpts from SAP 2000 illustrating torsion over-strength ratio calculation for pier in longitudinal and transverse direction respectively.

Pier Height

Pier height is varied from 5m to 15m, and the shear and torsion over-strength ratio are obtained as shown in Figure 5. As the pier height increases, shear over-strength ratio increases in both longitudinal and transverse directions. As increasing the pier height while maintain the same column cross-section increases the flexibility as well as the corresponding ductility of the structure. The shear over strength ratio varies from 0.82 to 1.10 in longitudinal direction and from 0.87 to 1.10 in transverse direction. However, as the pier height increases, torsion over-strength ratio had very minor value. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions as the investigated structure was tangent and did not have any curves that may implement torsion on the column.

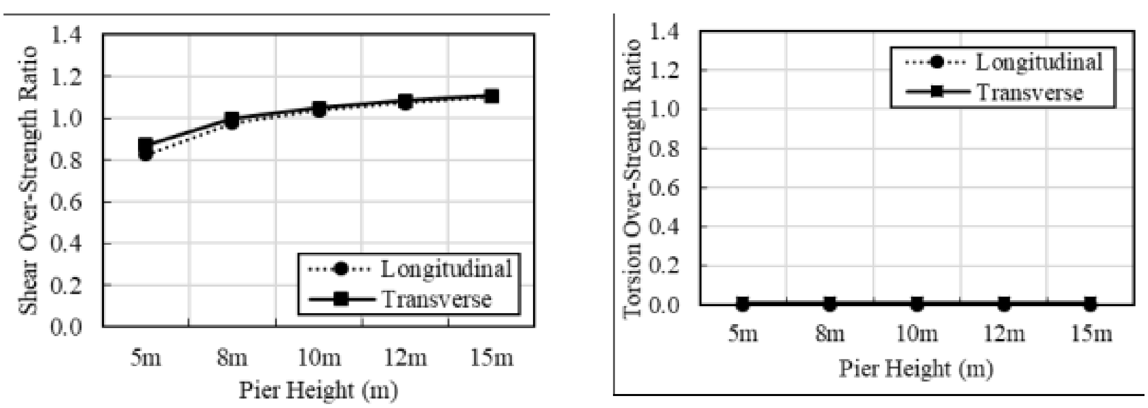

Figure 5. Relationship between pier shear and torsion over-strength ratios and pier height for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for pier cap as shown in Figure 6. As the pier height increases, shear over-strength ratio increases in both longitudinal and transverse directions. The shear over-strength ratio varies from 0.34 to 1.10 in longitudinal direction and from 0.05 to 0.34 in transverse direction. However, As the pier height increases, torsion over strength ratio increases in longitudinal direction and decreases in transverse direction. Torsion over-strength ratio varies from 0.40 to 0.54 in longitudinal direction and from 0.10 to 0.08 in transverse direction.

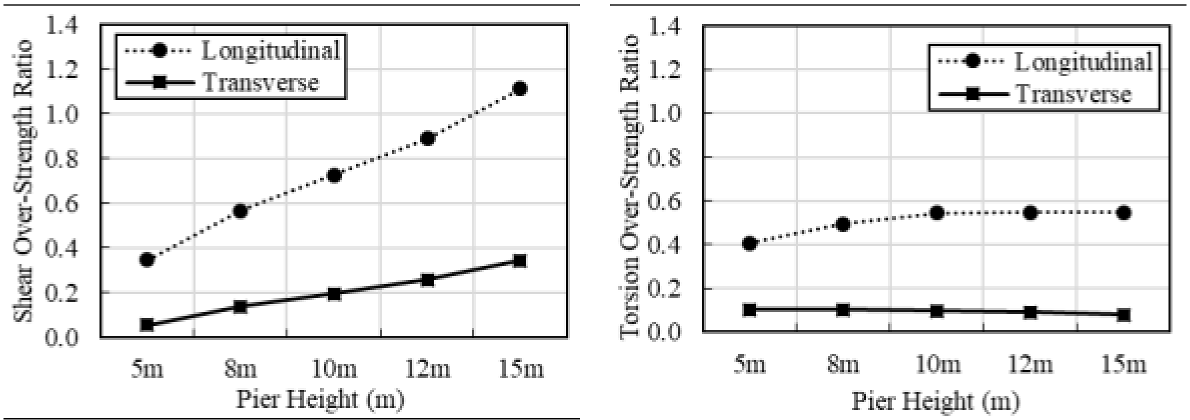

Figure 6. Relationship between pier cap shear and torsion over-strength ratios and pier height for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for beam-pier cap connecting element as shown in Figure 7. As the pier height increases, shear over-strength ratio increases in both longitudinal and transverse directions. The shear over-strength ratio varies from 0.32 to 0.38 in longitudinal direction and from 0.32 to 0.37 in transverse direction. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions as the investigated structure was tangent and did not have any curves that may implement torsion on the beam-pier cap connecting element.

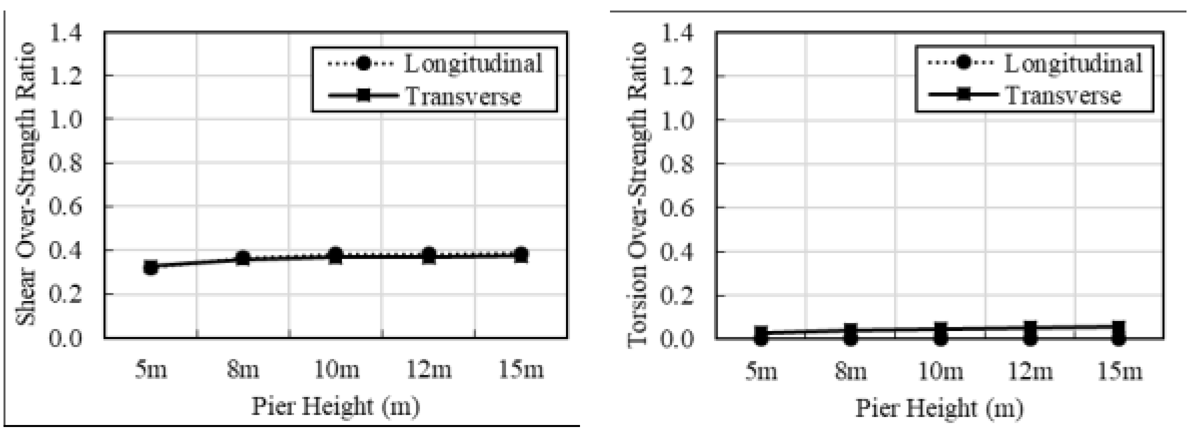

Figure 7. Relationship between shear and torsion over-strength ratios and pier height for beam-pier cap connecting element for longitudinal and transverse directions.

Span Length

Span length is varied from (20-24-24-20) to (28-32-32-28) and the shear and torsion over-strength ratio are obtained as shown in Figure 8. As the span length increases, shear over-strength ratio is nearly maintained the same without any effect in either the longitudinal or transverse direction. This occurs due the significantly low weight of the structure, which does not affect the overall structural mass. Shear over-strength ratio varies from 1.06 to 1.03 in longitudinal direction and from 1.05 to 1.04 in transverse direction. However, As the span length increases, torsion over-strength ratio represent minor capacity value. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

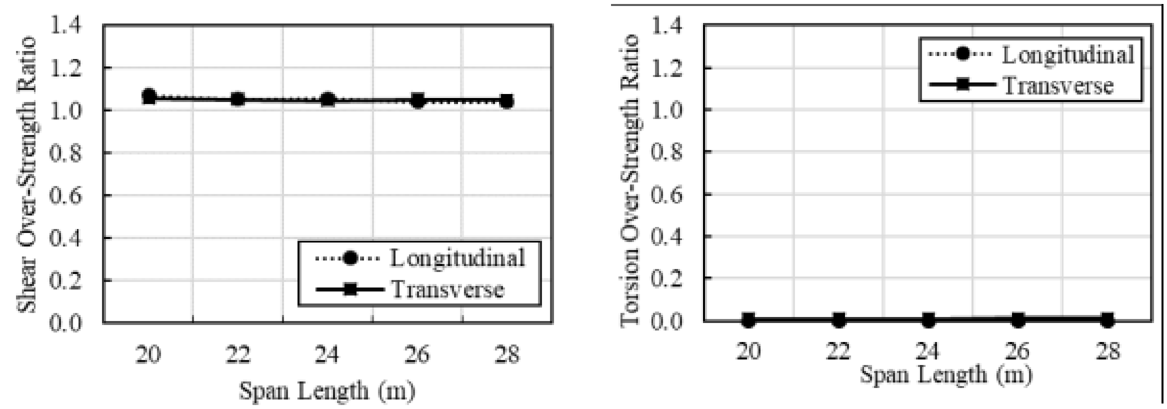

Figure 8. Relationship between pier shear and torsion over-strength ratios and span length for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for pier cap as shown in Figure 9. As the span length increases, shear over-strength ratio slightly increases in both longitudinal and transverse direction. Shear over-strength ratio varies from 0.7 to 0.77 in longitudinal direction and from 0.17 to 0.19 in transverse direction. However, as the span length increases, torsion over-strength ratio is nearly maintained the same without any effect in both longitudinal and transverse directions. Torsion over-strength ratio is 0.55 in longitudinal direction and 0.08 in transverse direction.

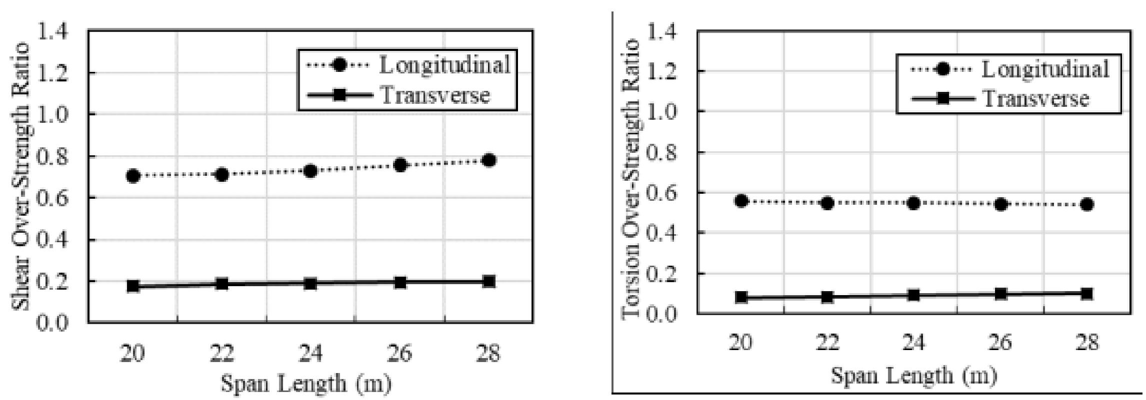

Figure 9. Relationship between shear and torsion over-strength ratios and span length for pier cap for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for beam-pier cap connecting element as shown in Figure 10. As the span length increases, shear over-strength ratio slightly increases in both longitudinal and transverse direction. Shear over-strength ratio varies from 0.36 to 0.38 in longitudinal direction and from 0.31 to 0.35 in transverse direction. However, as the span length increases, torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

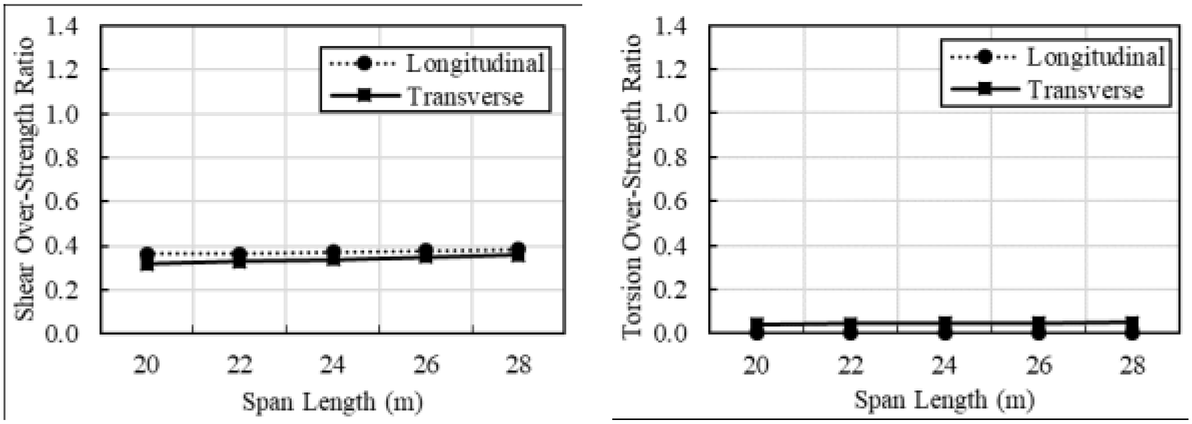

Figure 10. Relationship between shear and torsion over-strength ratios and span length for beam-pier cap connecting element for longitudinal and transverse directions.

Pier Reinforcement Ratio

When the pier reinforcement ratio is increased from 1.50% to 3% and the shear and torsion over-strength ratio are obtained as shown in Figure 11. As the pier reinforcement ratio increases, shear over-strength ratio decreases in both longitudinal and transverse direction. This reduction in over -strength ratio occurs due to the reduction in the column flexural capacity. Shear over-strength ratio varies from 0.97 to 0.76 in longitudinal direction and from 1.06 to 0.99 in transverse direction. However, As the pier reinforcement ratio increases, torsion over-strength ratio had very minor value. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

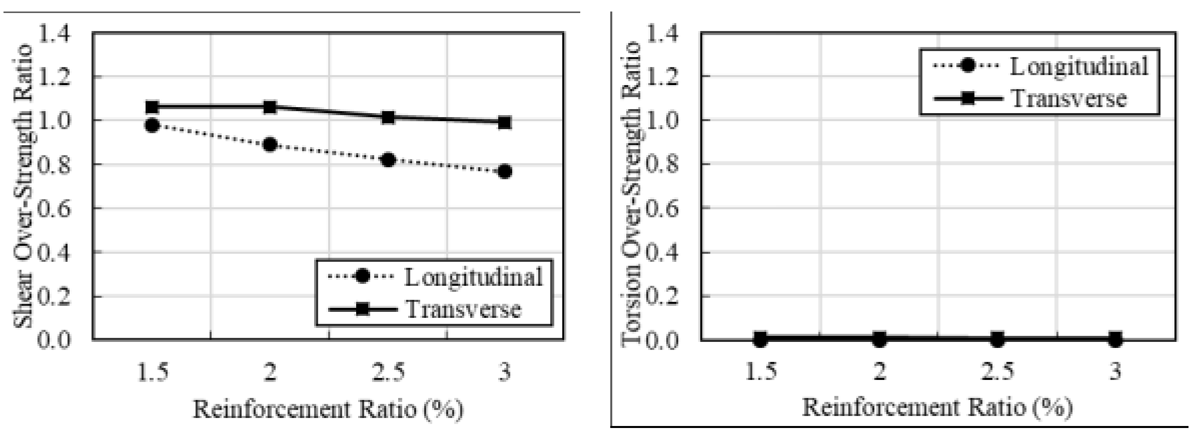

Figure 11. Relationship between pier shear and torsion over-strength ratios and reinforcement ratio for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for pier cap as shown in Figure 12. As the pier reinforcement ratio increases, shear over-strength ratio decreases in both longitudinal and transverse direction. Shear over-strength ratio varies from 0.69 to 0.41 in longitudinal direction and from 0.2 to 0.12 in transverse direction. However, as the pier reinforcement ratio increases, torsion over-strength ratio decreases in both longitudinal and transverse direction. Torsion over-strength ratio varies from 0.48 to 0.27 in longitudinal direction and from 0.1 to 0.07 in transverse direction.

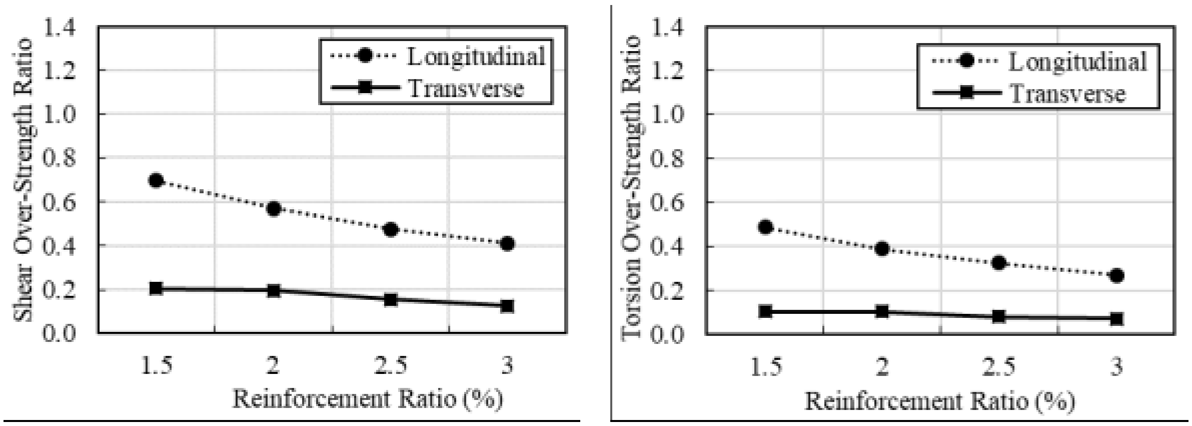

Figure 12. Relationship between shear and torsion over-strength ratios and reinforcement ratio for pier cap for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for beam-pier cap connecting element as shown in Figure 13. As the pier reinforcement ratio increases, shear over-strength ratio is slightly affected in both longitudinal and transverse direction. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

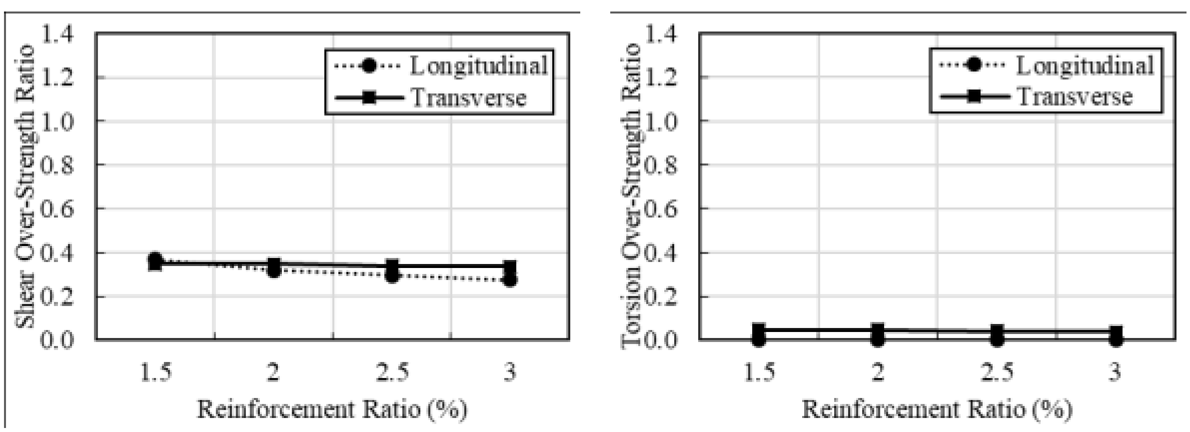

Figure 13. Relationship between shear and torsion over-strength ratios and reinforcement ratio for beam-pier cap connecting element for longitudinal and transverse directions respectively.

Pier Cross Section

When the pier cross-section is increased from 1500mm to 1900mm, the shear and torsion over-strength ratio is obtained as shown in Figure 14. As the pier cross-section increases, shear over-strength ratio slightly increases in longitudinal direction and slightly decreases in transverse direction. Shear over-strength ratio varies from 1.04 to 0.94 in longitudinal direction and from 1.03 to 1.08 in transverse direction. However, as the pier cross-section increases, torsion over-strength ratio had very minor value. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

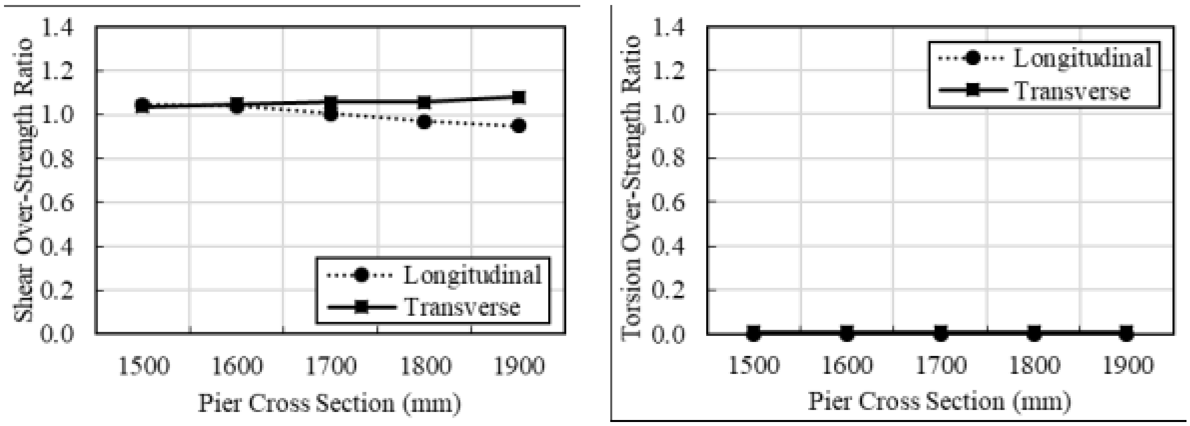

Figure 14. Relationship between pier shear and torsion over-strength ratios and pier cross section for longitudinal and transverse directions.

The shear and torsion over-strength ratio curves are obtained for pier cap as shown in Figure 15. As the pier cross-section increases, shear over-strength ratio decreases in both longitudinal and transverse direction. Shear over-strength ratio varies from 0.82 to 0.59 in longitudinal direction and from 0.19 to 0.14 in transverse direction. However, as the pier cross-section increases, torsion over-strength ratio decreases in both longitudinal and transverse direction. Torsion over-strength ratio varies from 0.56 to 0.42 in longitudinal direction and slightly varies from 0.1 to 0.08 in transverse direction.

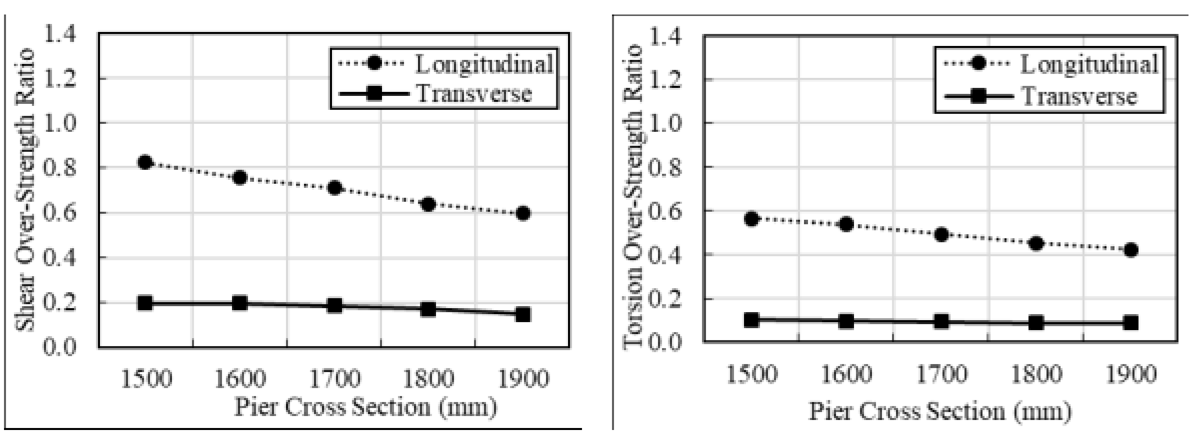

Figure 15. Relationship between Shear and Torsion over-strength ratio and Pier Cross Section for Pier Cap for longitudinal and transverse direction respectively.

The shear and torsion over-strength ratio curves are obtained for beam-pier cap connecting element as shown in Figure 16. As the pier cross-section increases, shear over-strength ratio decreases in both longitudinal and transverse direction. Shear over-strength ratio varies from 0.37 to 0.32 in longitudinal direction and from 0.35 to 0.32 in transverse direction. However, as the pier cross-section increases, torsion over-strength ratio had very minor value. Torsion over-strength ratio is approximately zero in both longitudinal and transverse directions.

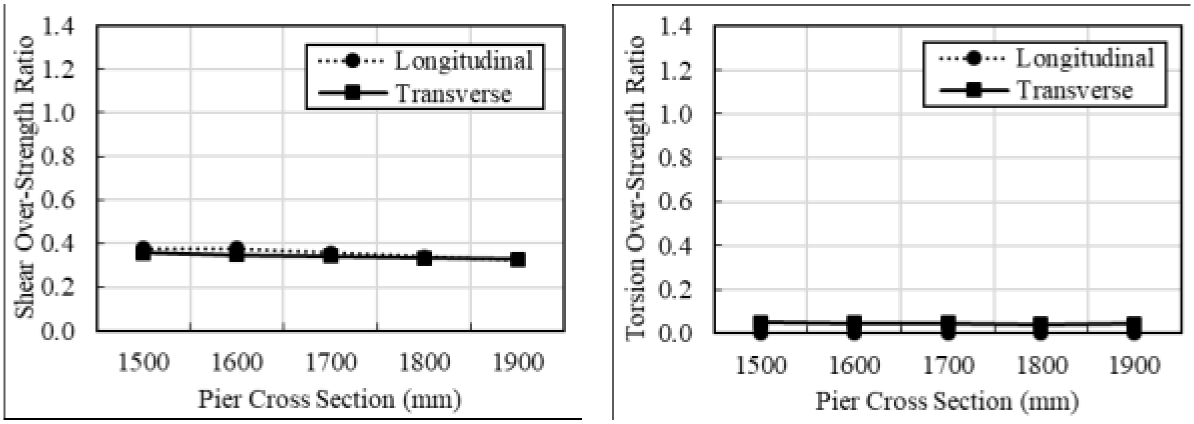

Figure 16. Relationship between shear and torsion over-strength ratios and pier cross section for beam-pier cap connecting element for longitudinal and transverse directions.

PARAMETRIC STUDY SUMMARY OF RESULTS

As per AASHTO Guide Specifications for LRFD Seismic Bridge Design – Section 8.5 (AASHTO 2022) as well as CALTRANS Seismic design criteria version 2.0 (CALTRANS 2019), the over-strength magnifier accounts for material strength variations between the column and adjacent members, and column moment capacities greater than the idealized plastic moment capacity. In this research the magnification due to plastic moment capacity is only considered. Based on the PA conducted of the MGWS including several investigated parameters, the following Table 4 summarizes the parametric study outcomes. It contains the ranges of the over-strength ratio of each member in the MGWS.

Table 4: Summary of over-strength ratios obtained from parametric study.

ELEMENT	SHEAR OVER-STRENGTH RATIO [Q / (M/H)]		TORSION OVER-STRENGTH RATIO (Mt / M)	
	Longitudinal Direction	Transverse Direction	Longitudinal Direction	Transverse Direction
Pier	0.82 to 1.06	0.87 to 1.10	0.00	0.00
Pier Cap	0.34 to 1.10	0.14 to 0.34	0.27 to 0.56	0.07 to 0.105
Beam-Pier Cap Connecting Element	0.27 to 0.38	0.32 to 0.37	0.00	0.03 to 0.05

CONCLUSIONS

Based on the analysis conducted of the MGWS including several studied parameters, the following conclusions were extracted:

- The shear and torsional capacity of the pier and pier cap must be relatively greater than the moment capacity of pier in order to develop sufficient ductility of the structure under seismic loads.
- The shear over strength ratio for the pier cap and pier shall be maintained at a ratio of 1.1 and beam pier cap connecting element shall be maintained at a ratio of 0.38 to assure that this element will not be subjected to premature failure during earthquake.
- The torsional capacity of the pier cap shall be maintained at 0.56 the column flexural capacity.
- Torsion capacity for the pier and the beam-pier cap connecting element represent minor capacity value compared to the column flexural capacity as all as the investigated structures were tangent and did not have any curves that may implement torsion on the column or the beam-pier cap connecting element.

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A Look Back to the Future—The Disney Monorails

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ABSTRACT

Walt Disney originally envisioned the monorail as a reliable and safe public transit system for the future. The first Disney monorail system opened in June 1959 as merely an attraction taking people on a scenic trip around Disneyland in Anaheim, California, while also showcasing the practicality of monorails for use as public transportation. When Walt Disney World opened in Orlando, Florida, in 1971, the Disney monorail was an important feature of the new amusement park, and today over 50 million annual passengers ride the monorail system. Although monorails have not become a popular public transit alternative in the United States, they are probably the most recognized icons of Disney parks, and what many visitors consider as future transportation. This paper explores the history of the Disney monorails at Disneyland, Walt Disney World, and the Tokyo Disney Resort, the evolution of the Disney monorail trains, characteristics of the systems, operations, and challenges.

INTRODUCTION

Walt Disney initially envisioned building a tourist attraction adjacent to his studios in Burbank, California, in response to people wanting to visit the movie studios. His original plan was to build a small play park, known as Mickey Mouse Park, to be located on an eight-acre (3.2 ha) site across the street from the studio. His designers began working on concepts and the project grew much larger than the site could accommodate. Based on further analysis of potential growth, Disney bought a 160-acre (65 ha) site near Anaheim, southeast of Los Angeles, in 1953. The park was designed by a creative team selected by Disney and construction began in 1954. Disneyland opened on July 17, 1955. Since its opening, the park has undergone several expansions and major renovations, and today almost 17 million annual visits are made to this famous theme park. The second Disney theme park was Walt Disney World in Florida. It opened in 1971. Other Disney parks include Tokyo Disneyland (1983), Disneyland Paris (1992), Hong Kong Disneyland (2005), and Shanghai Disneyland Park (2016).

Walt Disney had a personal fondness for railroads and rail systems, which have been included in all Disney parks. He was always looking for inventive new ways of moving park guests and this thinking can still be seen today as monorail systems are an important feature of the original Disneyland, Walt Disney World, and the Tokyo Disney Resort. Table 1 presents a summary of the three parks and Table 2 provides a summary of a few characteristics of the Disney monorail trains.

The first monorail prototype dates back to the early 1800s in Russia, and since then various monorail designs have been proposed and implemented. Modern monorail designs can be divided into two broad classes, *straddle-beam* and *suspended*. The most common type is the straddle-beam, in which the train straddles a steel or reinforced concrete beam 2 to 3 feet (0.6 to 0.9 m) wide. A rubber-tired carriage contacts the beam on the top and both sides for traction and to stabilize the vehicle. This style was popularized by the German company ALWEG. There is also a historical type of suspension monorail developed by German civil engineer Eugen Langen in the late 1800s. It was built in Barman-Elberfeld (now known as Wuppertal, Germany) and Vohwinkel (now a section of Wuppertal) and opened in 1901. The system is known as the Wuppertal Suspension Railway or Wuppertal Schwebebahn and has operated successfully for over 120 years. French engineers developed a suspended monorail concept with fully enclosed passenger cars suspended under a steel and concrete box beam with an opening in the bottom in which the rubber wheels of the train run inside the track. This provides better protection for the wheel systems and track in harsh weather. A test track was built in France by SAFEGE, a consortium of French companies. SAFEGE systems are the leading type of suspended monorails, and although no systems were built in France, three systems have been built in Japan. The Chiba (Japan) Urban Monorail system is the world's largest suspended monorail network. Straddle-beam monorails are more common and most monorails are powered by electric motors fed by dual third rails, contact wires, or electrified channels attached to or enclosed in their guidance beams.

Table 1. Disney Parks with Monorail Systems

Monorail System Information						
Park Opened		**Opened**	**Lines**	**Guideway Length**	**Stations**	**Comments**
Disneyland	1955	1959	1	2.5 mi. (4 km)	2	Anaheim, CA original short line through Tomorrowland; guideway extended in 1961 for Disneyland Hotel station (replaced in 1999 with Downtown Disney station)
Walt Disney World	1971	1971	3	14.7 mi. (23.7 km)	5	Lake Buena Vista, FL double-beam loop and in 1982, a line opened to connect EPCOT to the system
Tokyo Disney Resort	1983	2001	1	3.1 mi. (5 km)	4	Urayasu, Chiba, Japan one-way loop with connection to Japan Railway (JR)

In 1952, while on a European trip, Walt and his wife, Lillian, had a chance to ride the Wuppertal Schwebebahn. Apparently, the swaying motion was reported to have made Mrs. Disney queasy, leading her to wonder aloud, "Why can't they run the cars on top of the track?" The thought stayed with Walt. Six years later, Walt and Lillian were on another European trip and while driving on a country road in Fuhlgen, Germany, outside of Cologne, they drove onto a road that ran between the grounds of two campuses of the Alweg Research Corporation. A monorail train passed above the road right in front of them. Walt had discovered the monorail and on his return to the United States, he dispatched Joe Fowler, director of construction, and

Roger Broggie, chief of engineering design, to Germany to meet with the Alweg group and explore how to apply the Alweg design to Disneyland. (Kurtti)

Table 2. Disney Monorail Trains

Park		In-Service	Trains	Cars/Train	Length	Pass./Train	Builder
Mark I	Disneyland	1959-61	2	3	85 ft (26 m)	86	Disney Studios
Mark II	Disneyland	1961-69	3	4	112 ft. (34 m)	108	Disney Studios
Mark III	Disneyland	1969-87	4	5	137 ft. (42 m)	160	WED Transportation
Mark IV	Walt Disney World	1971-91	5/6*	5/6*	171 ft. (52 m)*	204*	Martin Marietta
Mark V	Disneyland	1986-2008	4	5	150 ft. (46 m)	132	Ride & Show Engrg., MBB
Mark VI	Walt Disney	World 1989-present	12	6	203.5 ft. (62 m)	360**	Bombardier Transportation
Mark VII	Disneyland	2008-present	3	5	140 ft. (43 m)	120	Dynamic Structures
Type X	Tokyo Disney	2001-2021	5	6	275 ft. (84 m)	537	Hitachi Rail
Type C	Tokyo Disney	2020 - present	5	6	275 ft. (84 m)	564	Hitachi Rail

*Note on Mark IV trains – in 1978, a sixth car was added to some trains to become 201 ft. (61 m) in length and a capacity of 244 seated passengers per train.

**Note on Mark VI trains – cars redesigned to accommodate standings passengers so train capacity is 360 passengers (120 seated and 240 standees)

DISNEYLAND

Disneyland consists of several themed lands and one of these areas was Tomorrowland. Disney wanted to feature numerous attractions that depicted views of the future and outer space, and early plans included moving sidewalks and a suspended monorail system. However, when Disneyland opened in 1955, several of its attractions were not ready and many of the initial attractions were corporate exhibits. One of the initial attractions was Autopia, which gave visitors a view of the National Interstate System that was to be built in the future, as well as a modern home with conveniences such as picture phones, television remote controls, and a microwave oven were displayed. Following his discovery of the Alweg monorail on his trip to Germany, Disney directed his team to include a monorail based on a straddle-beam design to be part of the expansion plans that were being developed for Tomorrowland. Disney designer, Bob Gurr, headed a team that transformed the boxy Alweg vehicles into something more futuristic for the park. Gurr then headed a team of studio craftsmen that designed and manufactured the locomotive, passenger cars, and train chassis, suspension, and propulsion systems. The job of building the monorail was originally assigned to the Standard Carriage Works, but was later moved to the Disney Studios to be finished in time for the dedication of the Tomorrowland expansion. Then U.S. Vice President Richard Nixon and his family officially dedicated the all-new Disneyland-Alweg Monorail System on June 14, 1959. They were also the first passengers to ride the new system.

Art Linkletter, master of ceremonies for the dedication, proudly hailed the premier of the newest Disneyland attraction: “You’re about to see the debut of a revolutionary new form of transportation: the Monorail. It will be a daily demonstration of an innovative solution to urban mass transportation problems.” (Kurtti)

On opening, the monorail was merely an attraction taking passengers on a scenic ride of eight-tenths of a mile (1.3 km), beginning and ending at the Tomorrowland Monorail Station. The track layout was meticulously engineered to include curvatures 120 feet (37 m) in radius, over- and underpasses, and grades up to 7 percent, to demonstrate the applicability of the system under real-world construction and topographic conditions. Two three-car trains operated on the guideway and they were identified as Mark I versions (Figure 1). One train was painted red and the second train was blue.

Figure 1. The Mark I Red monorail train operating in Tomorrowland (from collection of Werner Weiss, Bill Nelson 1959)

In 1961, the guideway was extended to a total length of 2.5 miles (4 km) with a new station at the Disneyland Hotel. The travel time to complete a round trip on the route is about 7 minutes, traveling at an average speed of 30 mph (50km/h). Some minor upgrades and improvements were made to the Mark I trains. A fourth car was added to each train, and an additional third train (painted yellow) was built to create a Mark II fleet. The fleet of Mark II trains was completely replaced in 1969. An entirely new design, Mark III, with four five-car trains (red, blue, yellow, and green) were built by Walt Disney Imagineering through WED Transportation Systems, and then in the late 1970s, rebranding of the system was completed with new graphics. The Alweg name was removed from the system to become the “Disney Monorail System.”

By the early 1980s, the Mark III trains were showing their age and wear, so in 1985, Disney began phasing out the Mark III trains one by one. The notable difference was the loss of the bubble-top driver’s area in favor of a streamlined look of the Mark IV trains that had been developed for the Walt Disney World in Florida. The Mark V trains were built by Ride and Show Engineering, Inc., incorporating bodies that were produced by Messerschmitt-Bolkow-Blohm of Germany. The phased replacement of the four trains was completed by spring 1988. The Mark V fleet remained in service for nearly twenty years.

In 1999, the monorail was closed for periods of time due to the construction of the Disney California Adventure theme park and guideway infrastructure rehabilitation. It was also during this time that the Disneyland Hotel Station was demolished and a new Downtown Disney Station was built in the same location.

Like the process used for the Mark III to Mark V conversion, the refurbishment of the Mark V trains to new Mark VII versions was done one train at a time began in 2006. The process was completed in 2009 and today, the fleet consists of three Mark VII trains (red, blue, and orange). The new trains were designed and manufactured in-house by Walt Disney Imagineering and TPI Composites, and built by Dynamic Structures. The Mark VII trains feature a sleek/retro style nose and reconfigured seating. These five-car trains have seating for 120 passengers.

Figure 2. The Mark VII Orange monorail train currently operating at Disneyland (Yesterland website, Werner Weiss, 2013)

WALT DISNEY WORLD

In the early 1960s, Disney began looking for land to build another park because Disneyland was limited from expanding by the developments that sprung up around the park. Several locations were explored before Disney selected a site in central Florida. The new development was referred to in-house as “The Florida Project” and to avoid a burst of land speculation, Disney used various dummy corporations to acquire over 25,000 acres (10,000 ha) of land. In late 1965, Walt Disney announced his ambitious plans for a new megaproject in Florida which would include the expected theme park and resort amenities, and a planned community to be known as EPCOT (Experimental Prototype Community of Tomorrow).

Walt Disney died on December 15, 1966, during the initial planning of the complex, but he did draft the first plan and a monorail was a key part of the development. After Walt's death, the company wrestled with undertaking the project, but Walt's older brother, Roy Disney, came out of retirement to make sure that Walt's biggest dream was realized. Construction began in 1967, building a resort similar to Disneyland, but abandoning Walt's planned community concept. The first theme park, the Magic Kingdom, opened on October 1, 1971. Today Walt Disney World contains four separate theme parks (Magic Kingdom, EPCOT, Disney Hollywood Studios, and Disney's Animal Kingdom), two water parks, four golf courses, numerous resorts, and areas for shopping, dining, and entertainment.

The Walt Disney World Monorail opened in 1971 with four stations: Transportation and Ticket Center, Disney's Polynesian Village Resort, the Magic Kingdom, and Disney's Contemporary Resort. The EPCOT line and station were added in 1982 when the EPCOT theme park was completed, and in 1988, the Grand Floridan station was added when this resort was built. Since then, no additions have been made, and no expansions are currently being planned. A double-beam track circles the Seven Seas Lagoon serves the Transportation and Ticket Center, the Magic Kingdom, and the resorts. There are two distinct routes on the system with three different services. The Magic Kingdom Express service runs counter-clockwise around the outer loop to provide direct service between the Magic Kingdom and the Transportation and Ticket Center. The Magic Kingdom Resort service runs clockwise around the inner loop with stops at the Magic Kingdom, the Transportation and Ticket Center, the Contemporary Resort, the Polynesian Village, and the Grand Floridian Resort. The third service is the EPCOT line and it runs between the Transportation and Ticket Center and EPCOT, with trains operating on a single-beam on a clockwise loop. A spur track at the Magic Kingdom connects the Express and Resort lines to the maintenance shop. Another spur line connects the EPCOT and Express lines northeast of the Transportation and Ticket Center. There are 14.7 miles (23.7 km) of guideway in the system.

The original trains that went into service in 1971 were Mark IV monorail trains manufactured by Martin Marietta. Five and six-car trains with seating for 204 and 244 passengers, respectively were used, and each train was identified by a colored stripe, and given a name according to that color. The rolling stock was updated in 1989 to Mark VI trains manufactured by Bombardier Transportation. Design changes were made to the cars to provide more headroom and the ability to accommodate standees. There are six cars on Mark VI trains with fewer seats but a higher passenger capacity (120 seated, 240 standees). In 2014, the system was automated of provide a more efficient service with enhanced safety, more frequent train dispatch, faster switching, and train arrival information. Drivers are still seated in the front cab, but only supervise the train in the case of an emergency. The trains operate at an average speed of 30 mph (50 km/h) with a top speed of 40 mph (70 km/h). All Mark VI trains were refurbished by Bombardier Transportation between 2019 and 2022 with new brakes, new interiors, and repainted exteriors. Today, there are twelve trains, and each train is identified by a colored stripe and named according to that color.

TOKYO DISNEY RESORT

The Tokyo Disney Resort is a theme park and vacation resort located in Urayasu, Chiba, Japan, just east of Tokyo. It is fully owned and operated by the Oriental Land Company under a license from the Walt Disney Company. The resort opened in 1983 as a single theme park - Tokyo Disneyland. Today the resort also includes several hotels, a shopping complex (Ikspiari), and a second theme park, Tokyo DisneySea, which opened in 2001. The resort activities are linked by the Disney Resort Link monorail to the Maihama Station, a station on the JR Keiyo Line. It is an automated straddle-beam monorail operated by the Maihama Resort Line Company, Ltd., a subsidiary of the Oriental Land Company. The line opened in July 2001 prior to the opening of the DisneySea theme park.

Figure 3. The Mark VI Peach monorail train currently operating at Walt Disney World (Bombardier Transportation)

Figure 4. The Type C Yellow monorail train currently operating at the Tokyo Disney Resort (Japan Transportation Guide)

Trains travel on the loop alignment in one direction and stop at each of the four stations on the 3.1-mile (5 km) route. The four stations are Resort Gateway (Japan Railways (JR) Maihama Station), Tokyo Disneyland, Bayside, and Tokyo DisneySea. It takes approximately 13 minutes to make one circuit, with a top speed of 30 mph (50 km/h). The line is operated using a fleet of five six-car monorail trains built by Hitachi Rail. Each train (Figure 4) is finished in a different color and up to four trains operate on the loop at any one time, running with a minimum headway of 3 minutes. The trains are driverless and are controlled at a central control center, however, a Disney cast member rides on trains to ensure safety in boarding and travel. Each train has a capacity of over 500 passengers. In 2020, a two-year program to replace the original train sets was undertaken and has been completed.

CONCLUSION

Since Walt Disney introduced the monorail over 60 years ago at Disneyland, millions had ridden the monorail at one of the three Disney parks. They have created special memories for park visitors. Although monorail systems have been overlooked in North America as a viable transportation alternative, cities in China, India, Japan, Brazil, and many others are building or operating monorails as integral parts of their public transit systems. The monorail is one of Disney's most enduring achievements as a symbol of his eternal belief that "there's a great big beautiful tomorrow, just dream away."

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An Examination of Factors Affecting APM Conductor Rail System Reliability

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ABSTRACT

Conductor rail systems (CRS) typically comprise less than 5% of an APM system's total cost, yet they can have an outsized impact on an APM's reliability. Critical variables to conductor rail performance include performance specifications; design, development, and testing; interface coordination with other subsystems; installation quality; and maintenance. Interface coordination between the conductor rail system and other APM subsystems such as the vehicle, guideway, guideway switches, and power distribution system must receive proper attention in the specification and design stages of a project. This paper identifies a sampling of critical aspects of interface coordination and draws upon specific examples of incomplete or incorrect interface specifications and their consequences. The author provides recommendations for interface specifications between the CRS and the associated APM subsystems.

INTRODUCTION

A power rail system consists of electrified conductors mounted on or along the guideway to provide traction and/or hotel power and/or data to the APM vehicles. Power is transferred from the conductors to the vehicle by means of a sliding contact typically called a collector shoe or brush. The power rail system must interface with the guideway, vehicle, power distribution system, and track/guideway switches and is a critical subsystem of an APM.

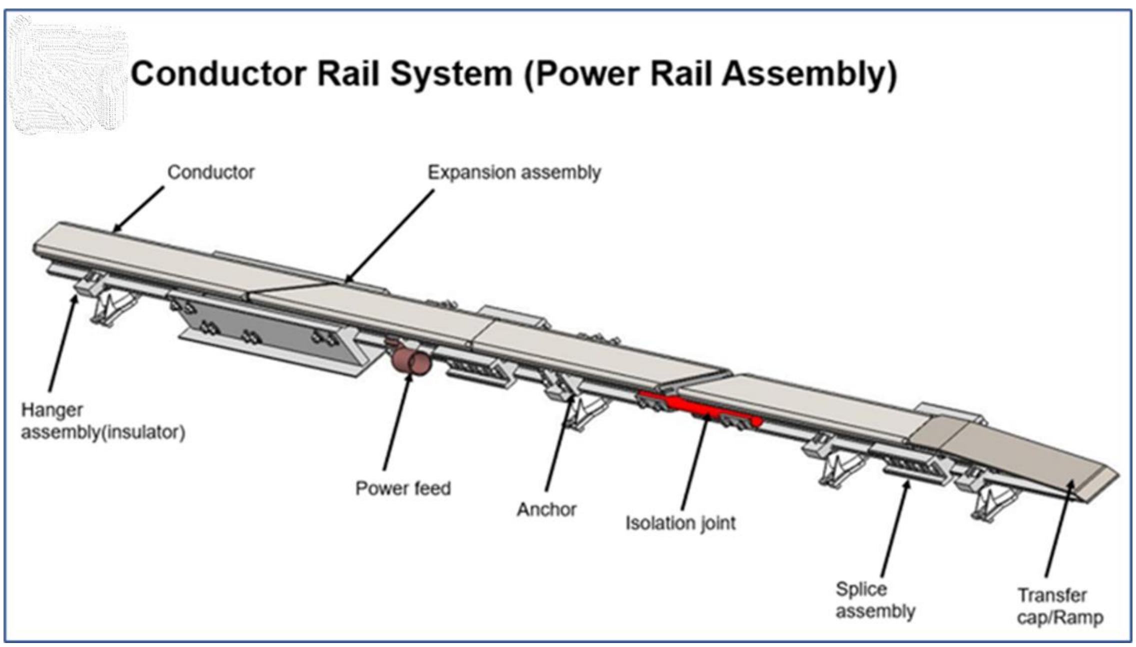

Figure 1. Example of CRS Components

Conductors: typically ranging from 200A to 4500A capacity and voltages up to & including 1500VDC deliver power (voltage and current) to the vehicle

Insulators: mechanically support the conductors under all load conditions while insulating them from the surrounding infrastructure

Splice Assemblies: mechanically and electrically connect power rails to each other and to the accessories

Power Feed Connections: feed cable connection points to the CRS

Anchor Assemblies: mechanically fix the conductors to the guideway to manage thermal expansion

End Engagement or Ramps: manage the engagement and disengagement of collector shoes

Isolating Joints: electrically isolate one section from another while providing continuity of collector shoe contact

Expansion Joints: absorb thermal expansion and contraction of the 3rd rail while maintaining electrical continuity and collector shoe contact (An alternative to using end engagements to create expansion gaps)

Protective Covers: provide an increased margin of protection from incidental contact with live 3rd rail

Mechanical considerations in the CRS design present greater technical challenges than electrical considerations. Management of thermal expansion and contraction, deflection under collector contact, and resisting the electromagnetic forces from short-circuit are much more complex than the application of Ohm's law. Electrical erosion/wear of the stainless-steel contact surface due to arcing can significantly reduce system reliability and life. Environmental concerns such as UV degradation and corrosion from moisture and environmental pollutants must also be considered. Furthermore, the interaction of the CRS with adjoining subsystems, (i.e., guideway, vehicle, power distribution, and track switches) must be precisely and completely described and considered in the design of the CRS components and system. (Forman 2013)

There exists a wide assortment of APMs in the market, each with unique vehicle and guideway characteristics. Each requires a unique CRS solution.

Figure 2. Aeromovel APM

Figure 3. Alstom APM

CRS FAILURE MODES

The APMs shown above use a CRS for either traction and hotel power or hotel power only. Despite the differences in these APMs, all have the potential for incurring CRS failure modes. Fortunately, these failure modes can be prevented, or at least mitigated. By examining the characteristics of the interfaces, we can apply effective interface management to increase CRS reliability. While not an exhaustive list, the following explanations and examples are intended to underscore the necessity of establishing complete and detailed interface specifications.

Figure 4. Doppelmayr APM

Figure 5. Intamin APM

Figure 6. Mintsubishi APM

Figure 7. Woojin APM

Electrical Erosion - All APMs use a sliding contact or collector shoe to transfer power from the CRS to the vehicle. Electrical erosion is a natural consequence of sliding contact, however, within the proper range of contact pressure and contact surface alignment (<1mm across splice joints) this electrical erosion is micro in scale and of minimal impact. It is the make/break switching of power at isolators and switch gaps that produce macro-arcing and subsequent significant erosion of the CRS contact surface. Similar macro-erosion can occur when collector contact is interrupted or contact force falls below acceptable levels. (Howe et al 2021)

Using modern contact shoe materials at normal collector contact pressures, electrical erosion is many times greater than the mechanical wear of the CRS contact surface. This is illustrated in Figure 8, below where typical collector contact pressures are less than 50cN/cm^2.

Mechanical Wear – Mechanical wear of the CRS contact surface is minimal except when incorrect collector shoe materials are used, or collector contact forces are excessively high.

Insulation Breakdown may occur in overvoltage conditions or when there is a prolonged excessive voltage differential at an isolating section or switch gap.

Mechanical failure of insulating supports, anchors and expansion joints may occur under cases of poor thermal expansion management or excessive guideway movement normal to the longitudinal axis of the CRS. Short Circuit events may impart explosive mechanical forces on conductors and insulating supports.

FOUR CRITICAL INTERFACES WITH THE CRS

With a basic understanding of the CRS and common failure modes affecting CRS reliability, now we shall consider 4 critical interfaces of the APM system with the CRS and examine how these interfaces can affect CRS reliability.

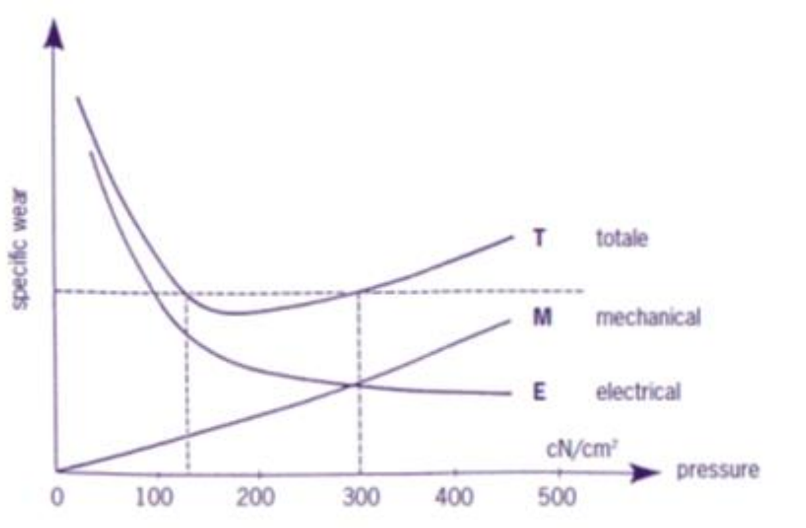

Figure 8. Contact surface wear relationship to sliding contact pressure. (Koenitzer 2017)

1. Interface of the CRS to the APM Guideway

A primary consideration for the guideway to CRS interface is the position and orientation of the insulating supports. CRS supports should bear only the weight of the conductors and not be subjected to loads resulting from attachment to irregular surfaces. Irregular surfaces may have excessive twist and deviation in the vertical and horizontal planes. Where necessary, conductors can be pre-curved to closely match guideway geometry to minimize the force to align them to the guideway. Pre-curving is performed on large conductors (>2500A) from 150m to 50m radius and smaller conductors (<2500A) from 100 to 5m radius. Though aluminum stainless-steel conductors have some flexibility, forces from elastic deformation of the conductors to "fit" them to an irregular guideway or supports can become excessive and lead to CRS component failure. Anchor Assembly failure is typically an indication of poor expansion management.

Such deviations can be minimized with indicating jigs or fixtures to consistently position insulating supports (Figure 9), use of an insulating support which is installed on a guidebeam or running surface (Figure10) or accommodating variation in the insulating support mounting surface with slotted, adjustable brackets. (Figure 11).

The objective of proper and precise insulated support installation is to produce a system with minimal variation between the vehicle path and collector contact surface. This keeps collector contact pressure in an optimal range and minimizes electrical erosion of the CRS contact surface. The conductors must then follow the guideway alignment geometry in plan, elevation, and super elevation. (Figure 12) Precise and detailed guideway centerline data is essential for a precise and detailed CRS. (Figure 13).

Figure 9. Insulator Position Jig in Use

Figure 10. CRS Support on Guidebeam

Figure 11. Alignment Vehicle for CRS Support Brackets

Figure 12. Horizontal & Vertical and Superelevation Guideway Geometry

Figure 13. Pre-Curved Conductors

Figure 14. CRS Expansion Joint

Figure 15. Guideway Expansion Joint

Due to the high coefficient of thermal expansion of aluminum, aluminum stainless-steel conductors undergo significant movement in revenue service. Ambient temperature variation plus the heating effects of current can result in CRS length changes greater than 125mm over 100m. Such movement can impose high forces on CRS components if not properly managed. Proper thermal expansion management includes quantifying the thermal movement of the guideway to which the CRS is attached, ensuring adequate available expansion joint stroke, and the installation of well-aligned and low friction insulated supports. (Frost and Knox 2016)

2. Interface of the CRS to the Vehicle

First and foremost, clearance between the vehicle (body, wheels, bogie and frame) and CRS must be ensured throughout all vehicle load conditions and degraded modes. This includes flat tire and worn collector shoe conditions. Furthermore, adequate collector contact to the CRS must be ensured to enable train operation and to prevent damage to the CRS contact surface due to reduced collector shoe contact area and subsequent damaging electrical erosion. (Mersen 2018)

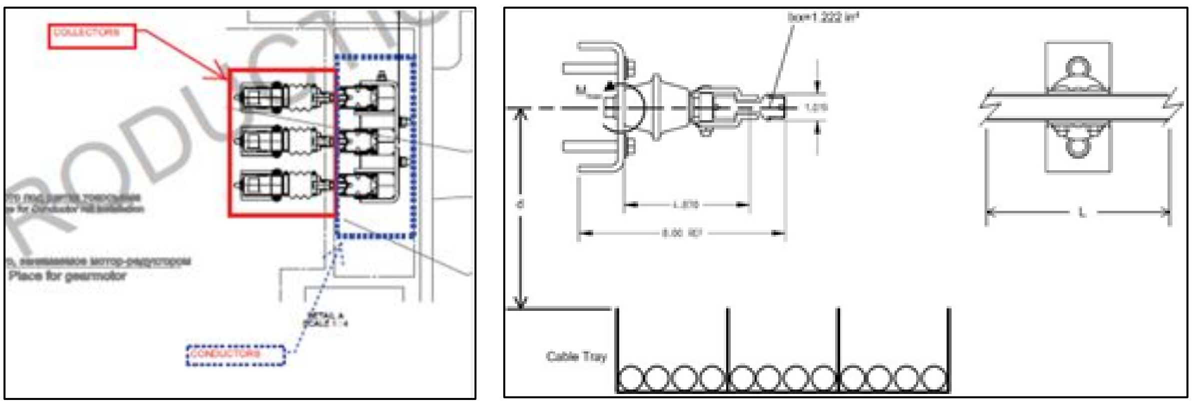

Figure 16. CRS Clearance Coordination for 3-phase AC (left) and Single Pole DC (right)

Of significant importance is matching the CRS specifications to the electrical requirements of the train. A train operating in excess of the current capacity of the CRS may permanently damage the conductors. Once significant erosion of the stainless-steel contact surface occurs, the conductors must be replaced.

3. Interface of the CRS to the Power Distribution System (PDS)

Interface of the CRS to the PDS goes beyond the connection of substation feeder cables to the conductors. Isolating Joints (IJs) are used to segment the CRS into sections or zones of specified length that are separately fed to ensure adequate power to the trains and can be independently switched on or off to facilitate maintenance. (White 2009) There will always be arcing at the IJs as a train crosses an isolating joint due to even the slightest voltage difference between one side or the other. When a train is drawing high current as crosses an IJ, the arcing can be quite significant. Therefore, it is recommended to position IJs where the train will be drawing minimal to low current to extend the life of the IJs.

Mishaps, though often avoidable, do occur. In one instance, substation switches were improperly configured creating a significant voltage differential (>300VDC) across the IJ. As the train crossed the IJ, passing from normal voltage to abnormally low voltage, it would draw a large arc across the IJ. Repeated train passages and flashover events eventually degraded the insulating material in the IJ to the point where the UL94V0 compliant (non-combustion supporting) insulating material caught fire whenever a train passed (Figure 18.)

Figure 17. Isolating Joint Assembly for 1000A CRS

Figure 18. Failed Isolating Joint due to excessive repeated flash over

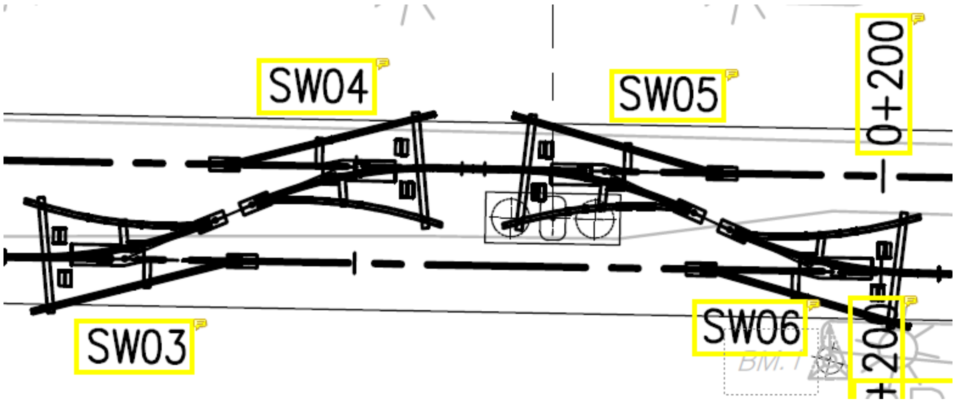

Figure 19. A Dual Crossover Switch with 12 total gaps in the CRS

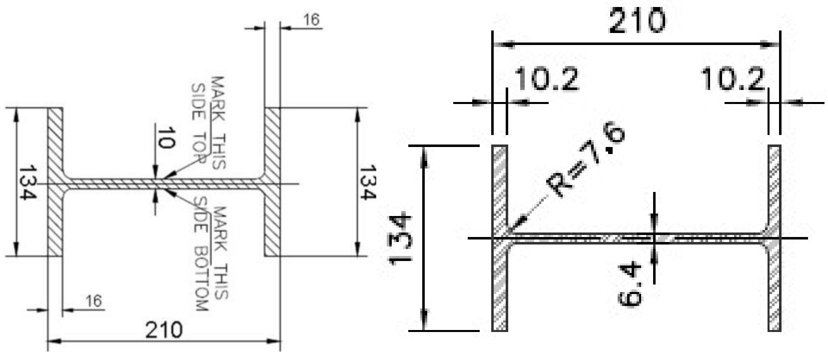

Figure 20. Not identical guidebeams created misalignment of the CRS

Figures 21a, b, c, d. A variety of switch designs each with advantages and disadvantages for CRS integration

4. Interface of the CRS to the track/guideway switches

Switches pose unique challenges to the reliability of the CRS. Switch designs may contain wear points that reduce the repeatability and precision of the alignment of the switch beams over time and decrease the life of the CRS conductors attached to the switch beams. Deflection of switch beams under train passage may also create slight misalignment of conductors and conductor contact surfaces. The accumulated effects of millions of collector shoe passes creating millions of electrical arcing events may require premature replacement of CRS components. The more gaps in the CRS at a switch, the greater the likelihood of misalignment and shortened life of CRS components.

A rubber tired APM with a center guidebeam had guidebeams of slightly different geometry on the switch beams than those of the main guideway sections. (Figure 20) This offset the conductor contact surfaces by several mm, resulting in collector arcing and breakage before the root cause was identified and corrected.

CONCLUSION

The CRS is a relatively simple subsystem of a modern APM, however, understanding the interface of the CRS with the other APM subsystems can be a complex task. Designers and systems integrators must dedicate time and attention to developing detailed and thorough interface specifications. Subsystem experts should be allowed, if not required, to meet face-to-face to educate each other about the critical and (apparently) not so critical aspects of their respective systems. Design integration should be based not only on new subsystem/system condition, but also the condition of systems as they mature over use and time. Applying lessons learned from the O&M sides of the business will further inform the design and continuous improvement of these vital transportation systems.

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Analysis of Automated Transit Network Systems with Battery-Electric Vehicles in Automated Mobility Districts

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ABSTRACT

The paper provides an overview of the insights and findings of the National Renewable Energy Laboratory's (NREL) ongoing research on the implementation of automated mobility districts (AMDs). AMD is a term coined by NREL to describe a geographically defined district or major activity center located in a dense urban setting with mobility applications provided by automated/autonomous vehicle (AV) systems spanning internal circulation and first-mile/last-mile connections to regional transportation hubs. Research over the past five years has focused on understanding the evolution of AMDs, beginning with demonstrations of automated shuttles prior to the pandemic, to more integrated on-demand mobility systems currently in initial stages of deployment. Initial insights and findings from earlier studies include the need for designation of a "jurisdiction having authority," a clear vision of a complete system to provide end-to-end mobility services, and the requisite intelligent infrastructure to complement AV technology. NREL's most recent phase III research investigates station boarding/alighting (curb) issues, the full electrification of fleets, and the need for a systems engineering methodology (SEM) to properly analyze the complexities resulting from the convergence of automation, on-demand mobility, and electrification of the transit systems within the AMD. The paper reviews the findings of AMD research conducted during phases I, II, and III, with special emphasis on phase III results with respect to a descriptive example of the proposed SEM when a "digital twin" analytical model is used to simulate the transport fleet's battery-electric vehicle miles of travel and associated duty cycles through a rigorous analytical assessment with a comprehensive modeling process.

INTRODUCTION—FOUNDATIONAL EARLY RESEARCH

The National Renewable Energy Laboratory (NREL) has researched automated mobility districts (AMDs) for more than five years, with findings presented in three phases of work on the conceptual development and deployment of fully automated transport systems in AMDs. The associated documentation of Phase I research (Young and Lott 2020) and Phase II research (Young and Lott 2022), as well as multiple published technical papers documenting Phase III research on AMD implementation, describe the observations and assessments of what has been learned from the emerging automated/autonomous vehicle (AV) technology industry applied to systems of movement within areas of dense development. This body of work has evaluated the implementation challenges and synergies of automated/autonomous and electric vehicle (A/EV) deployment in managed fleets and the associated practical findings of the necessary infrastructure that will facilitate early deployment in large-scale AMDs.

The results of the recently completed Phase III of this AMD implementation research is being published by NREL in 2024 as the 3rd edition of *The Automated Mobility District*

Implementation Catalog. The Phase III research findings were initially published in 2023 through multiple papers featuring lessons learned from prior studies of fully automated, on-demand transport systems over the past two decades (Lott and Young 2023a). These earlier studies addressed AV systems operating on dedicated transitways, thereby limiting the operational complexities of the AV fleets interacting with pedestrians, micromobility roadway users, or other human-operated vehicles in mixed traffic—operating conditions that tend to mask more fundamental operational factors. These studies of earlier small-vehicle automated mobility systems—which historically were referred to as "personal rapid transit" from the 1970s to the 2000s, and more recently as "automated transit networks" (ATNs) from the 2000s forward—provide valuable insight into the future of large-scale AMD operations.

The research to this point has focused on mobility systems, or rather a system of systems, within a geographically defined district or major activity center located in a dense urban setting, referred to an AMD, with mobility applications spanning internal circulation and first-mile/last-mile connections to regional transportation hubs provided by fully automated fleets (Young and Lott 2023).

Multiple AV Fleets. The functional purpose of AV fleet operations within an AMD is to provide essential mobility for internal district circulation, as well as external access/egress through first-mile/last-mile connections to intraregional transit and perimeter parking facilities. Multiple AV fleets with different vehicle types, sizes, and operations, each characterized by different routes and dispatching methods, will be the norm within large-scale AMDs, just as manual fleets of traditional fixed-route transit, taxi, and ride-hail companies, paratransit, and other services are today. The various operating modes may include fixed-route and fixed-schedule transit, combined with on-demand microtransit providing direct origin-to-destination passenger service. Although these different transit operating modes typically use different size vehicles, with each vehicle type comprising a unique AV technology, the different vehicle fleets would all have fully automated management of dispatching, station (or curb) dwell times, and service levels provided throughout the day.

Automated Transit Network Operational Mode. The term automated transit network system was adapted from the automated guideway transit industry[1]. Small-vehicle ATN systems typically utilize dedicated transitways with "off-line" stations that allow vehicles to pass by each station on the mainline transitway without requiring a station stop. This off-line station capability contrasts with traditional train, metro, and light-rail that typically stop at all stations. The off-line station configuration allows a small ATN vehicle to be uniquely dispatched to serve a given passenger's personal origin-to-destination transport request. This ATN mode of operations is comparable to on-demand ride-hailing services provided by transportation network companies like Uber or Lyft, but with a dedicated fleet of small- to medium-size automated transit vehicles that are dispatched to provide personal and/or shared-ride services. Off-line stations are comparable to dedicated curbside and/or pickup/drop-off zones, apart from the main travel way. The fleet management supervisory software of an ATN system determines each vehicle's dispatch assignments to and from pickup and drop-off locations/stations, temporary storage areas, and maintenance locations, along with the vehicle's associated dwell periods at each of those locations. As such, previous studies and methods of analysis of ATN systems provide

[1]The basic definition of what characterizes an ATN system has been codified in the ANSI/ASCE-21 Automated People Mover Standards (ASCE 2021).

extremely valuable insight into AV fleet operations within an AMD. Note that although dedicated guideways may no longer be needed to facilitate full vehicle automation (as is demonstrated by Waymo operations in Arizona and California today), the operational complexities of on-demand, electrified, and off-line stations provide a close paradigm to envisioned AMD systems.

NREL's PHASE I–III TOP-LEVEL RESEARCH FINDINGS AND CONCLUSIONS

Through the process of documenting the early pilot deployments of AV technology for public mobility and performing related assessment of similar advanced transit technology applications, the authors have gained insight into the complexity of fully automated operations of an AMD's mobility systems. To this research on AV operational complexity has been added, in Phase III, assessments of the convergence of vehicle fleet electrification, along with off-line (curb) station operations. These aspects significantly complicate the fleet management challenges for a large-scale AMD implementation requiring a systems engineering methodology (SEM) approach. The following findings from Phase I through III are of major significance as they relate to operational complexity, fleet size implications, and necessary infrastructure investments.

- <u>Systems-Level Vision for AMD</u> – Early demonstrations of automated shuttle technology shared a common vision of fully automated public mobility, though early demos were significantly limited in size and scope. These demos shared a larger vision, what NREL defines as an AMD, acknowledging that the early work was laying the groundwork for a more effective, equitable, and sustainable public mobility system. This vision is critical, as is the need for a jurisdiction having authority—i.e., the need for an appropriate public entity capable of setting standards, policy, financing, and other governing aspects of AMDs for the sustained, consistent, coordinated, and safe operation of multiple AV fleets providing mobility service within an AMD.
- <u>Intelligent Infrastructure</u> – The importance of intelligent roadway infrastructure has been realized to facilitate cooperative automation functions between multiple fleets and traffic management infrastructure. This concept was specifically identified as being important for providing greater safety, operational efficiency, and environmental/sustainability results of multi-fleet operations. Intelligent infrastructure is believed to be essential when AMDs reach a scale where multiple AV fleets, each with hundreds of vehicles in operation during peak periods, service our urban districts. Applications have been studied for key roadway intersections (Lott et al. 2021) where individual vehicle-based perception technology is insufficient to provide an operating picture to safety maintain speed with the traffic stream (AVs compensated by slowing operations, becoming an impediment to normal travel flow). Intelligent infrastructure is also being studied for application in station operations in the boarding and alighting areas in transit stations (Young et al. 2022)[2].

[2]An accessible version of this paper is available as a preprint: https://www.nrel.gov/docs/fy22osti/81978.pdf.

- Off-Line Stations with Parallel Berth Configuration – Stations have significant (and often dominant) impact on the operational efficiency and system throughput capacity of AV fleets, and the placement of stations off the main travel lanes, combined with various configurations that provide parallel boarding berths, drives major design considerations. This addresses a critical aspect of automated, on-demand systems with respect to energy use and fleet management since a parallel station berth configuration allows for flexible boarding—i.e., allows one party more time (if needed) than a subsequent party without disruption (or only minimal disruption) to station efficiency or throughput capacity (Lott et al. 2022)[3]. This also has bearing on system resiliency, allowing for single vehicle failures without significant impact to system operations.
- Vehicle Fleet Electrification – AV technology is a natural fit with electric-propulsion vehicle fleets for energy reduction and greenhouse gas mitigation. But the vehicular design with battery-electric propulsion systems has major implications as it converges with AV operations (Lott and Young 2023b). Other aspects identified in the research are:
    - Fully automated fleets will be best served by fully automated battery charging capability for optimal energy and service management.
    - Off-line stations with parallel berth configuration allow vehicles to dwell for an extended time until they are dispatched into service.
    - Battery charging in station berths is a vital option for “opportunity charging” during off-peak periods without disrupting station capacity and performance levels.
    - “Deep charging” of vehicle batteries at high-power, DC fast-charge stations with nominal dwell times can also be accomplished in fully automated mode in the depot or in storage areas specifically designed for this purpose.

Conclusions on Resilient and Sustainable AMD Implementation Elements. The operational impacts of battery-electric vehicles and the need for periodic recharging, combined with the complexities of mixed transit mode routes and on-demand operations with station off-line (curb) boarding and alighting, have been a particular focus of the latest Phase III AMD research. The following points summarize the high-level seminal conclusions drawn from the composite of the Phase I–III research completed to date:

1. Maximizing safety and throughput capacity of AV systems will require the application of “intelligent infrastructure” to roadways and potentially to AV stations/curbfronts specifically identified as passenger pickup and drop-off zones.
2. System-of-systems view and approach are required to achieve the full vision of effective, safe, and efficient public mobility using AV fleets, including appropriate jurisdiction authority for management and monitoring of the AMD system.
3. Electrifying AV fleets will require trade-off analyses of vehicle type, fleet configurations, and service mode operation, combined with battery-electric vehicle charging strategies and vehicle characteristics of operating range, charging time, charging facility size, and infrastructure power supply requirements.
4. Demand-responsive operations of small- to medium-size vehicles allow energy consumption and fleet operations to be optimized when vehicles are only moving (and sized) in direct proportion to ridership activity.

[3] An accessible version of this paper is available as a preprint: https://www.nrel.gov/docs/fy22osti/81976.pdf.

5. A systems engineering design and analysis methodology that simulates all modes, vehicles, and travelers is needed to analyze the fleet size, station and battery charging infrastructure, operating plan, and energy use based on the numerous variables of the combined fleet automation, electrification, and multiple fleet transit services. In modern times, this is referred to as a "digital twin."

The research findings and conclusions summarized above frame the premise that there is a need for new tools and methodologies for application in large-scale AMD implementation projects. The following sections present the proposed SEM, with the concepts discussed in terms of the nature and benefit of the associated analytical approach.

SYSTEMS ENGINEERING METHODOLOGY FOR AMD SITE IMPLEMENTATION

NREL's ongoing research is transitioning to assessing the analysis process necessary to perform the conceptual and preliminary engineering studies of AMD sites. Working from the foundation of the first three phases of research of prototypical AMD implementations, ongoing research is addressing the SEM necessary for progressing beyond planning-level studies. The methodology needed must encompass the automated operations (and capabilities) of AV fleets with blended fixed-route and on-demand point-to-point service modes. Fleet operations must be analyzed in the context of vehicle battery recharging parameters and constraints, as well as associated operational provisions at charging stations (vehicle servicing capacity and power limitations). Because of this interdependent complexity, the remainder of this paper will refer to A/EV deployments as the basis for AMD implementation.

Past studies of ATN system applications provide valuable insights for applying the proposed methodology to early engineering studies of large-scale AMD site deployments in the near- to medium-term future. In particular, previous ATN studies provide insights on the operational management required for dispatching fleets of small vehicles (4–20-passenger capacity) into operation for on-demand, direct origin–destination service. Previously studied ATN applications provide internal district circulation and connections to regional and interregional transit at major intermodal stations (Lott and Young 2023a), as envisioned for AMDs comprising A/EVs utilizing public roadways. Although these studies encompass a single system, they form the basis of understanding the SEM approach for an AMD at scale.

On-Demand Dispatch Operational Complexity. A representative ATN study of a conceptual connector to the Bay Area Rapid Transit (BART) system on Alameda Island from the 2000s provides as an example of the proposed analytical SEM approach. This study illustrates key aspects of the proposed SEM needed for modern AMD analysis. This study is simple in its level of detail, but it illustrates key analysis capability necessary for AMD system modeling.

Figure 1 shows a location where a conceptual ATN system was studied for the BART system in San Francisco, California, approximately 20 years ago. The ATN concept was identified by BART as a "group rapid transit" technology that had an 18-passenger vehicle capacity with off-line stations configured with parallel berths. Figures 2 and 3 illustrate the complexity of vehicle operations that must be analyzed in a manner that allows the use of energy drawn from the onboard battery storage for on-demand service. The system modeling simulation's ability to emulate the dispatching of vehicles into service in response to a passenger's demand call is critical, including the aspects of "empty vehicle management" to position vehicles where needed in anticipation of high service demand, while allowing vehicles to remain dormant during times when demand is low.

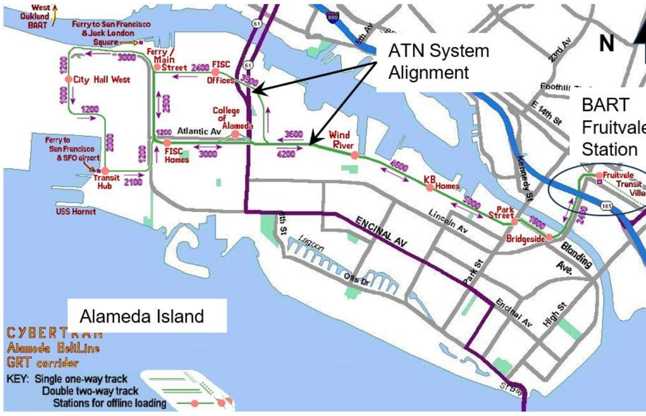

Figure 1. BART study of a conceptual ATN system that would create an AMD on Alameda Island. Source: Kimley-Horn and Associates, Inc.

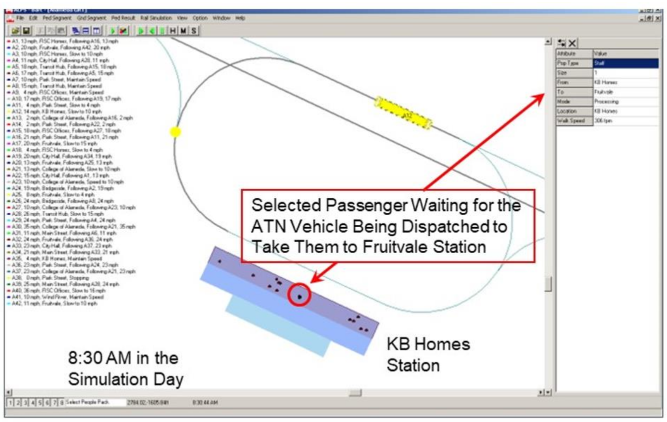

Figure 2. ATN vehicle on-demand dispatch is driven by specific passenger person-trip flows through the AMD simulation. Source: Kimley-Horn and Associates, Inc.

Not only is a simulation framework that tracks each rider and vehicle (more recently referred to as agent-based simulation) critical, iterating the simulation over a range of realistic and representative demand and operational scenarios, measured in the hundreds or perhaps thousands, is also necessary to expose and address system-level operations concerns. In the BART representative study, the iteration of various scenarios revealed that a mixed fleet of vehicle sizes, with large vehicles servicing high-demand stations on a fixed schedule, complemented by a smaller fleet of on-demand vehicles servicing lower-demand stations, provided improved performance compared to an on-demand system with 18-passenger vehicles.

Figure 3 identifies the sequence of five ATN vehicles operating eastbound (left to right) through the transitway network. The following lists the status of each vehicle that the simulation model was reporting at approximately 8:30 a.m.:

1. A42, 11 mph current speed, bound for Fruitvale Station, and slowing to 10 mph.
2. A2, 20 mph current speed, bound for Fruitvale Station, and following A42.
3. A24, 19 mph current speed, bound for Bridgeside Station, and following A2.
4. A36, 23 mph current speed, bound for Park Street Station, and following A24.
5. A32, 24 mph current speed, bound for Fruitvale Station, and following A36.

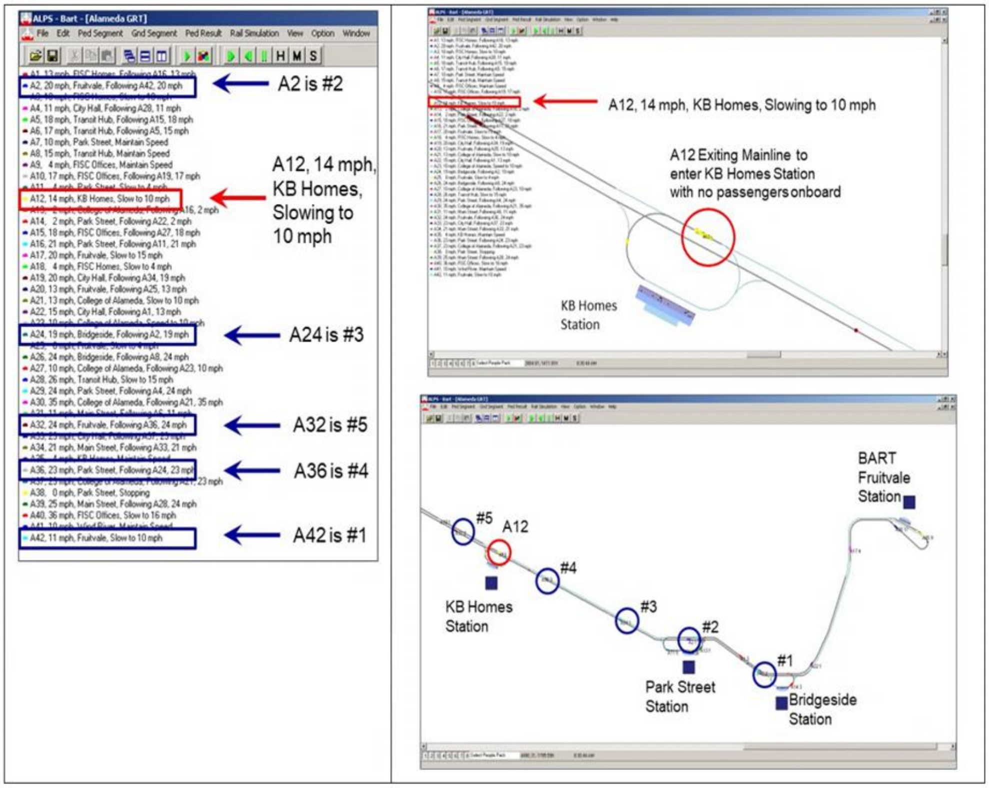

Figure 3. Operational sequence of following-vehicle movements traveling eastbound illustrate the analytical complexity of on-demand dispatch operations and essential performance parameters. Source: Kimley-Horn and Associates, Inc.

Although a relatively simple simulation example, the methodology exhibits an essential requirement of the system simulation in that vehicles are constrained to the operating conditions of other vehicles—i.e., the vehicle immediately ahead—or, in other words, network congestion of other vehicles on the transitway as well as congestion within stations from boarding and alighting. This particular simulation modeling study for the BART ATN included only a single mode. A robust system simulation methodology would be capable of simulating mixed-mode travel paths that may have components of walking, driving/parking, and other travel mode uses (e.g., commuter bus, rail transit, or vertical takeoff and landing regional access modes). The application of this modeling technique to roadway-based A/EV operations in mixed traffic will have many more human-driven vehicles and other pedestrians and roadway users with which the fleet vehicles interact. Multimodal simulations are necessary to apply the SEM analysis approach for many AMD conceptual and preliminary engineering studies, assessing not only the vehicle-to-vehicle interactions within the same fleet, but also queuing issues within the stations, vehicle boarding and alighting, and micromobility interactions. The fundamental principle of tracking each individual person moving through the AMD, as well as each vehicle's unique performance and operations, is the basis for modeling larger and more extensive AMDs with multiple A/EV transit fleets.

Vehicle Battery Charging Operations. Detailed analysis of battery-electric vehicle performance and power consumption is based on including propulsion system characteristics in the simulation. Figure 4 shows the net force required to propel an electric motor-driven rubber-tired vehicle of a typical bus size after all losses are included—classically defined as the "tractive effort" curve. Some of the key parameters and the energy required to accelerate a vehicle are enlarged in the inset. Each type of electric propulsion vehicle being studied in the analysis would have its characteristic data input to the model to represent its performance and energy use during the simulated operations.

A similar analysis is needed and would be defined for each battery-electric vehicle in each operating A/EV fleet as part of the analysis process for a conceptual AMD implementation site. As the operational simulation of multiple fleets is modeled, the associated propulsion power and energy consumption of each vehicle would also be continuously calculated to account for the changes in passenger load, vehicle speed and associated acceleration/braking, and grade variations as the vehicle maneuvers along its travel path. A simple illustration of these simulation-based derivations of these parameters from a previous ATN study is shown in Figure 5 for one of the station-to-station links of the BART ATN system described above. The changes to speed shown in the figure are representative of an A/EV's operations in a modern AMD as the vehicle progresses through traffic signals and maneuvers through other vehicular traffic along its route when dispatched between a passenger's origin and destination station.

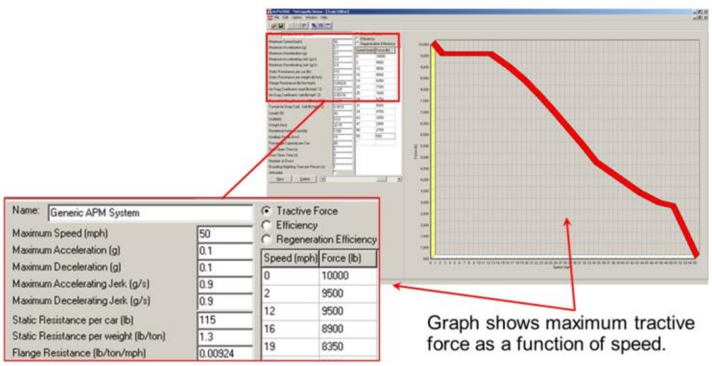

Figure 4. Electric propulsion system's tractive effort curve used for power and energy analysis. The parameters shown represent the propulsion equipment's characteristic values for a large A/EV technology. Source: Kimley-Horn and Associates, Inc.

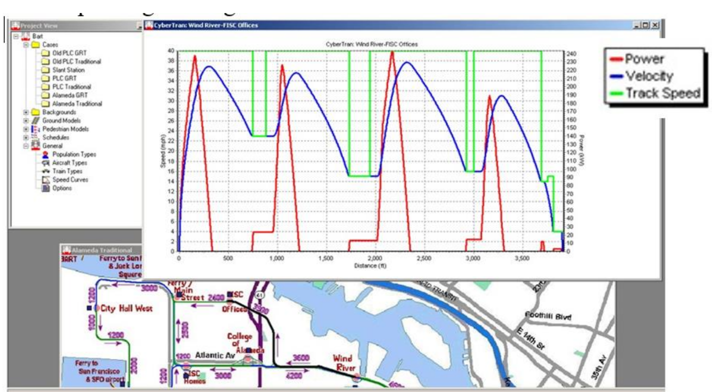

Figure 5. Electric propulsion system's power consumption during travel speed variations for a unique route determined by its dispatching to carry an on-demand passenger from the associated origin and destination station. Source: Kimley-Horn and Associates, Inc.

The continuous calculation of each vehicle's propulsion energy consumption, as well as its regenerative braking power generation, is essential for assessing battery-electric vehicle deployment during on-demand fleet operations. Additionally, with respect to opportunity charging of vehicles, the simulation must accurately reflect each vehicle's dwell times when stopped in station berths or in temporary storage areas, since these times contribute to the accurate calculations of energy use and the vehicle battery's state of charge throughout the day. Furthermore, the SEM simulation will provide output to the district's energy distribution digital twin, which monitors the overall energy demand across all sectors, renewable energy generation, and the status of local energy storage as well as the electrical grid.

CONCEPTUAL AND PRELIMINARY ENGINEERING OF AMD DEPLOYMENT SITES

The methodology summarized above is considered essential to conceptual and preliminary engineering of a prospective AMD's mobility systems in terms of the implementation costs and associated operating costs for a given pattern of person-trips that drive the mobility systems' ridership demand. As previously emphasized, the SEM assessment/analysis process must thoroughly address the battery charging requirements of each fleet vehicle during the operating day and the associated fleet operational impacts for various battery-electric vehicle charging strategies.

From the combined analysis of passenger demand, fleet operations, and associated battery-electric vehicle charging operations, a method is developed to establish the vehicle fleet size, anticipated passenger service levels, and battery charging infrastructure requirements for the AMD and its identified stations/curbfronts for mobility system access. The types of engineering-level analytical studies envisioned for the proposed methodology include the following:

Planning and Conceptual Engineering Phase: Starting from the conceptual initial deployment phase, the system scope (route coverage area, network configuration, and necessary fleet size) and implementation cost is developed. Then the work advances to the definition of an initial systems and facilities procurement plan. From this initial work, a conceptual definition of the ultimate implementation phase is developed in terms of the systems and facilities plan.

Preliminary Engineering Phase of Initial Deployment: Early engineering studies advance the initial deployment of multiple AMD mobility systems in terms of the scope of the final design, procurement, and installation, including the associated cost estimates for the systems, facilities, and components of the A/EV fleets and mobility functions. This engineering work includes the procurement plan and technical specifications for the systems, facilities, and component parts and services.

Real-Time Digital Twin Application: Integration of the simulation model into the deployed system for a real-time digital twin that resides within the operation control center and allows future time analysis based on existing conditions in system operations. Additionally, the real-time SEM interfaces with other district systems, such as an energy digital twin to co-optimize for energy efficiency and resiliency across multiple sectors within the district.

Early conceptual studies, followed by increasingly more detailed preliminary engineering studies, are necessary to optimize aspects of the planning and design of a multi-fleet AMD implementation. Figure 6 illustrates the flow of information within the proposed SEM by which the battery-electric vehicle fleets operating in mixed-mode service—some with fixed-route and fixed-schedule dispatching and some with dynamic on-demand dispatching—can be studied as a composite of each vehicle's individual, moment-by-moment performance and operations within a simulation model.

CONCLUSIONS ON SYSTEMS ENGINEERING METHODOLOGY FOR AMDS

This paper reviews the top-level insights and finding from NREL's automated mobility district research over the past five years and presents a proposed system engineering analysis approach for AMDs comprising multiple fleets of A/EVs operating in a geographically constrained environment to provide circulation within the district as well as first-mile/last-mile services to regional transit, interregional transit, and parking facilities. The method draws on previous work to simulate ATNs for conceptual and pre-engineering analysis of A/EV systems constrained to a guideway network. System simulations of ATNs over the past two decades are relevant for A/EVs within an AMD (providing public mobility but not confined to a guideway network) in that they characterize the importance of parallel berth stations (pickup and drop-off zones) to efficiently manage a system with heterogeneous demand in terms of both time and energy. Furthermore, these simulations that track the power draw of individual vehicles point to the need for a simulation that tracks each individual traveler and each vehicle across multiple fleets for performance as well as planning, engineering, and operations.

For travelers, key performance parameters include wait time, travel, queueing, and accessibility while for vehicles they include traditional measures such as speed, dwell time, tractive force, and energy, as well as parameters critical to newer battery-electric propulsion systems such as the state of charge of the battery pack. More critically, the proposed systems engineering simulation methodology will allow for evaluating mobility in conjunction with fleet energy management that will determine fleet size, charging strategy (both deep and opportunity charging), and overall system energy performance and traveler experience. The level of detail in each phase of the SEM for an AMD site application is anticipated to be progressively more detailed—advancing from concept evaluation to pre-engineering and a real-time, digital-twin-embedded operations management tool.

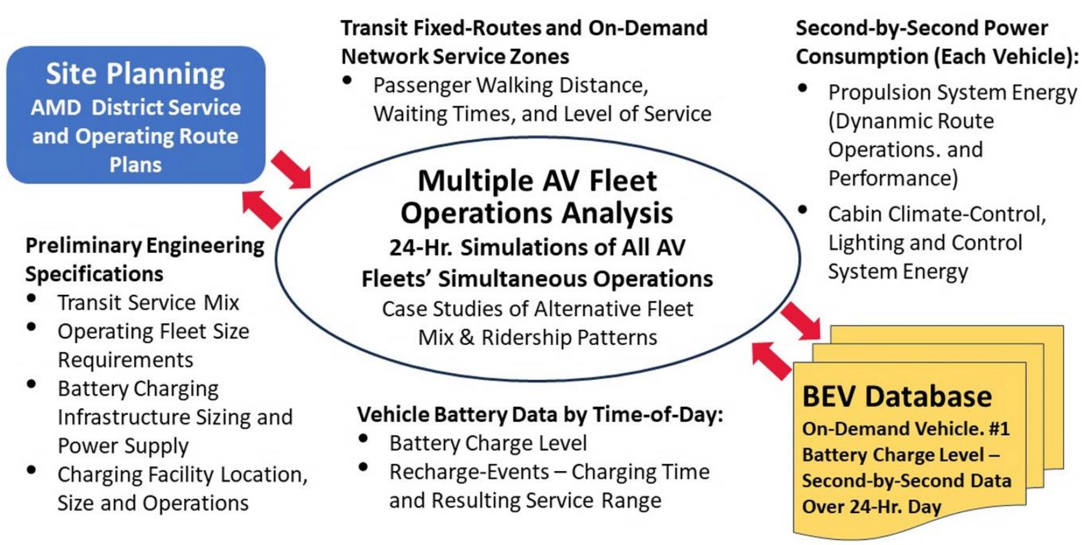

Figure 6. A systems engineering methodology that provides an analytical approach and key performance indicator derivations suitable for AMD planning and design.

The modeled parameters from the simulation methodology (i.e., the digital twin) will span systems, traveler mobility, and energy, as detailed below:

Mobility:

- A/EV system access walking time and distance from district trip origins.
- Access point (stations/curbfronts) comfort and convenience.
- Walking distance/time between AMD A/EV circulation systems and other transportation mode access points (e.g., regional transit).

Passenger Service Level:

- Average and maximum station waiting time.
- Total trip time = waiting time + in-transit travel time.

Fleet Size:

- Peak period operating fleet: Number of vehicles.
- Off-peak period operating fleet: Number of vehicles.
- A/EV battery-related duty cycle.
- Empty vehicle management operational strategy.
- Percent spare vehicles.

Infrastructure:

- Station/curbfront locations, size, and configurations.
- Intelligent roadway infrastructure: Locations and perception/control features.
- Vehicle battery charging facilities/provisions: Number of charging positions, charging power levels (Level 1, 2, or 3 [DC fast charge]), and charging facility total power supply requirements.

The systems engineering approach described herein applied in the early design phases will allow trade-off analysis of cost and complexity to identify an optimal solution for the most critical elements of an AMD's implementation. The resulting digital twin provides an effective planning and engineering tool as well as the input and output needed to link to energy and other digital twins for further overall district-level system benefits.

Looking forward, the SEM can be used not only in the capacity described above, but also to investigate new forms of mobility that have the potential to augment and improve the systems of systems. In Phase IV of NREL's AMD research, the introduction of A/EV-only roadways (or guideways) will be investigated as a means to leverage the benefits of automated control, while allowing full reuse of the existing roadway system (in that A/EVs can navigate both traditional roadways and special-use guideways/roadways) much in the same way that high-speed freeways and interstates allowed for the benefits of modern automobiles through restricting access to lower speed modes of travel.

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Identifying Impacts of Integration of Autonomous Vehicles into On-Demand Transportation

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ABSTRACT

Shared autonomous vehicles (SAVs) are the result of the convergence of autonomous vehicles (AVs) and on-demand transportation. They are expected to significantly impact the mobility landscape; however, they must be thoroughly assessed prior to their widespread deployment. This study examines the repercussions of widespread use of SAVs and analyzes how it will affect the environment, public transportation, land use, and vehicle ownership. The impacts were identified and categorized in accordance with their causes, and the frequency with which they were cited in the literature was established for each. The findings demonstrate that a variety of factors influence the effects of SAVs, and while they have the potential to reduce barriers to mobility and transportation inequity, there is a need for policymakers to enact policies that will ensure that the technology facilitates improvements to the transportation system.

Keywords: autonomous vehicles; shared autonomous vehicles; autonomous mobility on-demand; public transportation; policy

INTRODUCTION

Autonomous vehicles (AVs) have radically transformed the transportation sector. Several states in the United States now allow them to be tested on public roads to determine whether they function safely in mixed-traffic situations, and this has stimulated a lot of interest among researchers such as Channamallu et al. (2023) who conducted analyses of the collision and disengagement reports published by the California Department of Motor Vehicles to compare the behavior of AVs with conventional vehicles.

In addition to more than ten pilot projects in Singapore, Japan, Dubai, and Europe, 17 shared autonomous vehicle (SAV) pilot projects had been implemented in the United States by February 2018 (Patel et al. 2023a). SAVs offer numerous advantages such as expanded road capacity, increased mobility, improved safety, greater transportation equality, and reduced emissions (Alexander et al. 2022), and they mitigate the environmental effects of conventional vehicles, a critical issue in the transportation sector since transportation accounts for 24% of emissions globally (Jones and Leibowics 2019). Numerous studies have been published that assess the impacts of SAVs and address a range of subjects, such as parking (Zhang and Guhathakurta 2017) and consumer interests (McBain et al. 2023). They are a promising and emerging mode of transportation, and as such, a large body of research has been published on the subject, making a comprehensive synthesis of the studies necessary.

Most research papers on SAVs seem to focus on just one aspect, such as how SAVs integrate with public transportation (Etminani-Ghasrodashti et al. 2021a) or how they affect parking (Winter et al. 2021). For example, Zhao and Malikopoulos (2020) performed a thorough analysis of SAVs but did not address their implications for policies. Similarly, Narayanan et al. (2020) analyzed how SAVs affect the economy, transportation supply, traffic, and safety, and while they summarized the literature on researchers' perspectives of SAV policies and considered a policy and operational framework, they failed to identify policies that could address the impacts of SAVs. The significance of policy in the deployment of SAVs cannot be overstated, and papers such as that of Alexander et al. (2022) that evaluate how cities can use climate action to address the environmental effects of SAVs are important. Yet, there is a void in the research. This paper seeks to close this knowledge gap by examining the effects of integrating AVs into on-demand mobility and proposing policies that address *all* of the effects covered in the literature, not just those that have an environmental impact.

The following objectives were developed to assess the effects of combining automation and on-demand mobility: (1) determine how SAVs affect the environment, public transportation, land use, and vehicle ownership; (2) categorize the factors that contribute to their impacts; (3) ascertain how frequently each factor is mentioned in the literature; and (4) create a comprehensive list of policy recommendations that address the impacts and support the community and existing infrastructure by maximizing the benefits and minimizing the drawbacks of SAVs. AV manufacturers, transportation experts, and lawmakers are the nucleus of those that will find value in the conclusions of this research, as they will have a significant influence on how society benefits from the technology.

METHODOLOGY

An online search was initiated through databases such as Science Direct, Sage Publications, and the ASCE Library to create a database of articles that contained any of the keywords or phrases (shared autonomous vehicles, autonomous vehicles, and autonomous mobility on demand) in their title, list of keywords, or abstract. The selected papers were screened, and those that did not fit the criteria shown in Figure 1 were excluded. The final database of 166 articles represents the state of SAVs as reported in the literature.

RESULTS & DISCUSSIONS

Identifying the Impacts of Integrating Autonomous Vehicles and On-Demand Mobility

Autonomous driving systems and on-demand mobility are two new mobility trends that have the potential to significantly change travel behavior and the effects of transportation on society (Alexander et al. 2022). This study examines the many aspects of SAVs and explores how they will impact the environment, transportation networks, and public policy. The three categories depicted in Figure 2 are examined in the following sections to provide a comprehensive overview of the implications of on-demand autonomous vehicles. Most of the literature reviewed pertained to modeling the effects of sophisticated, advanced autonomous driving systems, as the technologies are constantly evolving. It is challenging to precisely forecast the overall benefits of this mobility trend for the transportation system, as their impacts rely heavily on advancements in policies, market response, and technological advancements (Massar et al. 2021).

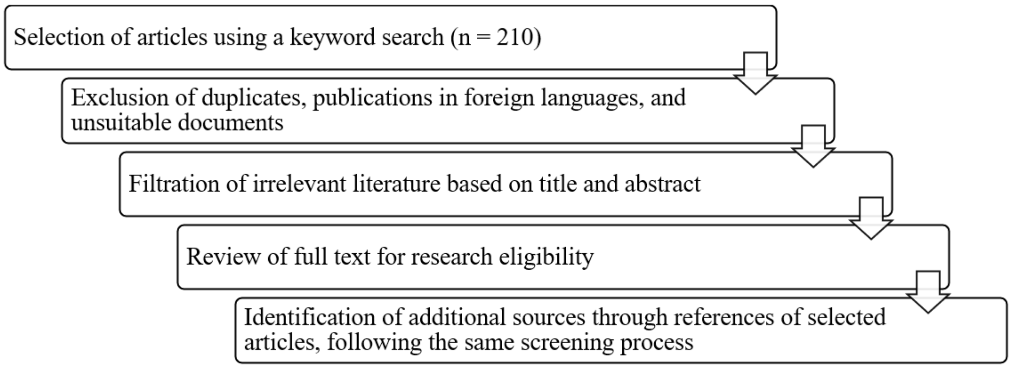

Figure 1. Multistep screening and exclusion process to identify relevant literature

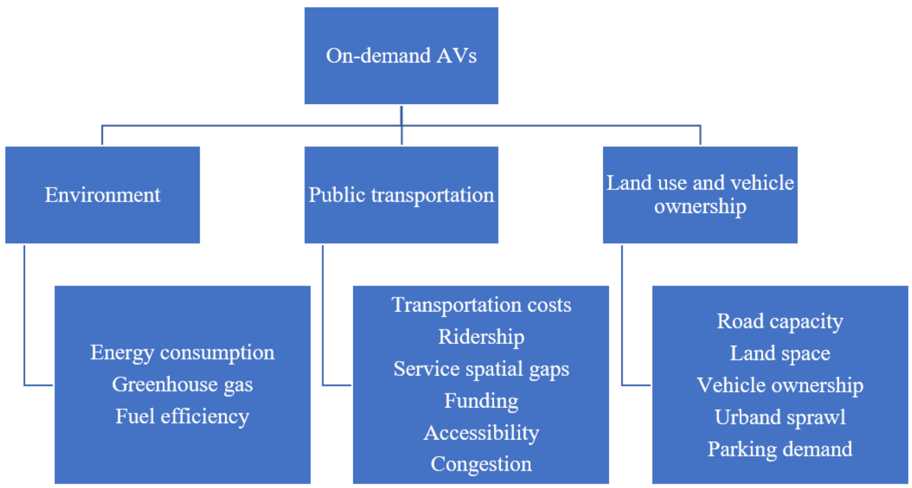

Figure 2. Classification of the impacts and implications of SAVs

Effects of SAVs on the Environment

The transportation industry bears the dubious distinction of being the fastest growing source of greenhouse gas emissions (Pamidimukkala et al. 2023a), accounting for 24% of all greenhouse gas emissions worldwide (Jones and Leibowicz 2019). It uses 27% of the world's energy, of which 75% originates from non-renewable fossil fuels (Dia and Javanshour 2017). Since 75% of transportation-related emissions worldwide are attributed to private passenger vehicles, decarbonizing the unsustainable traditional transport systems is an essential component of any meaningful, large-scale effort to mitigate climate change (Jones and Leibowicz 2019). The expected environmental effects of SAVs are displayed in Table 1[1].

[1]It is crucial to note that Table 1 discusses the long-term effects of SAVs, considering high penetration rates and technologically advanced autonomous driving systems. Early stages of SAV deployment will involve low penetration rates, where increased energy use and greater traffic congestion are likely consequences.

Table 1. Effects of SAVs on the environment with frequency of citation

ID	Variable	Effect	Influential Factor	Frequency of Citation
E1	Energy consumption	Decrease	▪ Reduced traffic congestion	42
			▪ Decreased parking demand	25
			▪ Utilizing renewable energy sources instead of fossil fuels	19
			▪ Increased efficiency	10
			▪ Compact vehicles	3
		Increase	▪ Increased vehicle miles traveled	36
			▪ Utilization of conventionally powered SAVs	6
E2	Greenhouse gas emissions	Decrease	▪ Reduced traffic congestion	42
			▪ Decreased parking demand	25
			▪ Utilizing renewable energy sources instead of fossil fuels	19
			▪ Replacing existing bus lines with autonomous buses	14
			▪ Increased efficiency	10
			▪ Compact vehicles	3
		Increase	▪ Increased vehicle miles traveled	36
			▪ Modal shift from public transportation to SAVs	34
			▪ Greater car dependency	17
E3	Fuel efficiency	Increase	▪ Utilizing renewable energy sources instead of fossil fuels	19
			▪ Energy efficient operation	5

As illustrated in Table 1, a number of factors, such as improved efficiency, less traffic, the use of alternative fuels, smaller cars, and fewer parking requirements, could contribute to widespread adoption of autonomous driving technologies and thereby reduce energy consumption and carbon dioxide emissions. Arbib and Seba (2017) analyzed the then-current market and consumer and legislative dynamics and projected that autonomous driving systems have the potential to reduce the transportation sector's energy demands by up to 80%. When AVs and on-demand transportation are combined, greenhouse gas emissions can be significantly reduced, which will decarbonize the transportation industry (Patel et al. 2023b). According to Greenblatt and Saxena (2015), autonomous taxis have the potential to reduce emissions by 87% to 94% per mile when compared to conventional vehicles. This is primarily because of factors like improved fuel efficiency from lighter, redesigned vehicles; decreased air friction; and lower greenhouse gas emissions. It is important to note that these numbers might not accurately represent the real world and its circumstances; instead, they portray an optimistic long-range view of the effects that SAVs are expected to have on the reduction of emissions.

A decrease in greenhouse gas emissions is not guaranteed, even though it is anticipated that SAVs will have a positive environmental impact (Alexander et al. 2022); the effects of using on-demand AVs on travel behavior and vehicle operations will determine the results. Users may choose to forego public transportation and other active transportation options in favor of this convenient and affordable mode of transportation (Jones and Leibowicz 2019; Alexander et al. 2022). Reduced emissions, represented as E2 in Table 1, can be achieved through increased fuel efficiency, less traffic congestion, a lower demand for parking, and the switch from fossil fuels to renewable energy (Greenblatt and Saxena 2015; Wadud et al. 2016; Narayanan et al. 2020). On the other hand, on-demand mobility may have the opposite effect if the lower cost of travel encourages more people to travel or encourages those who already travel to increase the frequency and/or distances of their trips (Jones and Leibowicz 2019). According to Clewlow and Mishra (2017), those who do not drive will probably become more car dependent, which will increase transportation inequality and further entrench the use of automobiles. An increase in the number of vehicle miles traveled would also necessitate more “deadheading” or driving a car without a passenger for redistribution purposes (Manders et al. 2020). Transportation-related greenhouse gas emissions may decrease by half or double, depending on which effects predominate (Wadud et al. 2016). According to Massar et al. (2021), at higher penetration rates (60–80%), maximum emission reductions are likely to be realized. At lower penetration rates, however, emission reductions are likely to be offset by easier and faster travel, leading to an overall increase in greenhouse gas emissions.

According to numerous studies (Arbib and Seba 2017; Fulton et al. 2017), even if the electric SAVs travel twice as many miles as the private vehicles they replace (Jones and Leibowicz 2019), emission and energy reductions will primarily be realized by utilizing efficient electric vehicles for on-demand AV transportation, despite the fact that electric vehicles are a separate emerging transportation system with their own environmental implications (Pamidimukkala et al. 2023b). The need to change the source of their power generation from fossil fuels to renewable energy is highlighted by the fact that if they are conventionally powered, it would increase both the number of miles driven and the amount of energy consumed (Fulton et al. 2017; Narayanan et al. 2020). Reductions in emissions depend not only on electric SAVs but also on public acceptance of on-demand AVs and their incorporation into the current public transportation infrastructure (Etminani-Ghasrodashti et al. 2021b).

Effects of SAVs on Public Transportation

SAVs have the potential to improve equity and mobility by supporting public transportation systems (Narayanan et al. 2020). Integrating on-demand AVs with public transit will increase transportation equity by improving accessibility of transit and therefore the quality of life for marginalized and/or low-mobility individuals (Milakis et al. 2017). By offering first- and last-mile solutions, closing the spatial gap in public transportation services, increasing ridership, and decreasing spatial gaps, SAVs, when seen as an extension of the transit system, will enhance current transit and improve connectivity (Alexander et al. 2022). This type of demand-responsive transit can also be used for low-demand routes, e.g., where too few people are riding buses to enable them to operate efficiently. Adding SAVs to the transit system has the potential to reduce the number of empty vehicles operating and optimize transit routes, while offering users convenient services that lower costs and increase accessibility (Khan et al. 2022a). On-demand AVs allow governments to optimize utilization of their transportation resources and enhance multimodality by mitigating the mobility gaps that are present in the current system. The effects of shared autonomous mobility on the current public transportation systems are shown in Table 2.

Table 2. Effects of SAVs on public transportation with frequency of citation

ID	Variable	Effect	Influential Factor	Frequency of Citation
T1	Transportation costs	Increase	▪ Increased vehicle miles traveled	36
			▪ Greater operation and maintenance costs	4
		Decrease	▪ Reduced operation costs for autonomous buses	14
			▪ Elimination of low demand routes	3
T2	Ridership	Decrease	▪ SAV modal shift	34
			▪ Increased SAV dependency	14
		Increase	▪ Greater accessibility	29
			▪ Increased operation times	5
			▪ Real-time passenger information	3
T3	Service area spatial gaps	Decrease	▪ First- and last-mile solution	32
			▪ Offers service in areas not covered by existing lines	9
T4	Funding	Decrease	▪ Decreased public transportation ridership	27
T5	Accessibility	Increase	▪ Offers a transportation mode for those with limited mobility	18
			▪ Improved service area coverage	8
			▪ Increased operation times	5
T6	Congestion	Decrease	▪ Increased use of autonomous buses	14

Some researchers have expressed concern that SAVs' low cost and ease of use will encourage people to travel more, increasing the number of vehicle miles driven. They also fear that many of those who currently use public transportation will switch to an alternative mode of transportation (Zhao and Malikopoulos 2020), which will have a detrimental effect on active modes of mobility that were previously used for short-distance travel or as first- and last-mile connections to public transportation services (Milakis et al. 2017).The most feasible solution is to integrate on-demand AVs with the current public transport system so that they complement one another, create an effective and codependent system (Narayanan et al. 2020), and minimize the risk that SAVs will facilitate a modal shift from public transportation (Patel et al. 2023c). As shown in Table 2, the deployment of SAVs without considering the irreversible harm they can do to public transportation will lead to unsustainable growth, a decline in transit ridership, and ultimately a reduction in funding for public transportation (Alexander et al. 2022; Patel et al. 2023d).

Effects of SAVs on Land Use and Vehicle Ownership

Given that urban development and the transportation industry are inextricably linked, the implementation of automated on-demand mobility vehicles has the potential to revolutionize both travel behavior and land use (Etminani-Ghasrodashti et al. 2023a). Travel demands, infrastructure, policies, and technological advancements like SAVs all have an impact on the dynamic relationship between land use and transportation networks (Patel et al. 2022). SAVs have the potential to affect land use in a number of ways because they will either compete with or complement current transportation modes. Table 3 provides a list of the impacts of SAVs on land use and vehicle ownership.

Table 3. Effects of SAVs on land use and vehicle ownership with frequency of citation

ID	Variable	Effect	Influential Factor	Frequency of Citation
L1	Road capacity	Increase	▪ Reduced congestion	42
			▪ Reduced number of vehicles on the road	11
L2	Freed up land for housing and other purposes	Increase	▪ Reduced demand for parking	25
L3	Vehicle ownership rates	Decrease	▪ Lower cost of car ownership	8
			▪ Users not affected by costs of ownership	6
			▪ Decreased traffic concerns	4
		Unchanged	▪ Convenience of private vehicles	7
			▪ Loss aversion	3
L4	Urban sprawl	Increase	▪ Shift in parking demand to outskirts of cities	5
			▪ Increased number of people moving to rural or suburban areas that are farther from points of interest	3
L5	Demand for parking	Unchanged	▪ Travel behavior is unchanged	2

The majority of researchers predict that SAV technology will result in significant reductions in parking requirements (Dia and Javanshour 2017) and that changes in travel patterns will cause the demand for parking to shift outward, into the periphery of city centers. More than 20 parking spots can be eliminated by a single SAV (Zhang and Guhathakurta 2017), freeing up space for neighborhood development (Alexander et al. 2022). It is important to note, however, that the decrease is dependent on a number of variables, such as private ownership, the lack of a public transportation system, and SAV penetration rates (Milakis et al. 2017). In contrast to the expectation that there will be a significant decrease in parking needs, Grush et al. (2016) evaluated the parking demand in a mixed traffic environment and found that car dependency is expected to increase throughout the coming decades.

Users of on-demand transportation services enjoy all of the advantages of owning a vehicle but none of the financial burden of ownership (Jones and Leibowicz 2019). Given the high cost of ownership, it is unlikely that AVs will be used as privately owned vehicles (Freedman et al. 2018); it is more likely that they will be shared among family members or across companies. Accordingly, one SAV is anticipated to replace three to ten privately owned vehicles (Loeb and Kockelman 2019). When used in conjunction with public transportation, more than half of all privately owned conventional vehicles could be replaced by automated shared vehicles, indicating a shift in priorities from ownership to accessibility (Manders et al. 2020). According to Clewlow and Mishra's (2017) survey, ridesharing does not lead to a decline in the percentage of people who own a car. Grush and Niles (2018) concur, predicting that private automobiles will remain the norm for the foreseeable future. Therefore, even as autonomous driving technology continues to advance, the ease of personal vehicle ownership, aversion to losing the independence they represent, and various sociodemographic factors may make it difficult for people to give up their cars (Manders et al. 2020).

The improved accessibility and connectivity offered by on-demand autonomous mobility may encourage people to live a greater distance from their places of employment (Zhang and Guhathakurta 2017), and it is anticipated that the use of SAVs will result in a 40% to 273% increase in road capacity (Narayanan et al. 2020). These findings were supported by a land use model implemented in Austin, Texas, in which Wellik and Kockelman (2020) assessed the impacts of self-driving vehicles on the city’s land use. Compared to private AVs, SAVs were associated with reduced travel times, decreased congestion, greater urban sprawl, and reduced emissions (Wellik and Kockelman 2020). This should motivate policymakers to develop and enact land use and transportation regulations that prioritize lowering the number of vehicle miles traveled and to prepare for managing potential social inequity issues to prevent SAVs from unintentionally contributing to increased urban sprawl (Alexander et al. 2022).

Policy and Governance

Relationships between SAV policies and societal implications become more significant as the degree of automation increases. Solely depending on the technology to drive positive change and address the current issues in the transportation sector is not a feasible solution (Dean and Kockelman 2022). Proactive and forward-thinking policies are essential for optimizing the positive social and environmental impacts of on-demand transportation (Alexander et al. 2022). Lawmakers have an opportunity to enact rules that optimize the advantages of the technology while lowering the associated risks (Almaskati et al. 2023). Climate change is a major concern in the transportation sector (Alexander et al. 2022), but cities and municipalities have an opportunity to use climate action plans to formulate policies that guarantee that SAVs achieve lower emissions, reduce vehicle miles traveled, and improve transportation equity. Similarly, policymakers can establish an agenda that tackles environmental issues and supports the sustainable development of their communities. Legislative bodies should think about proactive and dynamic solutions that take into account the uncertainties related to both SAV technologies and climate change, as it is unclear how the short- and long-term benefits of vehicle automation will balance out (Milakis et al. 2017; Khan et al. 2022b).

The many facets and implications associated with AVs demand that policies address a wide range of issues to guarantee benefits in the early stages of SAV adoption. By encouraging rather than imposing active modes of mobility, policies and legislation can shape the automated vehicle industry in a way that supports the community and the current infrastructure and reduces the likelihood that SAVs will compete with the current public transportation system. Instead of causing a modal shift that further increases reliance on cars, the development of SAVs must be planned to support public transportation and promote active modes of mobility (Etminani-Ghasrodashti et al. 2023b; Khan et al. 2023). Since electrification of SAVs has been linked to optimistic reductions in energy consumption and emissions (Fulton et al. 2017; Pamidimukkala et al. 2023c), policymakers need to consider integrating SAVs and electric vehicle technology in order to optimize the benefits to the environment.

CONCLUSION

This study aimed to elucidate the effects of integrating AVs with on-demand mobility by discussing emissions and energy consumption, public transportation, land use, and vehicle ownership. The variables that may influence the effects were recognized and categorized based on the database, and the number of citations for each was recorded. The transportation sector contributes significantly to greenhouse gas emissions globally; however, SAVs have the potential to alter this as they are generally expected to have a positive influence on the environment. However, if the affordability and convenience of on-demand mobility leads to an increase in vehicle miles traveled (the most often cited factor after reduced congestion), then emissions may increase. When more people begin using SAVs rather than public transportation as their primary form of transportation, vehicle miles traveled may also rise. To prevent this, SAVs should be incorporated into the current system to function as feeder routes or serve rural areas with low demand, rather than being marketed as an alternative form of public transportation. This will enable governments to make the best use of their transportation resources and enhance connectivity.

The relationship between land use and transportation networks is dynamic and is impacted by infrastructure, regulations, travel demand, and technological advancements like SAVs. Though some researchers disagree and predict that car dependency will grow rather than decrease, many researchers concur that automated mobility on demand will dramatically reduce parking demands. Because of enhanced accessibility and connectivity to suburban and rural areas, the introduction of this technology may have negative effects on land use. If people move further away from their workplaces, increased urban sprawl could result. Politicians have the opportunity to prevent the negative effects of SAVs by enacting laws such as the 16 identified in this study that optimize the advantages of the technology while lowering the associated risks.

SAVs have the potential to lower mobility barriers and transportation inequity, but lawmakers must address environmental, public transit, and land use concerns if they are to improve the current transportation system. To provide transportation specialists with a deeper understanding of SAVs and their effects on the transportation industry, this study examined the implications of integrating AVs with on-demand mobility. Policymakers will benefit from the conversation about governance and policies for autonomous mobility on-demand and can use the information to develop legislation that is essential to the successful application of this technology.

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Investigating the Factors Contributing to Construction Cost Overruns during COVID-19

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ABSTRACT

The global crisis precipitated by the novel coronavirus brought forth considerable psychological distress and financial strife, notwithstanding governmental economic relief. This situation highlighted the degree of dependency among international markets by demonstrating the ripple effects from disturbances in one industry to another. Within this context, the construction sector endured significant hardship, facing operational disruptions, health and safety concerns, project deferrals, cancellations, and financial discrepancies. While extensive research has been conducted on the repercussions of the pandemic on the construction sector, the specific area of cost escalation has been less explored. This research endeavors to bridge this knowledge gap by exploring the contributory factors to cost escalations within the construction domain during the COVID-19 health event. A methodical inquiry was initiated through an online questionnaire targeting construction engineers and management personnel across the United States. From this, 124 complete responses were harnessed to construct an analytical model. The results from this analysis indicated that increased labor expenses, inflationary pressures, a hike in material costs, intensified demands from vendors and producers, the financial burdens of implementing COVID-19 testing, and the presence of medical staff on-site, as well as the additional expenditure on personal protective equipment and the ambiguity in determining COVID-19 as an allowable or non-allowable delay within contracts, were pivotal in causing budget overruns in construction projects during the pandemic. The outcomes of this investigation offer critical knowledge for decision-makers and project overseers within the construction field, delivering a clearer understanding and preparation for efficiently navigating the complexities introduced by a pandemic.

Keywords: COVID-19; construction; cost overruns; predictive model.

INTRODUCTION

The COVID-19 pandemic triggered significant mental stress and economic difficulties globally, notwithstanding the financial support measures implemented by various governments (Whitworth 2020). The crisis underscored the interconnectedness of global sectors by, illustrating how disruptions can ripple down to others (Golan et al. 2020; Safapour et al. 2023; Kermanshachi et al. 2023). For instance, reduced travel induced a decline in industries such as transportation, which particularly affected the construction industry by disrupting its supply chain and leading to substantial project cost increases (Adepu et al. 2022; Kisi and Sullbaran 2022; Subramanya and Kermanshachi 2021). Travel restrictions further compounded the problem by inflating transportation costs and, as a result, the cost of construction materials (Adepu et al. 2023a; Okorie et al. 2020). This situation was aggravated by a rising demand for some building materials, like lumber, which, coupled with decreased availability due to supply chain disruptions, led to cost overruns (Pamidimukkala and Kermanshachi 2021; Kisi and Sulbaran 2022). A surge of other issues, including project delays, cancellations, and budget overruns, also significantly impacted on the sector (Abubakar 2022; Hesna et al. 2021; Rouhanizadeh and Kermanshachi 2019).

The pandemic also led to changes in workforce dynamics, as fears of infection, job insecurity, and stress prompted many employees to abstain from work, resulting in disruptions to regular workforce distribution (Adepu et al. 2023b; Karthick et al. 2022a). To maintain productivity, companies responded by recruiting temporary labor, which entailed additional costs (Alsharef et al. 2021). Alongside these challenges, the pandemic ushered in a plethora of costly safety measures that construction sites had to comply with, incurring additional including, the supply of PPE, disinfectants, sanitizers, and on-site health personnel for COVID-19 testing (costs (Megahed and Hassan 2022; Adepu et al. 2022; Duan et al. 2023; Tan and Abdul-Samad F 2022). Moreover, the introduction of hazard pays for essential workers, particularly in the US, contributed to construction cost overruns (Hecker 2020). The crisis also resulted in increased caution from lenders, leading to a rise in project financing and insurance costs (Ofori 2020; Abubakar et al. 2022). Uncertainties surrounding insurance coverage and compliance with health and safety regulations due to the pandemic precipitated potential legal disputes and negotiations, thereby further increasing costs (Assaad et al. 2020).

The pandemic necessitated remote working, which led to unforeseen expenses for hardware, software licenses, VPNs, and cybersecurity measures for setting up a remote work infrastructure (Wang and Alexander 2021). The consequent surge in the use of digital communication tools and platforms led to increased operational costs, compounded by additional expenses for staff training, and necessitated the re-sequencing or re-scheduling of construction projects that increased administrative costs (Bogale et al. 2020). Changes in contract clauses due to the pandemic resulted in construction project delays, leading to potential cost increases (Khalef et al. 2021; Kermanshachi et al. 2022).

To prepare for potential future pandemics, it's crucial to examine the effects and transformations that the construction industry experienced due to COVID-19 (Adepu et al. 2023c). Researchers have recognized the adversities brought about by the virus and have developed strategies to mitigate its impact on the construction industry, however, the existing literature focuses on the health and wellbeing of the construction workforce rather than, on the impact of COVID-19 on key performance indicators essential for project success (Kisi and Sulabaran 2022). This research aims to fill this gap by focusing on how COVID-19 affected one of the most critical indicators for assessing performance and ensuring construction project success – the cost and analyzing it using multinomial logistic regression model.

LITERATURE REVIEW

The first signs of a severe acute respiratory condition began to surface in Wuhan, a city in China on December 12, 2019 (Pamidimukkala et al. 2021). On January 7, 2020, public health officials in China identified a novel coronavirus as the causative agent of the outbreak (CDC, 2023). Fast forward to March 21, 2020, the World Health Organization (WHO) proclaimed the escalating situation as a global pandemic. Following this period, the U.S. has witnessed a swift rise in the number of verified COVID-19 infections, and by, January 3, 2020, reported more than 20 million confirmed COVID-19 cases, alongside over 350,000 associated fatalities (Pamidimukkala and Kermanshachi 2021; Alsharef et al. 2021).

The ramifications of the COVID-19 health crisis on the construction sector were profound, necessitating a pivot from established operational protocols to emergent, adaptive strategies. The industry faced an upheaval in its standard practices, compelling entities to integrate new methodologies (Abdelwahed & Soomro, 2023; Parameswaran & Ranadewa, 2021). The pandemic's most pronounced effect was the heightened risk to construction workers' health, necessitating the implementation of safety measures like social distancing, augmented personal protective gear usage, and consistent health monitoring (Alsharef et al., 2021; Tan & Samad, 2022; Karthick et al., 2023b). Research by Pasco et al. (2020) suggested that construction workers had a fivefold increase in hospitalization risk from COVID-19 compared to other industries. Despite these precautions enhancing worker safety, they concurrently affected workforce efficiency.

The shift towards remote work required the adoption of advanced technologies and methodologies to sustain project management and communication standards. A pivotal issue brought forth by the pandemic was the labor shortfall, precipitating elevated labor costs (Megahed & Hassan, 2022; Abubakar et al., 2022; Karthick et al., 2022c). Additionally, the supply chain experienced severe disruptions, resulting in material and machinery scarcities, which, in turn, drove up demand and costs (Barua, 2020; Omotayo et al., 2022). Pre-pandemic, the construction industry was already encountering delays and budgetary exceedances. The pandemic, however, intensified these challenges, infusing a novel layer of intricacy (Kisi & Sulbaran, 2022; Alwaly & Alawi, 2020; Pamidimukkala et al., 2020; Aljohani et al., 2017; Gao & Touran, 2020). Cost overruns in construction are characterized by project expenses surpassing the initial estimates. Effective cost management is a critical indicator of an organization's efficiency and profitability and is commonly associated with the successful execution of a project (Hesna et al., 2021; Ammar et al., 2022; Safapour et al., 2017).

Construction projects are known to have difficulty completing projects on time and within budget due to their dynamic nature and multitude of contributing factors; however, these complexities were further magnified by the COVID-19 pandemic, which has served to exponentially increase the overall project costs (Hesna et al. 2021; Zamani et al. 2021; Kisi and Sulabaran 2022). According to reports from the Joint Center for Housing Studies (JCHS) of Harvard University, the input costs of new residential construction surged 23%, while costs related to remodeling rose 21%. A survey conducted by Kisi and Sulbaran (2022) revealed that projects spanning 3 to 6 months experienced the most significant median cost overruns, ranging from 8% to 9%, while projects with a duration of 1.5 to 2 years saw a cost increase between 6% to 7%.

Another survey conducted by Ling et al. (2021) predicted that for the next five years, almost 90% of the projects will have cost overruns of 5% or more. A study conducted by Hesna et al. (2021) revealed that labor, materials, occupational health and safety, and inaccurate cost estimation were some of the main factors contributing to cost overruns during the COVID-19 pandemic. Research by Romeli et al. (2022) on the economic impact of the COVID-19 pandemic on the construction industry in Malaysia revealed that higher costs for financing and insuring projects were major contributors to construction cost overruns. Increased costs for alterations in contractual terms and unclear guidelines in determining whether COVID-19 was an excusable or non-excusable contract delay were also responsible for cost overruns (Tariq and Gardezi 2023). Table 1 shows a list of factors that were identified as contributing to construction cost overruns during the COVID-19 pandemic.

Table 1. Factors Leading to construction cost overruns during COVID-19

#	Factors	Source
1	Inflation and surge in the prices of materials	Omotayo et al. (2022)
2	Heightened demands from suppliers and manufacturers	Abdullah et al. (2021)
3	Increased labor costs	Kisi and Sulbaran (2022);
4	Elevated costs associated with heavy machinery	Abdullah et al. (2021)
5	Rise in project financing and insurance expenses	Romeli et al. (2022)
6	Requirements for personal protective equipment, disinfectants, and sanitizers	Hesna et al. (2021)
7	Costs associated with COVID-19 testing or stationing healthcare personal on-site	Abdullah et al. (2021)
8	Alterations in contractual terms	Abubakar et al. (2022)
9	Unclear guidelines for determining whether COVID-19 was an excusable or non-excusable contractual delay	Hesna et al. (2021)

METHODOLOGY

The research methodology for this study unfolded over the four stages. An exhaustive review of published articles was conducted through scholarly search tools Google Scholar, Research Gate, Science Direct, and the American Society of Civil Engineers to identify the factors contributing to cost overruns during the COVID-19 pandemic. Then, the factors identified from the literature review were utilized to develop a survey questionnaire via QuestionPro, an online tool used for creating and disturbing survey. The survey was distributed among construction engineers and managers in the United States above 18 years of age, and a detailed examination was conducted to analyze, the demographic characteristics of the participants. Lastly, a predictive multinomial logistic regression model was developed to determine the extent of construction cost overruns during the COVID-19 pandemic, and the results were discussed.

Survey development and distribution

A 14-question questionnaire survey was developed, using the digital platform QuestionPro and based on insights gathered from literature review. The questions were divided into segments of demographic information and the factors that contribute to construction cost overruns during the COVID-19 pandemic, with most of them structured on a seven-point Likert scale. The survey link was distributed throughout the United States via emails, and 124 completed responses were received. No compensation was offered to the participants for completing the survey.

Descriptive data analysis

Figure 1 depicts the descriptive data analysis. An analysis of the survey respondents revealed a broad range of experiences and affiliations within the construction industry. By sector, the majority, 38% were employed in commercial construction: 28% in infrastructure, 14% in residential, 11% in heavy construction, and 9% in industrial. From an organization perspective, 44% identified as contractors, 33% as consultants, 12% as subcontractors, and 11% as project owners. Regarding the variety of projects, 40% of the participants reported engagement with governmental projects, 25% with privately funded projects, and the remaining 35% indicated involvement in both sectors. Looking at the size of the companies that survey participants came from, there was a relatively equal division among small, medium, and large enterprises, with each segment making up about one-third of the respondents.

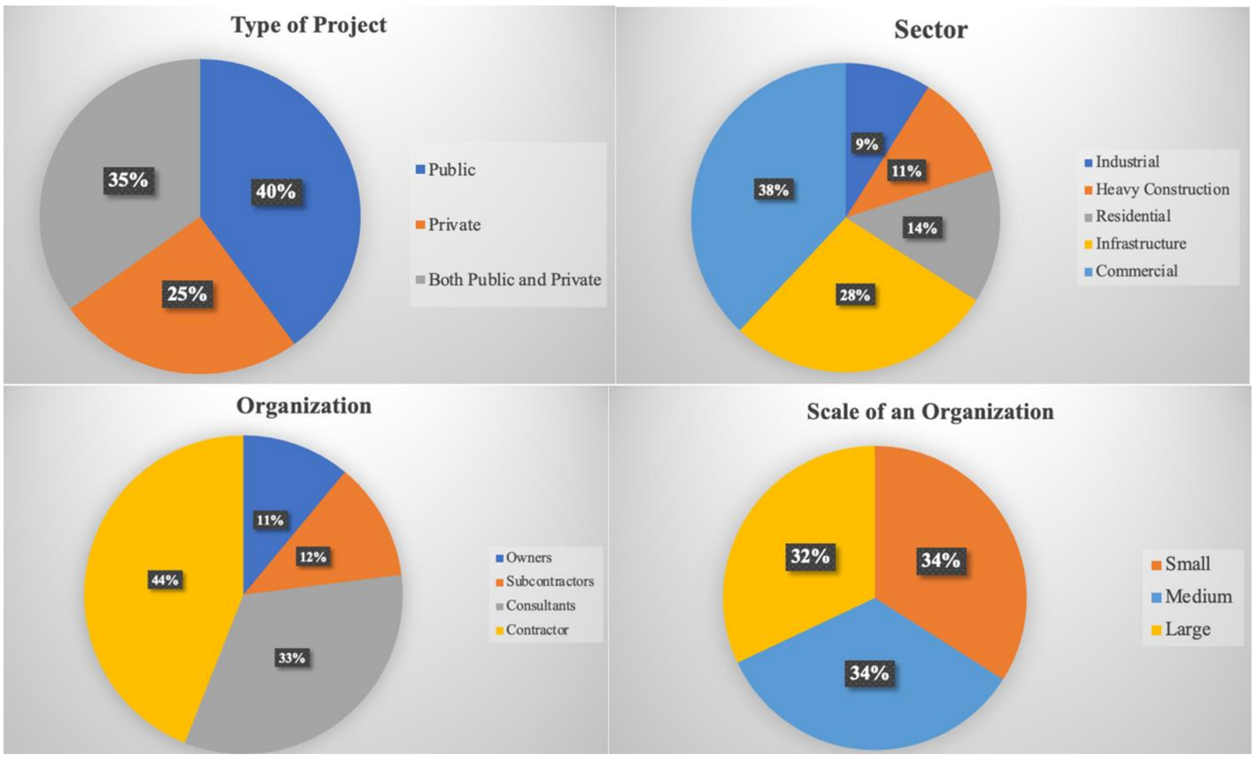

Figure 1. Descriptive analysis of survey participants

MODEL DEVELOPMENT AND RESULTS

The cleaned data was imported into a statistical tool, SPSS version 29, to develop the qualitative analysis and model. The dependent variable for the regression model was based on the question from the survey "Have you ever experienced construction cost overruns during the COVID-19 pandemic?" The responses of the survey were ranked on a seven-point Likert scale, where 7 was ranked as "always," 1 was ranked as "never," and 2, 3, 4, 5, and 6 were ranked respectively as "rarely, occasionally, sometimes, frequently and usually." Multinomial logistic regression was used to determine the factors contributing to construction cost overruns during the pandemic. The model included 10 independent variables, also called covariates, one of which was based on the scale of the construction organization (coded as SCALE) the respondents were employed by companies/agencies with 1 to 99 employees were considered small, those with 100 to 499 employees were considered medium, and those with 500 or more were considered large. Other variables included inflation and the surge in material prices (coded as MATERIAL), heightened demand from suppliers and manufacturers (coded as DEMAND), increased labor costs (coded as LABOR), elevated costs associated with heavy machinery (coded as MACHINERY), a rise in the cost of project financing and insurance (coded as FINANCING_AND_INSURANCE), the requirement for personal protective equipment, disinfectants, and sanitizers (coded as HEALTH_AND_SAFETY_MEASURES), alterations in contractual terms (coded as CONTRACTUAL_TERMS), and lack of clear guidance in determining whether COVID-19 was an excusable or non-excusable contract delay (coded as GUIDANCE).

As shown in Table 2. the model was developed from 129 observations, with 124 being valid and 5 missing. The dependent variable COST_OVERRUNS was assigned three levels according to its impact on the project: 0,1, and 2, indicating low, medium and high impact on 15, 90, and 19 of the cases, respectively.

Table 2. Case processing summary

		N	Marginal Percentage
COST_OVERRUNS	0.00	15	12.1%
	1.00	90	72.6%
	2.00	19	15.3%
Valid		124	100.0%
Missing		5	
Total		129	

The model fitting information shown in Table 3, demonstrates that the final model with predictors (also known in SPSS as covariates) enhances the understanding and prediction of the dependent variable COST_OVEERUNS more than basic model with no predictors. This indicates that the selected predictors in the model play a critical role in explaining the variations in COST_OVERRUNS.

Table 3. Model fitting information

	Model Fitting Criteria	**Likelihood Ratio Tests**		
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	188.750			
Final	33.797	154.953	20	<0.001

Table 4 shows that the Pseudo-R squares of Cox and Snell (0.0713), Nagelkerke (0.905), and McFadden (0.806) suggest that the model explains a substantial proportion of the variations in COST_OVERRUNS.

Table 4. Pseudo R-square

Cox & Snell R Square	Nagelkerke R Square	McFadden R Square
0.713	0.905	0.806

Table 5 depicts the results from the likelihood ratio test results, which indicate which indicate that the SCALE (P=0.012) of the company significantly influences the impact of cost overruns on it. This may be because larger companies have more resources to handle unexpected costs than smaller ones. Increased LABOR costs (P=0.002) are also significant in predicting cost overruns, which may be due to maintaining scarcity of workforce. As expected, since supply chains were severely disrupted during the pandemic, a surge in the prices of MATERIALSs (P=0.001), and inflation had a major impact on cost overruns, as did the heightened DEMAND (P=0.005), from suppliers and manufacturers. Which may have been caused by the increased demand for materials and services that exacerbated the supply-chain disruptions. PPE (P=0.024), the requirement for personal protective equipment, disinfectants, and sanitizers was also a significant factor, as the costs, associated with implementing safety measures can significantly increase total project costs. Likewise, the factor HEALTH_AND_SAFETY_MEASURES (P=0.018), which represents, the costs related to COVID-19 testing and/or stationing healthcare, personnel on-site, were significant and demonstrate the direct impact that the extra costs required to maintain worker safety during the pandemic had on the industry. Finally, the rise in the cost of FINANCING_AND_INSURANCE (P<0.001) was of major importance in predicting cost overruns, as the country's economic instability during the pandemic led to higher interest rates and insurance premiums.

The remaining variables, HEAVY_MACHINERY (P=0.776), CLAUSES (P=0.360), and GUIDANCE (P=0.241), are not considered significant predictors since their P-values are above the conventional threshold of 0.05. The reasons for this may be that the costs related to these factors remained stable during the pandemic, or that they had less influence on the specific model or data.

Table 5. Likelihood ratio test results

Effect	**Model Fitting Criteria**	**Likelihood Ratio Tests**		
	-2 Log Likelihood	Chi-Squared	Degrees of Freedom	P-Value
Intercept	113.986	80.189	2	< 0.001
Scale	42.719	8.921	2	0.012*
LABOR	46.456	12.659	2	0.002*
HEAVY MACHINERY	34.304	0.506	2	0.776
MATERIAL	47.199	13.402	2	0.001*
DEMAND	44.257	10.459	2	0.005*
PPE	41.232	7.435	2	0.024*
HEALH_AND SAFETY MEASURES	41.828	8.030	2	0.018*
FINANCING AND INSURANCE	49.434	15.637	2	< 0.001
CLAUSES	35.841	2.043	2	0.360
GUIDANCE	36.642	2.845	2	0.241

***Significant at 95% level of confidence**

CONCLUSION

The worldwide crisis incited by the coronavirus 2019 caused psychological strain and economic challenges, despite financial initiatives implemented by governments. This situation highlighted the intertwined nature of global sectors and demonstrates the ripple effect of how a disturbance in one sector affects others. Specifically, it had a profoundly negative impact on the construction industry by upending conventional work practices and forcing to them adopt revised practices. This study investigated the factors that played a significant role in the escalation of construction costs amid the COVID-19 pandemic. A survey was developed and distributed to collect data that was used to develop a predictive model using multinomial logistic regression and the SPSS tool. The study's findings concluded that factors such as increased labor costs, the inflation and a surge in material prices, heightened demand from suppliers and manufacturers, the costs related to COVID-19 testing and/or having health care professional on-site, additional PPE, and unclear guidelines for assessing whether COVID-19 was an excusable or non-excusable contract delay significantly influenced the construction cost overruns during the period of the pandemic. It is recommended that the construction industry seriously consider these factors and identify management practices that can minimize the impact of similar crises on the construction industry in the future. The findings of the study can offer valuable guidance to the construction business' professionals and decision-makers for identifying management strategies to prevent cost overruns during similar future crises.

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A Spatial-Temporal Analysis of Travel Time Gap and Inequality between Public Transportation and Personal Vehicles

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ABSTRACT

The increased use of personal vehicles presents environmental challenges, prompting the exploration of public transportation as an affordable, eco-friendly alternative. However, obstacles like fixed schedules, limited routes, and extended travel times impede widespread adoption. This study investigates the temporal evolution of spatial inequality in the travel time gap between public transportation and personal vehicles, reflecting disparities across states and time periods. Analyzing Census Transportation Planning Program data for six northeastern states in 2010 and 2016 reveals no significant increase in the travel time gap, but notable growth in inequality in a few urban and disadvantaged communities. Comprehending these trends is vital for fostering equitable advancements in transportation infrastructure and enhancing public transportation competitiveness.

INTRODUCTION

The surge in personal vehicle use has sparked substantial environmental concerns, prompting the emergence of public transportation as an affordable and eco-friendly alternative. Despite its advantages, widespread adoption faces challenges like fixed schedules, limited routes, low population density, and commuter perceptions. Among these challenges, the notable hindrance to widespread public transportation utilization is the substantial travel time gap between public transportation and personal vehicles. In a comprehensive review, Redman et al. highlighted studies targeting various quality attributes, emphasizing speed as crucial for increasing ridership (Redman et al. 2013). For example, a New York City study revealed a 15-minute reduction in commuting time leading to a substantial 25% increase in rail service ridership (Liao et al. 2020).

Measuring and comparing travel times between public transportation and personal vehicles is pivotal for assessing the efficiency and competitiveness of public transportation systems. A significant disparity in travel times between personal vehicles and public transportation could signify constrained mobility options, especially in rural areas, where accessibility to other regions may entail prolonged public transportation travel times, accentuating the challenges faced by individuals unable to afford a car or its associated expenses. While previous studies have delved into the travel time gap between public transportation and personal vehicles, fewer have explored the potential spatial inequalities of this gap. For instance, in urban areas with well-designed transit systems, certain regions may exhibit notably extended public transportation travel times to specific destinations (Dastgoshade, Hosseini-Nasab, and Mehrjerdi 2023). Averaging travel times may obscure variations in connectivity across subregions, underscoring the necessity of spatial inequality analysis for targeted improvements in public transportation connectivity.

Numerous studies have examined public transportation service equity, proposing various methodologies and often focusing on specific regions or demographic groups (Hosein Mortazavi and Akbarzadeh 2017; Jin, Kong, and Sui 2019; Yeganeh et al. 2018). Different theories, such as utilitarianism, libertarianism, intuitionism, and Rawls' egalitarianism, have been employed to define equitable distribution of public transportation resources (Nahmias-Biran, Martens, and Shiftan 2017; Pereira, Schwanen, and Banister 2017).

Among these studies, one research gap exists in understanding the temporal changes in the travel time gap and the associated inequalities. While public transportation systems are generally improving, some areas may still experience uneven enhancements, leading to connectivity disparities (Zhang and Zhang 2021, 2022). Urbanization and inflation are identified as contributing factors to these inequalities resulting from improvements in the public transportation system (Lv et al. 2019; Mishra and Agarwal 2019). Analyzing temporal changes becomes imperative for developing comprehensive transit improvement strategies that consider evolving socio-economic and infrastructural landscapes.

In order to address these gaps in current research, this study aims to scrutinize the travel time gap between public transportation and personal vehicles, assess its spatial inequalities, and examine how these factors change over time. Leveraging the Census Transportation Planning Program (CTPP) dataset, we compare the travel time gap between 2010 and 2016 in six states in the northeastern U.S. In current literature, the concept of equity takes on diverse definitions regarding what is deemed "fair," typically associated with individual and/or household characteristics. However, this study primarily analyzes spatial inequality, centering on variations in transit competitiveness across regions, without delving specifically into individual and/or household considerations. Departing from the examination of individual or household-level travel time, this study aims to provide an overarching perspective by assessing multiple states. In addressing two key research questions:

(1) How does the travel time gap between public transportation and personal vehicles evolve over time and vary across states in the U.S.?
(2) Is there evidence of spatial inequality in the travel time gap, and how does its temporal trend unfold, with variations across states in the U.S.?

This study can contribute to the field by comprehensively assessing public transportation competitiveness across distinct time periods and scrutinizing the associated inequalities. Through this evaluation, the objective is to offer valuable insights into the evolving dynamics of public transportation competitiveness, supporting informed decision-making in urban planning and policy formulation.

METHODOLOGY

Data Source

We leveraged data from the CTPP dataset, which procures tabulations of American Community Survey (ACS) 5-year (and historical Census decennial) data. Notably, the CTPP data stands out due to its inclusion of origin-destination flows from home to work at small geographies, differentiating it from ACS data. The dataset, designed to aid transportation analysts and planners, illuminates commuting patterns and modes of transportation.

It is important to note that this work serves as a preliminary study, focusing on a subset of states rather than aiming for a nationwide scope. This deliberate narrowing allows us to gain preliminary insights into the dynamics of public transportation competitiveness in specific regions. Our study specifically focuses in on six northeastern U.S. states: New York (NY), Maryland (MD), Pennsylvania (PA), Virginia (VA), New Jersey (NJ), and Massachusetts (MA). By concentrating our efforts on this regional subset, we aim to provide targeted and contextually relevant findings that can lay the groundwork for more extensive studies in the future.

We employed two series of CTPP data: 2010 (derived from the 2006-2010 American Community Survey) and 2016 (derived from the 2012-2016 American Community Survey). Each series contains the mean travel time for an origin-destination (OD) pair at the Census Tract level. The CTPP records data on five modes of transportation, each defined as follows (U.S. Census Bureau 2023):

- Drive alone: Individual occupancy of a car, truck, or van.
- Carpool: Involved a car, truck, or van with two or more individuals sharing the ride.
- Public transportation: Involved buses, trolley buses, streetcars, trolley cars, subways, elevated trains, railroads, or ferryboats.
- Taxi/Other: Involved taxicab, motorcycles or other unconventional methods.
- Bike/Walk: Traveled by biking or walking.

Our study specifically delves into analyzing travel times for two distinct modes of transportation: public transportation and drive alone, referred to as personal vehicles.

In order to mitigate bias, we excluded OD pairs that lacked data on travel times for public transportation or solo driving. This refinement yielded a dataset comprising 4,705 OD pairs, constituting 11.6% of the total. The majority of these exclusions were in regions with limited public transportation services, a reasonable decision allowing us to concentrate on comparisons in areas where public transportation services are available for meaningful evaluation.

Beyond state-level comparisons of travel time gap and inequality, our study also delved into the evaluation of disadvantaged communities (DAC). The data for identifying DAC originates from the Equitable Transportation Community (ETC) Explorer developed by the U.S. Department of Transportation (USDOT 2023). DACs are defined at the Census Tract level based on five components: Transportation Insecurity, Climate and Disaster Risk Burden, Environmental Burden, Health Vulnerability, and Social Vulnerability. The distribution of DACs and the study regions is visually represented in Figure 1.

Travel time gap and inequality Metrics

The travel time gap, denoted as g_{ab} for each OD pair, is established as a variable based on data at the Census Tract level. It is represented by the ratio of public transportation travel time over driving alone travel time. In order to capture travel time gap inequality within a broader region, such as a county or state, our goal is to identify a metric that effectively represents the heterogeneity.

While variance or standard deviation are commonly used as indicators of heterogeneity, we aim for a standardized measure for ease of comparison. Motivated by this consideration, we adopt the metric proposed by Pandey et al. (Pandey, Brelsford, and Seto 2022). The inequality of the travel time gap is denoted as I. This variable is constructed as a composite metric involving the mean (μ_g) and standard deviation (σ_g) the travel time gap. This approach ensures that the metric is standardized by the average and theoretically bounded, facilitating straightforward comparisons. For the travel time gap, the base unit is the Census Tract to Census Tract OD pair. However, for inequality, the base unit is aggregated to the residence Census Tract. The two metrics are illustrated in Table 1. The theoretical range of this inequality metric spans from 0 (indicating the lowest inequality) to 1 (representing the highest inequality). As the standard deviation of the travel time gap increases within a region, the corresponding inequality metric also rises.

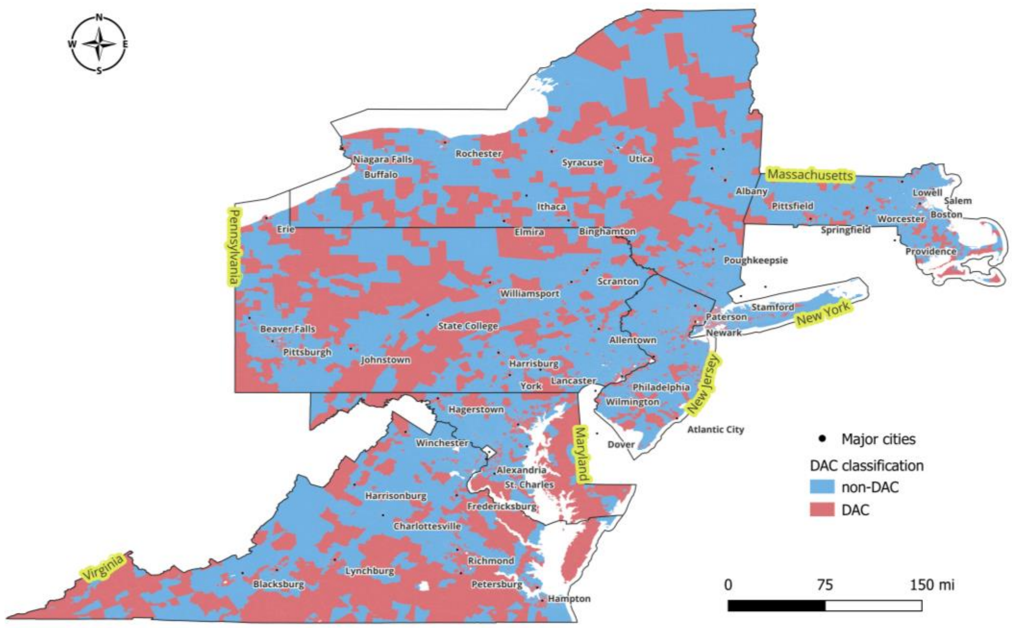
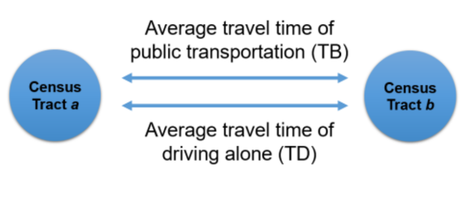
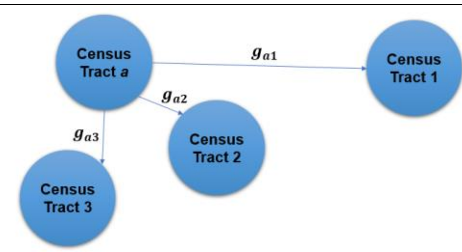


Figure 1. DAC distribution and study states

Table 1. Illustration of the travel time gap and inequality metrics

Travel time gap		Inequality	
Notation	Base unit	Formula	Base unit
g	Census Tract to Census Tract OD pair	$I = \frac{\sigma_g}{\sqrt{\mu_g(1-\mu_g)}}$	residence Census Tract
 Travel time gap: $g_{ab} = TB\ /\ TD$		 μ_g=mean(g_{ab}), σ_g=standard deviation(g_{ab})	

Paired T-test Method Through Hypothesis Testing

In this study, our focus is on testing the means of two key variables—travel time gap and inequality—between the years 2010 and 2016. Hypothesis testing, specifically the paired t-test, is employed for this purpose.

RESULTS

The analysis of travel time between the two modes of transportation reveals a slight increase from 2010 to 2016 for both modes across all studied states (Figure 2). Despite this observed uptick, it's important to note that these changes are not statistically significant at 95% confidence level at the state level. The modest variations in travel time do not reach a level of significance that would allow us to confidently assert a meaningful difference. This suggests that, while there may be a slight temporal trend in travel time, it doesn't attain statistical significance when considering the variability at the state level.

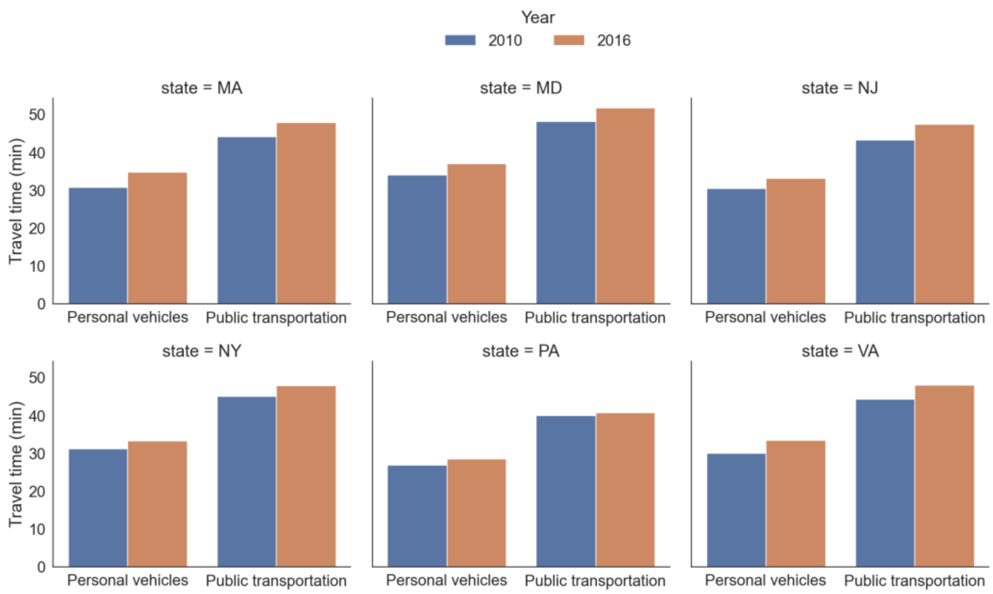


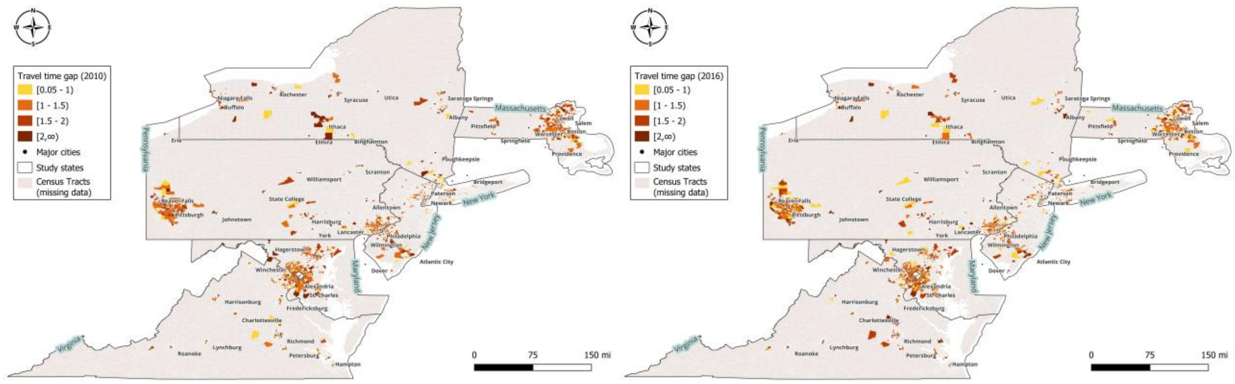
Figure 2. Travel time comparison between personal vehicles and public transportation

Research Question 1: How does the travel time gap between public transportation and personal vehicles evolve over time and vary across states in the U.S.?

The travel time gap across the six states is aggregated by residence Census Tract and presented Figure 3. The regions with available travel time data are predominantly situated in major cities and urban areas. This spatial concentration underscores that the analysis is focused on areas characterized by higher population density and urbanization, providing a targeted perspective on travel time gaps in these significant and interconnected locales.

Interestingly, from 2010 to 2016, both DAC and non-DAC regions underwent some change in travel time gap (Figure 4). While not statistically significant in all states, it indicates a noteworthy difference. Except for Pennsylvania, where DAC areas showed a decreasing trend (p-value=0.003), all other DAC areas demonstrated an increasing travel time gap trend. In contrast, all non-DAC areas exhibited a decreasing trend in travel time gap.

When comparing the travel time gap between DAC and non-DAC areas in 2010, significant disparities emerge. DAC travel time gap is statistically higher than non-DAC travel time gap in New York (p= 0.003), Maryland (p <0.001), Pennsylvania (p <0.001), Massachusetts (p <0.001), and New Jersey (p = 0.04). In terms of 2016, the DAC travel time gap remains significantly higher than the non-DAC travel time gap in all studied states, with p-values consistently lower than 0.001. This persistent significance underscores enduring disparities in travel time gaps.



(a) Travel time gap in 2010 (b) Travel time gap in 2016

Figure 3. Travel time gap temporal change

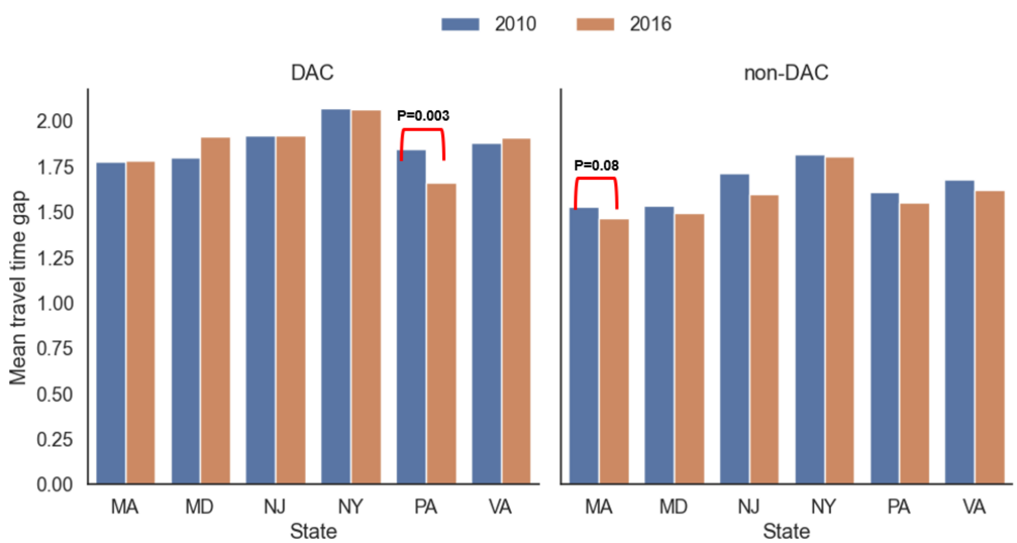


Figure 4. Travel time gap between 2010 and 2016 in DAC and non-DAC areas

Research Question 2: Is there a presence of inequality in the travel time gap, and how does its temporal trend unfold?

Figure 5 displays the distribution of mean and standard deviation of travel time gap inequality, along with the resulting inequality, across all six states. Although the mean travel time gap exhibits a decreasing trend, the standard deviation of the travel time gap is higher in 2016 compared to 2010, evident from the darker region in the figure. Consequently, there is a slight increase in inequality, as indicated by the shade area reaching slightly higher towards the "I=1" curve, representing the highest level of inequality. Figure 6 further illustrates the distribution of travel time gap inequality.

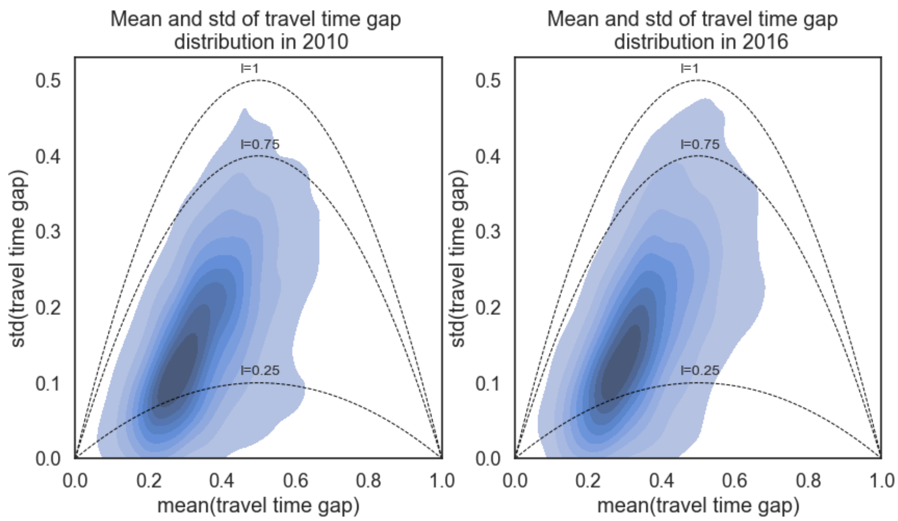
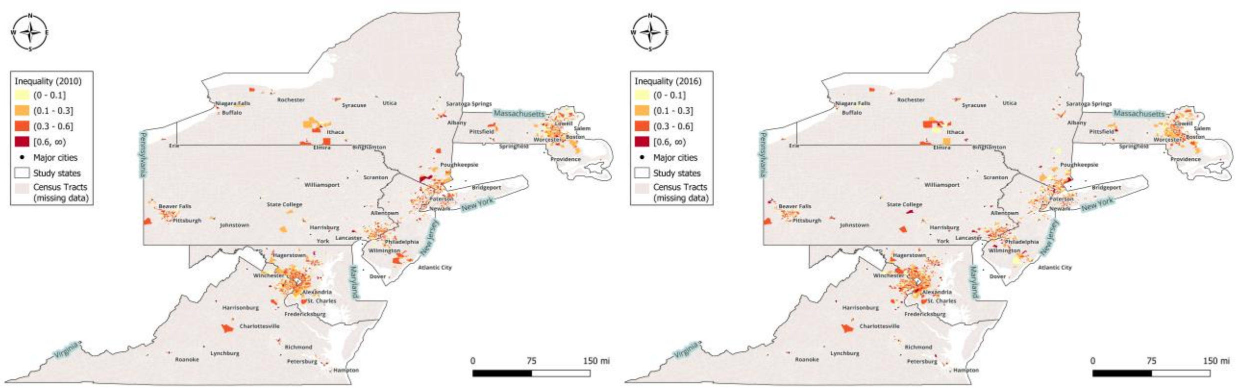


Figure 5. Mean, standard deviation, and inequality



(a) travel time gap inequality in 2010 (b) travel time gap inequality in 2016

Figure 6. Travel time inequality temporal change

Non-DAC areas witness a significant uptick in inequality compared to DAC in Maryland (p<0.001), New York (p =0.04), and non-DAC in Massachusetts (p =0.03), as shown in Figure 7. In the DAC vs. non-DAC comparison, non-DAC areas show slightly higher inequality than DAC areas in both 2010 and 2016. Particularly, DAC inequality is significantly higher than non-DAC in 2010 for all studied states except New York and Maryland with p-values lower than 0.001. In 2016, DAC inequality remains significantly higher than non-DAC for all studied states except Pennsylvania and New Jersey with p-values lower than 0.001.

When considering the trends of travel time gap and inequality together, a disparity emerges. In contrast to the decreasing trend observed in travel time gap, inequality demonstrates an increase. Specifically, DAC regions in Maryland and New York, despite no significant change in travel time gap, experience a notable increase in inequality. Furthermore, despite a significant decrease in travel time gap, non-DAC regions in Massachusetts simultaneously witness a significant increase in inequality from 2010 to 2017.

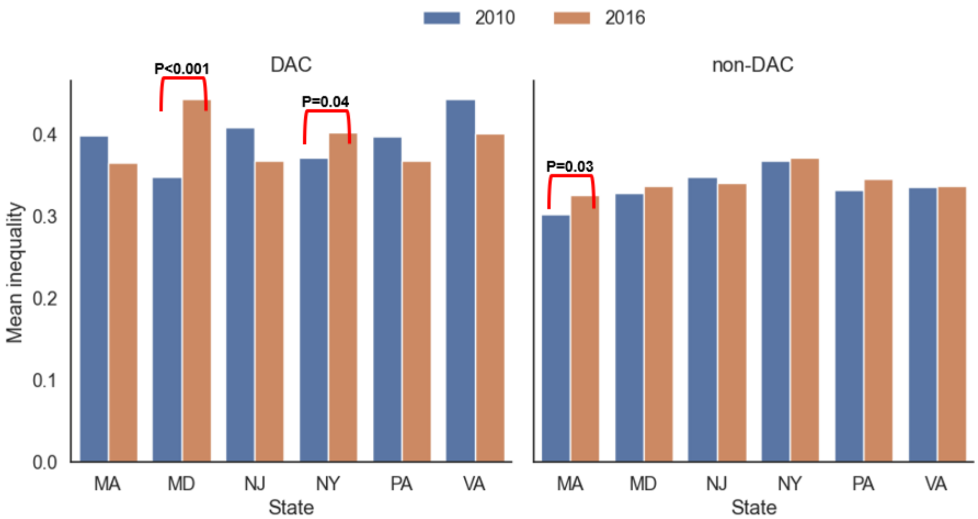


Figure 7. Inequality between 2010 and 2016 in DAC and non-DAC areas

In summary, these findings suggest that while the travel time gap between public transportation and personal vehicles may not exhibit a significant increase over the years, there could be an uptick in inequality in certain regions. These results underscore the importance of considering more than just the mean, as spatial inequality may reflect uneven improvements in public transportation services over time. The observed phenomenon may be attributed to disproportionate enhancements in public transportation provisions across regions, especially in DAC areas. In DAC areas, there might be improvements in public transportation accessibility, but these enhancements may not extend to other potentially underserved regions. This multi-year analysis provides valuable insights for agencies to identify regions where future public transportation improvements may be warranted.

Moreover, both the travel time gap and inequality are higher in DAC areas than in non-DAC areas, suggesting that DAC areas experience lower connectivity via public transportation modes. This finding aligns with previous research indicating that people residing in DAC areas might have fewer economic opportunities, limited access to essential needs, and reduced ability for recreations (Oviedo and Sabogal 2020; Yousefzadeh Barri et al. 2021).

CONCLUSIONS

This study examines temporal changes in travel time gap inequality between personal vehicles and public transportation, revealing a contrasting trend between travel time gap and inequality, as well as between DAC and non-DAC areas. While the travel time gap decreases, inequality increases, potentially due to disproportionate enhancements in public transportation, especially in DAC areas. Both the travel time gap and inequality are higher in DAC areas than in non-DAC areas, underscoring the lower connectivity in DAC areas and highlighting the disproportionate improvement in public transportation.

The paper contributes significantly to understanding temporal trends in public transportation competitiveness across regions, aiding agencies in identifying areas for targeted service improvements to boost ridership.

In Future work, we would like to extend this analysis to the entire U.S. Additionally, adopting more comprehensive equity metrics, connecting inequality to per capita measures, could enhance the spatial metric. Further exploration of factors influencing inequality can provide meaningful insights on improving overall equity in transportation services.

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Assessing the Impacts of Transit Signal Priority on Crash Severity: An Empirical Assessment Using Bayesian Logit Model with Unobserved Heterogeneity

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ABSTRACT

Transit signal priority (TSP) is a traffic management strategy to enhance the quality of public transit service while also providing substantial safety benefits. This study used a binary Bayesian logit model with random effects, which accounts for unobserved heterogeneity, to explore impacts of TSP on severity of corridor-related crashes in Florida. The analysis revealed deploying TSP was linked to lower crash severity, reducing the likelihood of fatal plus injury (FI) crash by 7.96%. The study also investigated other factors contributing to crash severity, including crash characteristics, driver characteristics, roadway geometry, and environmental factors. Distracted driving, vulnerable road users, and higher speed limits increase the risk of FI crashes, while higher average annual daily traffic (AADT) was linked to lower risk. Certain crash types, such as rear-end and sideswipe crashes, were also associated with lower risk of FI crashes. These findings hold crucial implications for transportation agencies when planning future TSP deployments.

BACKGROUND

Transit signal priority (TSP) is a strategy that prioritizes the movement of transit vehicles through a signalized intersection to grant better transit travel time reliability and minimize transit delay. Implementing TSP for public transportation at traffic signals is a crucial traffic management strategy adopted by smart cities to enhance the quality of service for public transit users (Fiori et al., 2021). It plays a pivotal role in breaking the congestion cycle that threatens gridlock in cities. Prioritizing public transit not only helps alleviate congestion but also makes it a more appealing mode of transportation as urban networks and traffic demands continue to grow. TSP offers various operational benefits such as improved travel time reliability, reduced transit delay, optimized dwell times, etc. (Ali et al., 2017; Alluri et al., 2020; Consoli et al., 2015; Hu et al., 2015; Mishra et al., 2020; Reza, 2012; Skabardonis & Christofa, 2011; Smith et al., 2005; G. Zhou et al., 2007; Zlatkovic et al., 2013). Moreover, its integration with other strategies, such as Connected Vehicle (CV) technology and Adaptive Signal Control Technology (ASCT), further enhances its effectiveness (Hu et al., 2015, 2022; Yang & Fan, 2023). However, do such operational benefits result in significant safety improvements? There have been differing findings regarding the safety impacts of TSP. Some previous studies suggest that TSP can enhance safety, while others indicate that it may not significantly improve safety (Ali et al., 2021a, 2022a; K. C. K. Goh et al., 2013, 2014; Li et al., 2017; Liang et al., 2023; Naznin et al., 2016a; Shahla et al., 2009; Song et al., 2021; Song & Noyce, 2018a, 2019a; Wu et al., 2023).

Previous research has explored the safety implications of TSP, focusing on its impact on reducing crash frequency and specific crash types (Ali et al., 2021a, 2022a; K. C. K. Goh et al., 2013, 2014; Li et al., 2017; Naznin et al., 2016a; Shahla et al., 2009; Song et al., 2021; Song & Noyce, 2018a, 2019a). For example, a study conducted by Song and Noyce (Song & Noyce, 2018a) in King County, Washington, evaluated the safety performance of TSP on 11 corridors. Using an empirical Bayes (EB) method, the study observed reductions of 13% in total crashes, 16% in property damage only (PDO) crashes, and 5% in fatal and injury (FI) crashes (Song & Noyce, 2018a). Similarly, in a study conducted in Portland, Oregon, Song and Noyce (Song & Noyce, 2019a) utilized an interrupted time series analysis (ITSA). They found a 4.5% reduction in total crashes and a 10% reduction in PDO crashes along TSP corridors (Song & Noyce, 2019a). However, the decrease in FI crashes after TSP implementation was not statistically significant. It is worth noting that both studies observed an increase in crashes involving pedestrians and bicyclists along the TSP corridors. Importantly, neither study explored the influence of TSP on crash severity.

In more recent studies, Ali et al. (Ali et al., 2021a) conducted research in Orange and Seminole Counties, Florida, utilizing the full Bayes approach to quantify the safety benefits of TSP across 41 transit corridors. The findings showed reductions in total, FI, and property PDO crashes by 12%, 14%, and 18%, respectively (Ali et al., 2021a). Another study by Ali et al. (Ali et al., 2022a) examined the safety impacts of TSP in Florida using an observational before-after full Bayes method with a comparison group. The analysis involved 12 corridors with TSP and 29 comparison corridors without TSP. The results indicated a reduction in total crashes by 7.2%, rear-end crashes by 5.2%, and angle crashes by 21.9% (Ali et al., 2022a). It is worth noting that there was an increase in sideswipe crashes by 6%. Notably, both studies did not investigate the influence of TSP on crash severity.

Another study by Song et al. (Song et al., 2021) evaluated the safety effects of TSP with bus speed volatility as a surrogate measure in Minnesota. The study used 30 signalized intersections and automatic vehicle location (AVL) data. As a surrogate measure, bus speed volatility was used to estimate TSP's safety effects. Higher bus speed volatility indicated more safety risks. The result indicated that bus speed volatility was significantly lower with a TSP request than without a TSP request. In other words, implementing TSP was found to improve safety. However, this study lacks specific details regarding the effects of TSP on crash frequency, crash types, or crash severity. Other studies conducted in Australia (K. Goh et al., 2013a; K. C. K. Goh et al., 2014; Naznin et al., 2016a), which specifically investigated the safety implications of TSP, consistently demonstrated a reduction in traffic crashes after deploying TSP. For instance, Goh et al. (K. Goh et al., 2013a) analyzed 56 TSP corridors using an aggregate approach, employing an empirical Bayes (EB) before-after analysis and a disaggregated level safety audit review. Their findings indicated a 14% reduction in total crashes and a 23% reduction in rear-end crashes. In a separate study, Goh et al. (K. C. K. Goh et al., 2014) analyzed 99 TSP sites using mixed-effect negative binomial (MENB) and backpropagation neural network (BPNN) models, estimating a significant 53.5% reduction in bus crash frequency. Naznin et al. (Naznin et al., 2016a) performed an EB before-after analysis on 29 TSP sites in Melbourne and reported a 13.9% reduction in traffic crashes associated with TSP implementation. None of these studies investigated the influence of TSP on crash severity.

While studies conducted in the United States and Australia have reported improved safety due to TSP deployment, two studies conducted in Toronto, Canada, have observed a deterioration in safety following the implementation of TSP (Li et al., 2017; Shahla et al., 2009). These studies have found correlations between TSP deployment and an increase in traffic crashes. For example, Li et al. (Li et al., 2017) conducted a study using a microscopic simulation approach and negative binomial regression models, observing increases of 1.6% in total crashes, 2.9% in angle crashes, 1.9% in rear-end crashes, and 2.1% in sideswipe crashes. Shahla et al. (Shahla et al., 2009) utilized a negative binomial regression approach and reported increased traffic crashes along 24 TSP corridors in Toronto, Canada. Excessive extended green time was stated as one possible reason for the increase in crash frequency along the corridors with TSP.

In previous studies, the focus was primarily on evaluating the effects of TSP on crash frequency or specific crash types. Some studies suggest that TSP can enhance safety, while others indicate that it may not have a significant safety improvement (Ali et al., 2021a, 2022a; K. C. K. Goh et al., 2013, 2014; Li et al., 2017; Naznin et al., 2016a; Shahla et al., 2009; Song et al., 2021; Song & Noyce, 2018a, 2019a). Some studies even used microscopic simulation approaches or surrogate safety measures to assess the safety effects of TSP. *Therefore, no prior studies examined the impacts of TSP on crash severity outcomes, such as non-injury, possible injury, non-incapacitating injury, incapacitating injury, or fatal*. Thus, there is a need for a comprehensive study that specifically evaluates the safety impacts of TSP in terms of crash severity. This study aims to address this gap by examining the effects of TSP on the severity outcomes of corridor-related crashes in Florida. It provides a corridor-level assessment to estimate the severity impacts of TSP deployment and investigates whether TSP significantly influences the severity outcomes of corridor-related crashes in the state.

A binary Bayesian logit model with random effects was employed in this study to analyze the effects of TSP on corridor-related crashes. This modeling approach was chosen because crash severity can be influenced by various observed and unobserved factors related to the corridor and crash characteristics. The model accommodates potential variations within the observed data and across signalized intersections by incorporating random effects. The methodology was applied to crash data from 10 corridors in Florida where TSP systems were deployed. The findings of this study can provide valuable insights for transportation agencies considering the implementation of TSP at the corridor level.

DATA DESCRIPTION

The study used observational before-after study data to determine the impact of TSP on the crash severity along the TSP-enabled corridors in Florida. Note that in this paper, "before-after" refers to utilizing TSP-enabled corridors with a minimum of two years of available data both before and after TSP deployment for crash severity modeling. A total of 10 corridors with a minimum of two years of before-after period data were chosen for the crash severity analysis. Table 1 provides further details about 10 TSP corridors, including the year of TSP activation and the total count of signalized intersections along each corridor.

This study aimed to investigate the impact of TSP on crash severity along the TSP-enabled corridors in Florida. The data analyzed for this study consisted of crash records from Seminole and Orange Counties in Florida from 2014 through 2018. Crash data were retrieved from the Signal Four Analytics database. The analysis did not include crash data in the deployment year to reduce the effect of driver acclimation to the TSP and the potential influence of the deployment activities. The crash data contained information on crash characteristics, environmental conditions, and crash contributing factors. The response variable included two levels of severity outcome of a crash, i.e., fatal plus injury (FI) and no injury (PDO). The explanatory variables considered in the analysis were crash types (angle, rear-end, sideswipe), vulnerable road users (VRU), alcohol involvement, distraction, weather condition, surface condition, lighting condition, time of day, and presence of TSP.

Table 1: TSP corridors

No.	TSP Corridors	TSP Activation Year	Corridor Length (miles)	Total Signalized Intersections	Number of Lanes	Speed Limit (mph)
1.	Americana Boulevard	2016	1.0	4.0	4	35
2.	Fairbanks Avenue	2017	2.0	6.0	4	30
3.	Goldwyn Avenue	2016	0.5	3.0	4	30
4.	Metrowest Boulevard	2016	1.0	4.0	4	40
5.	Michigan Street	2016	1.6	6.0	4	30
6.	Raleigh Street	2016	1.8	5.0	2	35
7.	Rio Grande Avenue	2016	2.8	9.0	3	35
8.	Universal Boulevard	2016	1.0	5.0	4	35
9.	Vineland Road	2016	2.75	10.0	4	45
10.	State Road 46	2017	2.0	4.0	6	55

Additional data, such as roadway characteristics data, including the average annual daily traffic (AADT), and speed limit, were also collected. AADT data were retrieved from the Florida Department of Transportation (FDOT) Florida Traffic Online web portal and FDOT shapefiles. Data on speed limits were collected from the FDOT's Roadway Characteristics Inventory, the Geographic Information System database, and Google Maps. The Google Earth Pro software historical imagery tool was used to verify that no geometric changes occurred at the study corridor during the analysis period.

Table 2 provides the descriptive statistics of the variables used in the analysis. After removing all crashes with missing attributes, 2,995 crashes were included in the analysis. Of the 2,995 crashes, 1,496 (49.9%) crashes occurred in the before period, and 1,499 (50.1%) crashes occurred in the after period, i.e., after TSP deployment. As indicated in Table 2, the proportion of FI crashes was lower (31.9%) after the deployment of TSP than in the before period (34.2%). This suggests that the deployment of the TSP resulted in the reduction of FI crashes.

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Table 2: Descriptive Statistics of Analysis Variables

Variable	Category	Before TSP Deployment		After TSP Deployment	
		Count	Percent (%)	Count	Percent (%)
Crash characteristics					
Severity *	FI	511	34.2	478	31.9
	PDO	985	65.8	1,021	68.1
Rear-end crashes	1 if rear-end	836	55.9	835	55.7
Angle crashes	1 if angle	334	22.3	320	21.3
Sideswipe	1 if sideswipe	251	16.8	262	17.5
VRU	1 if VRU	47	3.1	43	2.9
Driver characteristics					
Alcohol involved	No	1,474	98.5	1,481	98.8
	Yes	22	1.5	18	1.2
Distraction related	No	1,244	83.2	1,246	83.1
	Yes	252	16.8	253	16.9
Roadway characteristics					
AADT (vpd)	≤ 19,600	1,182	79.0	504	33.6
	> 19,600	314	21.0	995	66.4
Speed limit (mph)	< 40	882	59.0	919	61.3
	≥ 40	614	41.0	580	38.7
Environmental characteristics					
Weather condition	Clear	1,088	72.7	1,218	81.3
	Severe	408	27.3	281	18.7
Surface condition	Dry	1,225	81.9	1,318	87.9
	Wet	271	18.1	181	12.1
Lighting Condition	Daylight	1,017	68.0	1,025	68.4
	Dark	479	32.0	474	31.6
Time of a day	Off-peak	819	54.7	806	53.8
	Peak	677	45.3	693	46.2
TSP Status					
TSP Enabled	No	1,496	49.9	NA	NA
	Yes	NA	NA	1,499	50.1

Note: * represents the response variable; VRU = Vulnerable Road User; vpd = vehicle per day; mph = miles per hour; NA = not applicable.

METHODOLOGY

The binary Bayesian logit model was used to explore the influence of TSP on crash severity. The response variable in the model was crash severity levels (i.e., FI and PDO). Explanatory variables included contributing factors to the severity levels of the crashes. Although the traditional binary logit model is commonly used to address the problem of binary outcomes, prior studies have indicated the existence of unobserved heterogeneity in crash severity modeling (Alnawmasi & Mannering, 2019; Meng et al., 2017; Xiong et al., 2014; H. Zhou et al., 2020). Unobserved heterogeneity may cause individual heterogeneous effects on the response variable (Mannering et al., 2016). Hence, this study used a random effect (RE) modeling approach to account for the unobserved heterogeneity that may exist in the crash dataset, a random effect (RE) modeling approach was used in this study. The RE provides more flexibility in capturing variations within the observed data (Meng et al., 2020; Yu & Abdel-Aty, 2014).

The response variable, considered as a binary variable with a FI crash ($Y = 1$) and a PDO crash ($Y = 0$), can be defined with a vector of explanatory variables X_i, as presented in Equation 1.

$$Y_i = \begin{cases} 1\ for\ FI\ crash \\ 0\ for\ PDO\ crash \end{cases} \tag{1}$$

$$Y_i \sim Bernouli\ (\lambda_i)$$

$$logit\ (\lambda_i) = \beta_o + \beta_j X_i + \varepsilon_i$$

$$\beta_o \beta_j \sim N(0, 10)$$

$$\varepsilon_i \sim N(0, \sigma^2)$$

$$\sigma \sim Half\ Normal\ (0{,}10)$$

where,

λ_i presents the severity function of observation i,
β_j presents the vector of explanatory variables,
$N(0, 10)$ presents the prior distribution of the regression coefficient,
ε_i presents the stochastic error term, and
$Half\ Normal$ (0,10) presents the prior distribution of the disturbance term.

The RE term μ_i was introduced in the model to capture unobserved heterogeneity across the individual observations and was normally distributed across each observation with a mean of zero and a standard deviation of σ_i. The RE μ_i is assumed to be independent of the explanatory variables and the error term, ε_i. Equation 1 was modified to incorporate a RE as expressed in Equation 2.

$$logit\ (\lambda_i) = \beta_o + \beta_j X_i + \varepsilon_i + \mu_i \tag{2}$$

$$\mu_i \sim N(0, \sigma_i)$$

This study used Bayesian inference, which can incorporate prior parameter information, to estimate model parameters. The RE-logit model was estimated in the WinBUGS software using Markov Chain Monte Carlo (MCMC) simulation. In the Bayesian modeling technique, the prior distribution of each model parameter should be specified. In this case, the non-informative priors for the regression coefficients β_o and β_j were specified as the normal distribution with a mean of zero and standard deviation of 10. In the absence of informative priors commonly obtained from previous studies that performed similar analyses, non-informative priors were assigned to the model parameters, a common practice in the Bayesian models (Kruschke, 2013). The non-informative priors impose a minimal influence over the estimates and accept the data characteristics to dominate (Ntzoufras, 2009). The convergence of the MCMC simulations was assessed using the Gelman-Rubin Diagnostic statistic. A visual diagnostics approach was also used to evaluate the chains' convergence, including utilizing each parameter's autocorrelation and trace plots. The 95% Bayesian Credible Interval (BCI) was applied to examine the significance of variables.

RESULTS AND DISCUSSION

Model Results

The binary Bayesian logit model, with RE accounting for unobserved heterogeneity, was used to explore the influence of TSP on the crash severity levels. Table 3 provides the results of the binary Bayesian logit model. As indicated in Table 3, seven independent variables (i.e., TSP enabled, rear-end crashes, sideswipe crashes, vulnerable road users, distraction related, AADT, and the speed limit) were significant at 95% BCI. The negative sign of the model coefficient provides a potential indication of a decrease in the likelihood of a FI crash. On the other hand, a positive coefficient indicates an increase in the likelihood of a FI crash.

Effects of TSP on Crash Severity

As shown in Table 3, when TSP is enabled, the variable coefficient has a negative sign, indicating that when the TSP is enabled it decreases the risk of FI crashes. The odds ratio of TSP enabled was 0.920, suggesting that the deployment of TSP showed a potential decrease in the likelihood of a FI crash by 7.96%. This finding may be attributed to the TSP’s strategy, such as green extension, early red or green truncation, phase rotation, phase insertion, and queue jump, which effectively manage conflicting movements at signalized intersections. When TSP implements a green extension, it facilitates a smooth traffic flow by minimizing the need for abrupt/hard braking at signalized intersections. This not only enhances traffic efficiency but also improves overall traffic safety, thereby reducing the risk of FI crashes.

Similarly, green truncation, when timed with appropriate change and clearance intervals, allows motorists sufficient time to perceive the upcoming red signal and come to a complete stop at the traffic light, ensuring their safety and minimizing potential concerns. Additionally, TSP's ability to reduce stop-and-go movements improves traffic flow and decreases control delay, further enhancing intersection safety. These findings align with previous studies, which also demonstrated a reduction in FI crashes resulting from implementing TSP.

Effects of Other Contributing Factors on Crash Severity

Other contributing factors indicated that crash characteristics, such as rear-end crashes, sideswipe crashes, decreased the risk of being involved in a FI crash. As indicated in Table 3, the odds ratio indicates that rear-end crashes reduce the risk of being involved in a FI crash by 44.3%, while sideswipe crashes reduce it by 83%. Vulnerable road users were found to significantly impact the severity of crashes. Results revealed that angle crashes were associated with a higher risk of a FI crash. Driver characteristics, such as distraction related, were also associated with a higher risk of a FI crash. As noted in Table 3, distracted driving increases the likelihood of a FI crash by 25.7%. This finding was expected since distracted driving are associated with texting or using a global position system (GPS) device, which can increase the severity of crashes.

Table 1: Model Results for TSP Deployment

Variable	Category	Estimate	Est. error	95% BCI		Odds ratio
TSP Status						
TSP Enabled	No					
	Yes	**-0.083**	**0.149**	**-0.394**	**-0.201**	**0.920**
Crash characteristics						
Angle crashes	1 if angle	-0.002	0.141	-0.282	0.268	0.998
Rear-end crashes	1 if rear-end	**-0.586**	**0.132**	**-0.842**	**-0.311**	**0.557**
Sideswipe	1 if sideswipe	**-1.774**	**0.172**	**-2.112**	**-1.437**	**0.170**
VRU	1 if VRU	**2.693**	**0.394**	**1.951**	**3.505**	**14.776**
Driver Characteristics						
Alcohol involved	No					
	Yes	0.38	0.353	-0.324	1.054	1.462
Distraction related	No					
	Yes	**0.229**	**0.108**	**0.025**	**0.434**	**1.257**
Roadway characteristics						
AADT	≤ 19,200					
	> 19,200	**-0.159**	**0.123**	**-0.385**	**-0.091**	**0.853**
Speed limit	< 40					
	≥ 40	**0.199**	**0.09**	**0.019**	**0.371**	**1.220**
Signalized intersection density	Continuous	-0.004	0.130	-0.243	0.266	0.996
Environmental characteristics						
Weather condition	Clear					
	Severe	-0.136	0.133	-0.396	0.119	0.873
Surface condition	Dry					
	Wet	-0.093	0.159	-0.404	0.211	0.911
Lighting condition	Daylight					
	Dark	-0.016	0.098	-0.205	0.171	0.984
Time of a day	Off-peak					
	Peak	0.019	0.088	-0.155	0.186	1.019
Random effects	NA	0.156	0.111	0.014	0.422	
Constant	NA	-0.209	0.163	-0.522	0.11	

Note: bolded values present significant variables; AADT = Average annual daily traffic; TSP = Transit Signal Priority; BCI = Bayesian credible interval; NA = Not applicable; VRU = Vulnerable Road User.

Roadway characteristics such as AADT, and speed limit were found to impact the severity of crashes. The results in Table 3 revealed that when AADT were greater than 19,200 vehicles per day (vpd), crashes that occurred experienced a lower risk of being a FI crash. The odds ratio indicated a 14.7% decrease in the likelihood of a FI crash. A posted speed limit greater than 40 mph was associated with a higher risk of a FI crash. The odds ratio also revealed that higher speeds lead to a higher risk of sustaining more severe crashes. The odds ratio indicated that higher speeds increase the likelihood of a FI crash by 22%. This finding was expected since crashes that occur at higher speeds have a higher impact, causing more severe outcomes.

CONCLUSIONS

This study investigated the impacts of TSP on crash severity. To the best of the authors' knowledge, the safety effectiveness of TSP in terms of crash severity had not been studied prior to this research. The analysis was based on 10 corridors with TSP in Orange and Seminole Counties, Florida. For this study, crash data from the specified corridors for the years 2014 through 2018 were used in the analysis. The binary Bayesian logit model with random effects, which accounts for unobserved heterogeneity, was used in crash severity modeling.

The findings indicate that TSP generally leads to a lower risk of a FI crash. Overall, TSP generally was associated with a lower risk of FI crashes. More specifically, TSP reduced the likelihood of a FI crash by 7.96%. This reduction was statistically significant at a 95% BCI. This finding may be attributed to the TSP's strategy, such as green extension, early red or green truncation, phase rotation, phase insertion, and queue jump, which effectively manage conflicting movements at signalized intersections. For instance, when TSP implements a green extension, it facilitates a smooth traffic flow by minimizing the need for abrupt/hard braking at signalized intersections. Similarly, when green truncation is timed with appropriate change and clearance intervals, it grants motorists ample time to recognize the approaching red signal and safely come to a complete stop at the traffic light. This not only ensures their safety but also minimizes any potential concerns related to sudden stops. Thereby, improving traffic safety and reducing the likelihood of a FI crash.

Other contributing factors to crash severity, including crash characteristics, driver characteristics, crash, roadway geometry, and environmental characteristics, were also investigated. Distracted driving was associated with a higher risk of being involved in a FI crash. This observation was expected since distracted driving are associated with texting or GPS device, which can increase the severity of crashes. Other factors, such as vulnerable road users and speed limit were also associated with a higher risk of a FI crash. In contrast, higher AADT was associated with a lower risk of a FI crash. Additionally, certain crash types, such as rear-end crashes, and sideswipe crashes were associated with lower risk of a FI crash. The findings presented in this study could be helpful to transportation agencies seeking to deploy TSP at corridor level. Also, these results have practical implications for establishing TSP deployment guidelines in lowering the risk of greater crash severity. Moreover, transportation agencies could also use the study results to justify the deployment and expansion of TSP at corridors with high crash severities.

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Toward Equity in Accessing Public Transit: Pattern of Transit Deserts for Disadvantaged Populations

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ABSTRACT

Public transportation accessibility has a remarkable impact on the well-being of marginalized communities, especially those situated in underserved regions. However, disproportionate geographical distribution of transit services often results in disparities in accessing public transportation. Therefore, it is imperative to pinpoint areas where there exists a disparity between transit demand and supply, commonly referred to as "transit deserts," particularly concerning disadvantaged population groups. This study investigates the spatial accessibility of public transit with a specific focus on minority communities in northeastern Illinois, US. To accomplish this, we have introduced a needs gap index, which characterizes the incongruity between transit demand and supply for different demographic groups. Our analysis is based on data from the 2020 American Community Survey, aggregated at the census tract level. The outcomes of our study provide valuable insights into the geographic pattern of transit deserts, considering both the overall population and specific minority groups, encompassing various demographics such as race, age, and income. Notably, our analysis underscores that the Hispanic community experiences the most pronounced underservice compared to other racial groups. Furthermore, this study underscores the significance of concentrating on particular demographic cohorts when identifying transit deserts, instead of solely focusing on the entire population. By doing so, we aspire to provide a more comprehensive understanding of the disparities related to transit deserts in the study area. Ultimately, our findings can be instrumental in aiding policymakers and transit authorities in formulating strategies to enhance transit accessibility and promote equity within the public transportation system throughout the region.

BACKGROUND

Public transportation systems have a crucial role in enriching the lives of individuals, offering them avenues for employment, education, and healthcare access, ultimately contributing to a better quality of life (Ermagun and Tilahun 2020). Prioritizing the establishment of equitable access to these services emerges as a fundamental imperative for cultivating a community characterized by fairness and inclusivity, a sentiment underscored by Veeder (2019). These groups often grapple with social barriers, predominantly due to residing in neighborhoods with limited mobility alternatives (Walker 2008). However, recent evidence accentuates a disconcerting reality where these vulnerable segments consistently face insufficient transit service provision, encountering restricted accessibility to public transit services (Khojastehpour et al. 2022; Veeder 2019). The Economic Research division of the US Department of Agriculture (USDA) highlights the extent of this challenge, revealing that 40% of residents in rural areas grapple with a lack of access to public transportation (Brown and Stommes 2004). Furthermore, the USDA underscores the formidable challenges faced by rural low-income residents, hindered in benefiting from diverse social services due to inadequate and inaccessible public transportation options.

Analyzing disparities in accessing transit services is a crucial step in advancing equity within the realm of public transportation. In the United States, the Federal Transit Administration mandates transit agencies to scrutinize inequities and variations among different user groups. As a fulfilment to this requirement, spatial analysis techniques are extensively utilized, recognizing the inherently spatial nature of public transit planning (Asghrpour et al. 2023) . Within this framework, needs gap analysis is a prevalent method used to pinpoint spatial mismatches between the demand and supply of transit services (Currie 2010; Fransen et al. 2015; Javadinasr et al. 2022b). This approach involves utilizing socio-demographic data as a proxy for estimating transit demand, while the spatial accessibility of transit services represents the supply side. Consequently, the needs gap index functions as a metric for gauging the spatial misalignment between transit demand and supply. This analytical process aids in identifying regions underserved in terms of transit services through a spatial comparison of needs gaps. As an illustrative application, Currie (2010) applied needs gap analysis to identify underserved areas with a higher proportion of non-vehicle owner residents in Australia. They established a transit service frequency measure for each stop based on the total number of service arrivals per week, subsequently integrating this measure with the access distance to compute a supply index.

Our research focuses on Northeastern Illinois, a region characterized by a diverse population, including African Americans, Hispanics, and various minority groups. A study by the Brookings Institution (Grabinsky and Reeves 2015) highlights that the Chicago region, within Northeastern Illinois, holds the distinction of being the most racially segregated metropolitan area in the United States. Notably, 25% of African Americans and 17% of Hispanics reside in high-poverty localities, contrasting sharply with the 7.7% of White residents facing similar circumstances. Given this stark reality, there is a pressing need to characterize racial disparities in assessing transit accessibility equity within this culturally rich and diverse locale. Surprisingly, there is a notable absence of comprehensive studies examining transit accessibility equity in this specific region (Ermagun and Tilahun 2020). To address the deep-seated segregation, it becomes crucial to delve into racial disparities in transit accessibility equity within Northeastern Illinois. This study aims to provide invaluable insights, facilitating the identification of potential measures to advance equity. The outcomes of this research will be instrumental for policymakers and transit agencies. The findings will aid in pinpointing transit deserts and comprehending the disparities in accessing transit services. Ultimately, the study contributes to the broader goal of fostering equity within the transit infrastructure of Northeastern Illinois.

The concept of transit deserts, originally introduced by Jiao and Dillivan (2013), draws inspiration from the idea of food deserts. Food deserts refer to areas where residents face challenges in accessing healthy food. Similarly, transit deserts are characterized by regions where the availability of public transit falls significantly below the demand for it. Expanding on this notion, Aman and Smith-Colin (2020) conducted a study in the City of Dallas, focusing on social class dynamics at the census tract level to identify transit deserts. Building upon the insights gained from this previous research, our current study employs the needs gap approach to discern transit deserts within the northeastern Illinois region. Notably, we place a specific emphasis on investigating racial disparities in accessing transit services. By adopting this analytical framework, our research aims to make a substantial contribution to identifying and understanding transit deserts in this specific geographical area. This investigation holds significant potential to provide valuable insights that can inform strategic measures to bridge the gap between the demand for and supply of transit services. Ultimately, our research aligns with the broader objective of promoting social equity and enhancing the quality of life for all community members by facilitating improved access to essential transit resources.

DATA

This study aims to delineate transit deserts specific to various racial groups in northeastern Illinois, as illustrated in Figure 1, which serves as our designated study region. The study region encompasses seven counties: Cook, McHenry, Lake, Kane, DuPage, Kendall, and Will. To fulfil the research objectives, diverse datasets were employed, including information on the public transit system (locations of the transit stations) and socio-demographic data for the residents at the census tract level within the study region. In the subsequent sections, we present an in-depth overview of our dataset, providing detailed insights into its composition and specifics.

Public Transit System

We sourced data on public transit across various modes, including bus, rail, and Metra (commuter rail), from diverse channels within the study region. Concerning bus services, the Chicago Transit Authority (CTA) and Pace operate in the city and suburban areas, respectively. To establish the bus network, we amalgamated information from two databases: one from the CTA for the year 2022, comprising details on 10,819 bus stops, and another from the Pace Service Area Online Map (Katsambas 2022) containing 8,015 Pace bus stops. These datasets include stop locations, names, and route numbers. For the rail network, the CTA rail database (Chicago Transit Authority 2022) was utilized, offering information on 144 rail stations. Additionally, data on 247 Metra stations were extracted from the City of Chicago's database (City of Chicago 2012).

Socio-demographic Information

The socio-demographic information for the study region was collected at the census tract level using the American Community Survey (ACS) 2020 database, featuring 5-year estimates. Previous studies have used ACS information in similar analyses (Mirjalili et al. 2022). Table 1 presents a detailed overview of the summary statistics derived from this dataset. The table encompasses three key metrics: the population count for each social group, the proportion of each group relative to the total population, and the coefficient of variation (CoV) observed across census tracts. Regarding income classifications, individuals earning below $1,250 per month are categorized as falling below the poverty line. Moreover, in terms of disability status, individuals facing mobility limitations are identified as disabled. The CoV captures the level of variation for an indicator across census tracts implying that a lower CoV corresponds to a more homogeneous indicator. For instance, the highest variance is related to race while the lowest variance is attributed to age and gender.

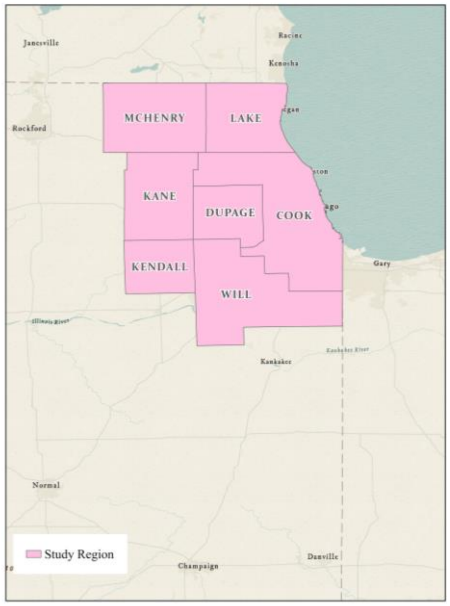


Figure 1: Northeastern Illinois (7 counties in Illinois, U.S.)

Table 1: Statistics of demographic information of the residents in northeastern Illinois

Cohorts		Total Count	% of Total Population	CoV* across census tracts
Total Population		5,169,517	100%	0.470
Gender	Female	2,659,831	51%	0.467
	Male	2,509,686	49%	0.537
Age	under 24	1,584,584	30%	0.637
	25 to 64	2,827,245	55%	0.533
	over 65	757,688	15%	0.638
Race	Asian	413,271	8%	1.733
	Black	1,205,824	23%	1.387
	White	2,345,983	44%	0.843
	Other	1,204,439	25%	1.347
	Hispanic	1,382,778	26%	1.193
	Non-Hispanic	3,786,739	74%	0.570
Income	below Poverty Line	695,076	14%	1.079
	above Poverty Line	4,474,441	86%	0.495
Disability	Disabled	249,385	8%	0.938
	Non-disabled	4,920,132	92%	0.531

* Coefficient of Variation

METHODOLOGY

Transit deserts demarcate geographic regions where the provisioning of public transit services falls significantly short from the associated demand for transit. Within the scope of this investigation, we employed a needs gap analysis to delineate transit deserts with a focus on distinct racial groups. As explicated in Eq. (1), the needs gap index is formulated by delineating the differential between the demand and supply of transit services. The resultant metric for each census tract (i) and demographic cohort (g), denoted as $Needs\ Gap_i^g$, is normalized within a 1-100 range. Importantly, a proximity to 100 in the needs gap implies a higher mismatch level between the demand for transit services and the supply.

As per the framework proposed by Carleton and Porter (2018), transit demand is delineated as the population of transit dependent people within a given cohort and census tract. In the context of Eq. (1), denoted as D_i^g, it signifies the population within a specific cohort (g) and census tract (i) that depends on transit services (termed as transit demand). The calculation of this transit-dependent population involves considering the proportion of individuals within the total population (P_i^g) for a given cohort and census tract who fall below the poverty line and do not own personal vehicles. This proportion is expressed as ρ_i^g within the relationship.

Furthermore, in alignment with Carleton and Porter (2018), our conceptualization of transit supply involves considering the resident population of a specific demographic cohort in each census tract that possesses an adequate level of transit accessibility from their residence. We computed the supplied population of demographic group 'g' in census tract i, denoted as S_i^g, by evaluating the proportion of each census tract's area A_i falling within the catchment buffer zones of transit stations, represented as A_i^b. The creation of these buffer zones took into account a walking distance of 5 to 15 minutes, depending on the transit mode considered (Carleton and Porter 2018; Javadinasr et al. 2022a; Sina et al. 2023b). To illustrate, Figure 2 showcases the catchment buffer zones for the Metra mode in comparison to the distribution of racial groups in the study region. The figure highlights that southern Cook County has a higher concentration of the African American community. Conversely, Hispanic and Asian communities exhibit multiple clusters in Cook, Kane, DuPage, and Lake Counties.

Moreover, similar to Carleton and Porter (2018), we define transit supply as the resident population of a specific cohort in each census tract having an appropriate level of transit accessibility (from their home location). We calculated the supplied population of cohort g in census tract i, S_i^g, based on the proportion of area of each census tract A_i falling into catchment buffer zones of transit stations A_i^b. To create the buffer zones, we considered 5 to 15 minutes walking distance, based on the transit mode (Carleton and Porter 2018; Asgharpour et al. 2023). In case of overlapped buffer zones, the union of overlapping buffer zones are considered to avoid duplication. As an instance, Figure 2 illustrates the catchment buffer zones of Metra mode compared to the distribution of race groups in the study region. As shown, southern Cook County has a higher proportion of African American community. On the other hand, Hispanic and Asian communities have several clusters in Cook, Kane, DuPage, and Lake Counties.

$$Needs\ Gap_i^g \sim D_i^g - S_i^g = \rho_i^g \cdot P_i^g - \frac{A_i^b}{A_i} \cdot P_i^g = \left(\rho_i^g - \frac{A_i^b}{A_i}\right) \cdot P_i^g \quad (1)$$

RESULTS AND DISCUSSION

We conducted an in-depth examination of transit accessibility within our study region by computing the needs gap index for all census tracts. This index functions as a yardstick for pinpointing transit deserts, where the availability of public transit significantly lags behind the demand. To illustrate these disparities, we crafted heatmaps that visually represent the spatial dispersion of needs gap values. Clusters of census tracts displaying elevated needs gap values signify areas characterized as transit deserts, as evidenced by the work of (Aman and Smith-Colin 2020). The significance of these heatmaps extends to an exploration of the distribution of underserved populations among various major racial groups within our study area, with a specific focus on Hispanic, African American, and Asian communities. This analytical process involved computing the needs gap for the overall population as a baseline against which the disparities for each racial group were evaluated.

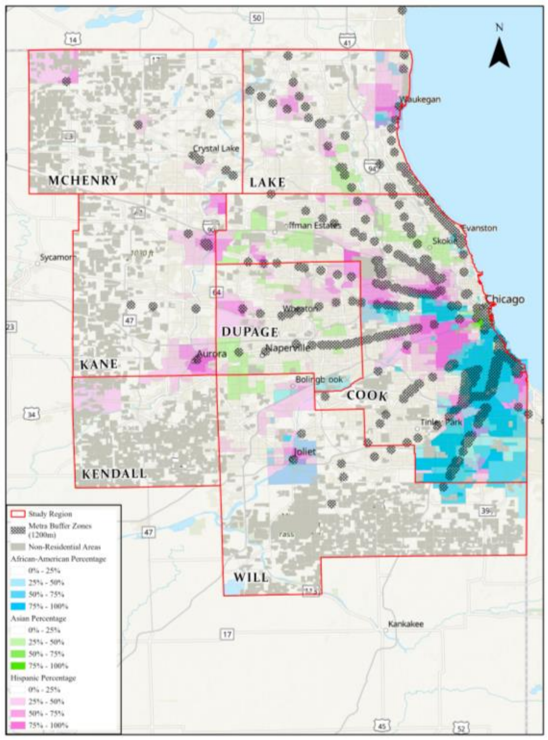
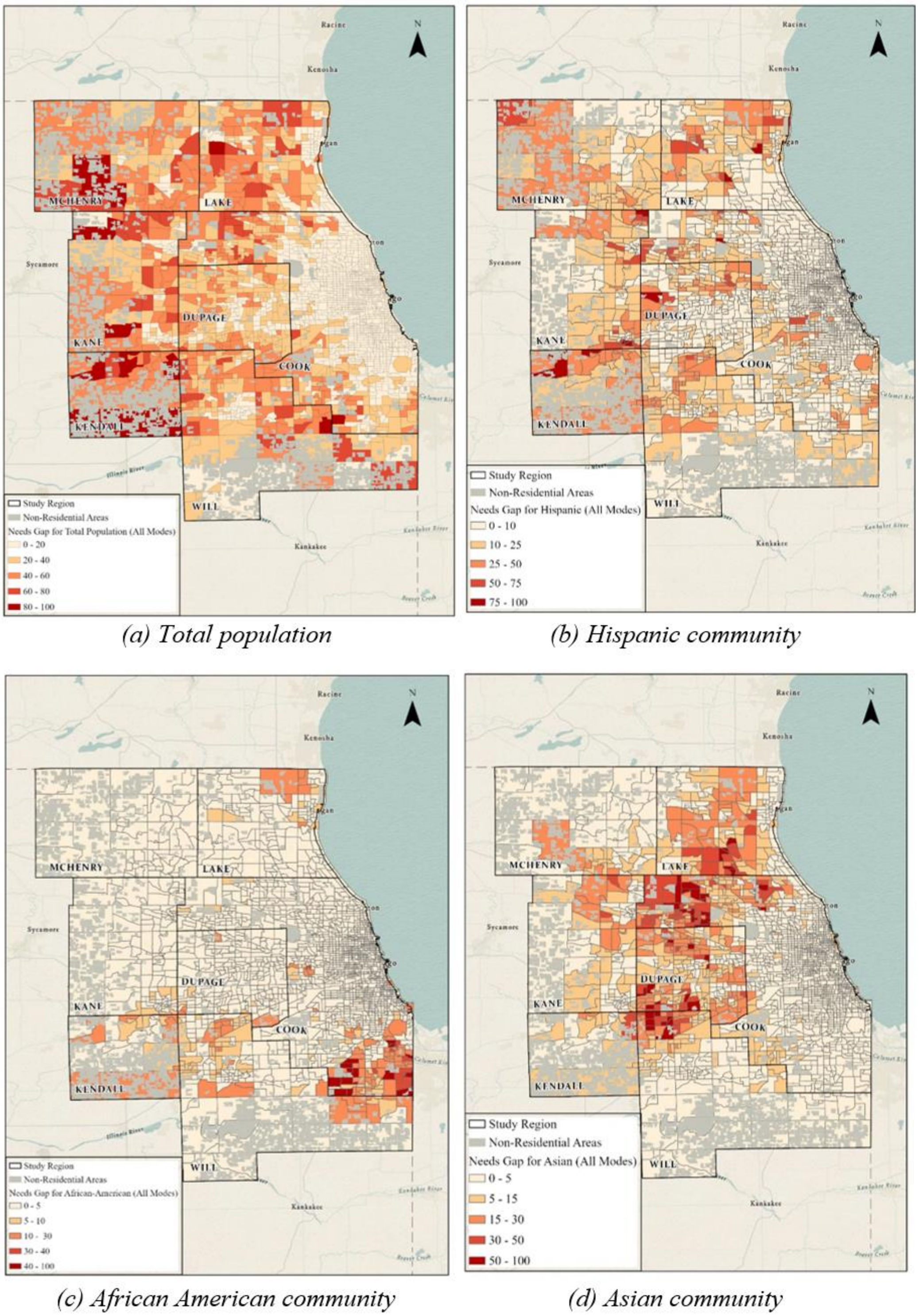


Figure 2: Buffer zones of Metra compared to distribution of race groups in the study region.

Figure 3 portrays the findings from our analysis of gaps in transit needs concerning (a) the entire population, (b) the Hispanic community, (c) the African American community, and (d) the Asian community. The evaluation of transit accessibility equality, regardless of social class, is evident in the needs gap assessment encompassing the entire population. The results for the overall population highlight transit deserts primarily situated in three western counties within the study region—namely, Kendall, McHenry, and Kane. It is noteworthy that suburban areas consistently encounter inadequate transit services, while the City of Chicago and central Cook County exhibit comparatively superior transit accessibility.

Shifting our focus to the Hispanic community, the examination underscores pronounced transit deserts in the northern part of Kendall County, the eastern regions of Kane County, the western areas of DuPage County, and Lake County. This pattern closely aligns with the observed trend for the entire population, where suburban locales consistently exhibit lower availability of transit services, especially when contrasted with the more adequately served transit network in the Chicago area. This emphasizes a consistent challenge in ensuring equitable transit access for both the broader population and the specific Hispanic community across various suburban regions.



(a) Total population *(b) Hispanic community*

(c) African American community *(d) Asian community*

Figure 3: Heatmap of Needs gap index within study region

Concerning the African American community, regions in northern Will, southern Cook, Kendall, and Lake counties emerge as transit deserts for this specific racial group. Notably, southern Cook County stands out as the most severely underserved area for this community, with the highest concentration of African American residents. It's essential to highlight that the transit desert characteristics for the African American community significantly differ from those observed in the analysis of the entire population. The distinctiveness in transit deserts underscores the need for targeted strategies to address the specific accessibility challenges faced by the African American community in these regions.

Concluding our analysis, transit deserts are noticeable within the Asian community, particularly in the central and northern regions of the study area. These areas encompass locations in DuPage, Lake, northern Will, and northwestern Cook County. Importantly, the transit deserts identified within the Asian community present notable distinctions when compared to those identified for the overall population. This underscores the nuanced nature of transit accessibility challenges, revealing specific patterns and variations within different racial or ethnic groups.

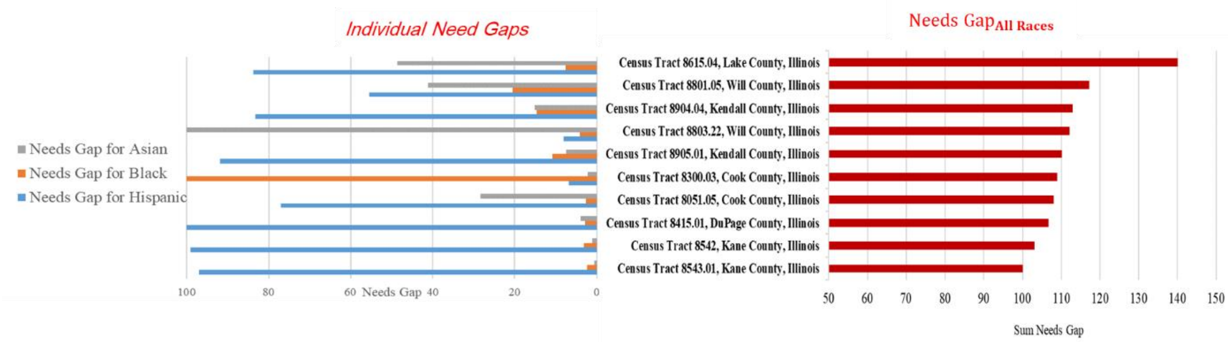


Figure 4: Comparison of needs gap among race groups

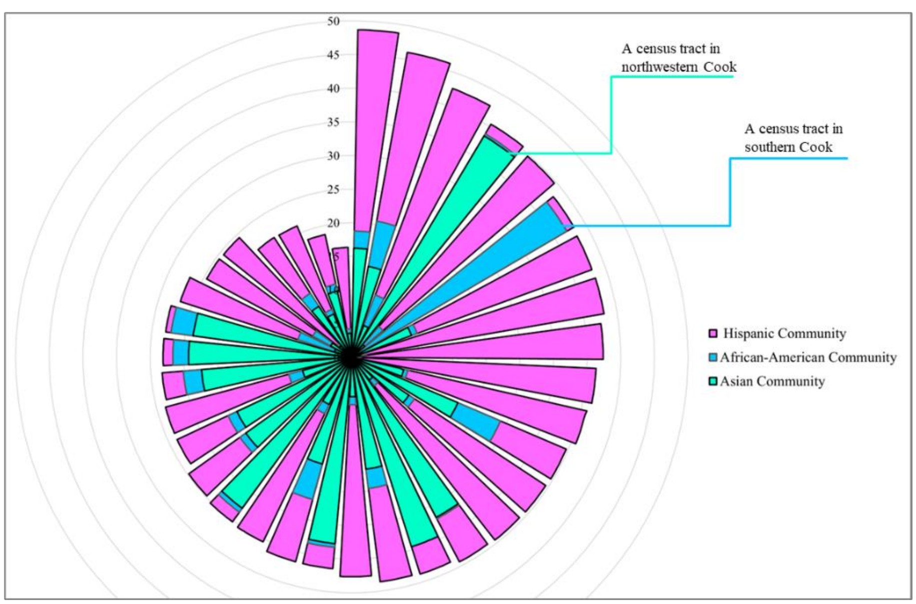


Figure 5: Needs Gap of Top 90% Percentile of Census Tracts and Associated Share of each Community.

In our quest to pinpoint the racial minority facing the most pronounced transit deserts, we conducted a ranking of census tracts based on the descending order of the average needs gap index across three distinct race groups. The results, showcased in Figure 4 on the right-side chart, highlight the top 10 census tracts with the highest average needs gap, along with their corresponding needs gap values for each race cohort. Notably, with the exception of one census tract in Cook County, the needs gap for the Hispanic community significantly contributes to the overall average needs gap across all tracts. This observation suggests that the disparity between transit supply and demand is particularly acute for the Hispanic community in comparison to other racial groups. The data underscores the critical nature of transit accessibility challenges specifically faced by the Hispanic community in the identified census tracts, shedding light on the urgent need for targeted interventions to address these disparities.

A similar pattern can be derived from Figure 5. In this figure, every radial bar represents the average needs gap value for a census tract and the contribution of each race group. As shown, in general, Hispanic community has the highest contribution to the average needs gap index implying that this community more reside in the areas with more unmet transit demand. However, in certain regions (e.g., northwestern Cook and southern Cook) Asian and African American communities are also underserved.

CONCLUSION

This study aims to delineate transit deserts, with a specific focus on racial disparities, within the racially segregated region of northeastern Illinois, encompassing Cook, McHenry, Lake, Kane, DuPage, Kendall, and Will counties. Employing a needs gap analysis based on American Community Survey data aggregated at the census tract level, we assess the mismatch between transit demand and supply using the needs gap index. Calculating this index for various cases, including the total population and distinct racial groups (Hispanic, African American, and Asian), we identify transit deserts for each scenario.

The results of the needs gap index for the total population reveal that transit deserts are primarily situated in the suburban Chicago area, specifically in Kendall, McHenry, and Kane Counties. This pattern suggests a general underservice of transit facilities for residents in suburban areas, irrespective of their racial background. In contrast, when focusing on the Hispanic community, transit deserts emerge in northern Kendall, eastern Kane, western DuPage, and Lake Counties. For the African American community, the most critical transit desert is identified in southern Cook County. Lastly, transit deserts associated with the Asian race group are predominantly concentrated in DuPage, Lake, northern Will, and northwestern Cook County.

These findings underscore the significance of accounting for racial disparities in identifying transit deserts, as they differ substantially from those observed for the total population. For example, while transit deserts for the overall population are concentrated in the Chicago suburban area, those for the African American community are predominantly located in the southern region. This distinction emphasizes that improving transit accessibility for specific racial groups, such as the African American community, necessitates targeted interventions beyond a broad, population-wide focus.

Comparing the needs gap results across the three racial minorities, it becomes evident that the Hispanic community is the most underserved race group in terms of accessing transit services in northeastern Illinois. Consequently, regional planners should consider implementing targeted policies, such as supplementing existing transit services with additional offerings, to address this racial gap effectively. In conclusion, our findings emphasize the imperative for coordinated efforts from transit agencies, policymakers, and community stakeholders to devise targeted solutions that bridge the gap between transit supply and demand. This collaborative approach aims to ensure equitable access to public transportation opportunities for all residents, regardless of their race or socioeconomic status, fostering a more just and inclusive urban environment conducive to the thriving success of all community members.

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Examining NHTS Data: The Correlation between Health, Gender, Racial Background, Physical Activity, and Bicycle Usage

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ABSTRACT

Bicycling is experiencing rapid growth as a mode of transportation in the United States. Cities are actively working to enhance the safety and appeal of biking, with these initiatives easing traffic congestion on roads and in public transit, promoting a cleaner environment, and encouraging physical activity. A better understanding of cyclists' travel habits could assist researchers in examining trip frequency in various scenarios. To address this, the study employed a regression model to analyze the correlation between bikers' race, physical activity, health, and gender as independent variables and the number of biking trips as the dependent variable. The findings revealed a significant correlation between health, gender, and physical activity, serving as independent variables, and the frequency of cycling trips, the dependent variable. However, there appears to be a minimal connection between race and the frequency of cycling journeys. This research provides valuable insights for transportation planners and decision-makers, enhancing their understanding of how health, gender, race, and physical activity impact cycling trip frequency.

INTRODUCTION

Addressing pollution and mitigating the challenges posed by heavy traffic in urban areas, along with recent transportation policies, have prompted individuals to favor more sustainable modes of transportation. These include walking, cycling, or using public transport, as opposed to relying on private cars (Šťastná et al., 2018). The most noticeable trend for the 2017 National Household Transportation Survey (NHTS) is that although private automobiles remain the dominant travel mode in American cities, the share of car trips has decreased slightly and steadily since its peak in 2001. In contrast, the share of transit, non-motorized, and taxicab (including ride-hailing) trips has steadily increased. Aside from this overall trend, there are essential variations in travel behaviors across income, home ownership, ethnicity, gender, age, and life-cycle stages (*Socioeconomics of Urban Travel in the U.S.*, n.d.). In recent years, cycling has seen a new beginning, triggered by the thrust towards greater environmental consciousness. In cities where cycling shares are low, efforts are being made to promote cycling as a viable mode of transport (Patel et al., 2020). Many U.S. cities are investing in making a more bike-friendly environment to reduce auto dependency. Studies have shown that improving bike lanes enhance bike users' perceived safety and comfort, but whether it also shifts mode choice toward biking remains unaddressed mainly (Hwang & Guhathakurta, 2023). Bicyclists face safety challenges due to inadequate cycling infrastructure and a lack of awareness among motorists, increasing the risk of accidents. Nighttime cycling adds to safety concerns, highlighting the need for improved lighting and reflective measures to enhance cyclist safety.

The enormous advantages of active transportation lead the transportation research focus toward enhancing walking and biking trips (Singh et al., 2022). Active transportation is usually defined as a human-powered mode of transportation, such as walking or bicycling from one place to another. Biking is an ideal solution for bridging first and last-mile gaps in transit riders' journeys. It offers sustainability, reduces environmental impact, promotes physical activity, and provides a cost-effective and convenient means to connect transit stops and final destinations efficiently. Integrating biking into transit systems addresses environmental, health, and economic considerations comprehensively. Physically inactive lifestyles are a major public health challenge, and research in the transportation field on influences on the choice to walk and bike may provide guidance toward solutions (Sallis et al., 2004). Active transportation modes have received increasing attention as sustainable transportation methods. These modes will help alleviate traffic congestion and transportation-related pollution (Wang & Zhou, 2017; Zhang & Mi, 2018). Bike sharing is rapidly growing and developing as a sustainable and green mode in some cities worldwide (Fishman, 2016; O'brien et al., 2014). Moreover, cycling is also considered one of the most environmentally friendly modes of transportation (Ansariyar et al., 2021). Active transportation (AT), commonly known as walking and bicycling, has positive physical and mental health benefits for all participating. Although participation in AT has health benefits, there are disparities based on various demographics (race/ethnicity, gender identity, age, education/income) (Elliott et al., 2022). Though active transportation through bicycling and walking can increase physical activity and positively affect health, factors that influence people's decisions to commute using active transportation modes remain underexplored and often fail to capture equity-related barriers. Increases in active transportation during the COVID-19 pandemic call for a better understanding of these influences (Cusack, 2021; Teixeira et al., 2023). People who walk or bike for transportation have physical activity built into their days; however, few prior studies exist to demonstrate how active transportation may support physical activity over time. People who walk or bike for transportation are more likely to maintain or increase their physical activity. This further proves the importance of creating built environments and policies supporting active transportation (Stroope et al., 2022).

his study aims to assess how health, age, race, physical activity, and gender impact the frequency of bike rides, exploring individual and collective influences on biking engagement. It seeks to identify correlations and patterns among these factors, specifically investigating the roles of health, racial backgrounds, physical activity, and gender in determining participation levels in bike riding. The study's novelty lies in its comprehensive analysis of these factors and its recognition of the potential complexity and interplay among them, aiming to provide a nuanced understanding of the factors shaping biking behavior.

BACKGROUND

As the need to shift our transportation habits towards active modes such as walking and bicycling becomes increasingly recognized, there is a growing awareness of the potential benefits for both our health and the environment. In order to assist policymakers, urban planners, and local administrators in making informed decisions, it is crucial to quantitatively assess the wide-ranging impacts of such a transition (Kamyab Moghaddam, n.d., 2017). The impacts of this change encompass numerous aspects, some of which pose significant challenges when it comes to evaluation. For instance, effects on the social fabric of communities, the overall well-being of the population, and even the crime rate can be complex to measure accurately. However, the health impacts of increased physical activity (PA) and reductions in air pollution hold particular importance. Evaluating their associated benefits, particularly in terms of reduced mortality, can be reliably assessed (de Bruijn et al., 2009; Pabayo et al., 2012; Rabl & de Nazelle, 2012).

Understanding the key factors influencing bicycle commuting is essential for developing effective policies toward a cyclable city (Muñoz et al., 2016). Several factors may influence an individual's decision to choose biking as a mode of transportation. Convenience: Biking can be a convenient option for short to medium distances, especially in urban areas where traffic and parking can be challenging. Health benefits: Biking is a low-impact exercise that can improve cardiovascular health, muscle strength, and overall fitness. Environmental concerns: Biking is an eco-friendly mode of transportation that does not produce greenhouse gas emissions, making it an attractive option for people concerned about climate change. Cost: Biking can be a cost-effective option, as it does not require fuel or maintenance costs associated with a car. Social factors: Biking can be a social activity that allows people to connect with others in their community and meet new people. Time savings: In some cases, biking may be faster than other modes of transportation, especially during peak traffic hours. Personal preferences: As with any transportation choice, personal preferences such as comfort, safety, and ease of use may influence an individual's decision to choose biking (Kim & Lee, 2023; McDonald, 2008; Pucher et al., 2010).

Li et al., in their study, explored the multifaceted roles of public bike-sharing systems, categorizing trips into leisure and transportation. Their study revealed spatial and temporal variations in bike-sharing patterns, highlighting factors such as residential densities and transit routes that influence trip types (Li et al., 2024). Hasnine et al., in their investigation, explored factors influencing the physical health condition and trip distance of e-bike users in Toronto, Canada, using a survey. Employing a Bivariate Ordered Probit model, their study revealed that e-bikers from low-income households face higher health risks, and individuals making longer e-bike trips tend to be in excellent health. The findings suggest targeted strategies for different demographics, emphasizing their effectiveness in promoting e-bike usage (Hasnine et al., 2020). The effectiveness of various factors, such as race, physical activity, health, and gender, time and distance and accessibility on bike riding as a means of transportation, can significantly influence individuals' engagement in this mode of transport. Understanding the effectiveness of these factors is essential for designing targeted interventions, policies, and initiatives that promote bike riding across diverse populations. By considering the unique circumstances and experiences associated with race, physical activity, health, and gender, transportation planners and policymakers can develop strategies to address barriers, enhance accessibility, and create supportive environments that encourage and enable more individuals to choose biking as a sustainable mode of transportation.(DeMaio, 2009; Pucher et al., 2010).

Race, physical activity, health, and gender have been selected as important factors for bike riding. These factors were chosen due to their potential influence on individuals' engagement in using bikes as a means of transportation. Race highlights equity's importance and ensures equal access to cycling opportunities across diverse communities. Physical activity is significant in recognizing the motivation and ability of biking, particularly for those with limited accessibility. Health contributes to an individual's knowledge and awareness of the benefits associated with bike riding. Finally, gender acknowledges the potential differences in participation rates and challenges faced by individuals of different genders. By examining these factors, we can gain insights into the complexities that shape bike riding behaviors and develop strategies to promote inclusive and accessible bike-friendly environments for all individuals.

DATA AND METHODOLOGY

Data

The NHTS is an inventory of daily travel by the American public (noncommercial or personal travel). The Federal Highway Administration (FHWA) Office of Policy has conducted the survey since 1969. It is the only source of national data that allows trend analysis of travel behavior by U.S. residents that includes travel data by all means of transportation and for all purposes. In contrast, the census collects detailed geographic data on workers and the usual commute characteristics. The NHTS includes information about the daily commute by workers in the sample and all other travel by all people in each sampled household, including specifics about the household vehicles used for travel. The data are widely used in energy and safety analysis, active travel and health, equity and underserved population studies, and to assess the impact of transportation policies (McGuckin, 2021). Using the NHTS 2017 dataset, the study explores the relationship between a biker's race, physical activity, health, and gender as independent variables to the frequency of their trips as a dependent variable., as well as the reasons for not biking more. Two main factors will be examined: the influence of infrastructure on biking frequency, and safety concerns as a deterrent to biking more often.

Health: In this study, the variable of Health Level is categorized into five distinct levels, as follows: excellent, very good, good, fair and poor. By organizing health levels into these five categories, we can capture a range of health backgrounds and provide a comprehensive analysis of how health influences bike riding as a means of transportation.

Physical activity: This study classified the variable of physical activity into two categories:

First category with people who has rarely or never engaged in any physical activity. The second category with people who has some light or moderate physical activities or some vigorous physical activities. This categorization enables the exploration of physical activity. It allows for an assessment of how physical activity influence the likelihood of individuals engaging in bike riding.

Gender: Gender can play a role in bike riding rates and preferences. Cultural norms, safety concerns, and infrastructure design may influence gender disparities in bike riding as a means of transportation. In this study, the gender variable was categorized into two distinct categories: male and female.

Race: In this study, the variable of race is considered and categorized into four major groups: White, Black, Asian and other. By including these specific racial categories, the study aims to explore potential variations, experiences, and influences related to bike riding as a dependent variable within different racial groups.

METHODOLOGY

The regression model in question was developed to analyze the relationship between bikers' race, physical activity, health, and gender as independent variables and the number of biking trips as the dependent variable. In other words, the model was designed to determine if there is a relationship between an individual's level of health, age, and the number of biking trips. Regression analysis is a statistical technique that is commonly used to identify and understand the relationships between variables. In this case, the model examines how changes in health level, race, gender and physical activity influence the number of biking trips an individual takes. By using this model, researchers can identify patterns and trends in the data and determine which variables are most strongly associated with changes in the number of biking trips taken.

Many studies use statistical analysis to develop policies to improve traffic safety, investigate and forecast travel behavior, and pinpoint deficiencies in transportation policy (Javid & Sadeghvaziri, 2023b, 2023a; Sadeghvaziri et al., 2023). The model can generally be expressed as Equation 1, where n represents the sample size, y denotes the dependent variable, X is the explanatory variable, β is the unknown regression coefficients, and ε is the error term.

$$y = X\beta + \varepsilon \tag{1}$$

$$r_i = y_i - \hat{y}_i \quad i=1, 2, \ldots, n \tag{2}$$

$$\hat{\beta}_{OLS} = \arg\min_{\beta} \sum_{i=1}^{n} r_i^2(\beta) \tag{3}$$

Based on the estimated coefficients β ̂, the dependent variable can be estimated as y ̂. The residual ri is then calculated for each observation based on Equation 2. A typical regression analysis relies on the Ordinary Least Squares (OLS) method, which computes the model's coefficients to minimize the sum of squared residuals, as indicated in Equation 3.

ANALYSIS

The statistical analysis involves a regression model, which considers variables such as gender, health, race, and physical activity. The outcomes of this regression model can be observed in Table 1.

TABLE 1. Results of the Regression Model

Category	Estimate	Std. Error	P-Value
(Intercept)	0.36134	0.01835	2.99135E-86
Health	-0.11724	0.00348	5.3067E-248
Gender	-0.16840	0.00636	4.6799E-154
Race	0.00116	0.00024	2.2202E-06
Physical Activity	0.24221	0.00509	0

The study's findings reveal a substantial relationship between the Level of health, gender, and physical activity, all of which serve as independent variables, and the number of biking trips, which acts as the dependent variable. Participants' Level of Health was found to have a discernible impact on their biking behavior, with individuals having healthier condition tending to engage in more biking trips compared to those with lower fair and poor health levels. Furthermore, gender was identified as another influential factor, indicating differences in biking patterns between male and female participants. The results suggest that one gender might be more inclined to take biking trips than the other. Additionally, physical activity emerged as a significant predictor of biking activity. Those physically active were more likely to participate in biking trips than individuals less physically active. The analysis revealed that race, considered an independent variable, has a a limited correlation with the Number of Biking trips, which serves as the dependent variable.

The findings of the study indicate that (Figure 1) a higher percentage of healthy people (11.32%) have used biking as a mode of transportation, compared to a lower percentage of less healthy people (3.02%).

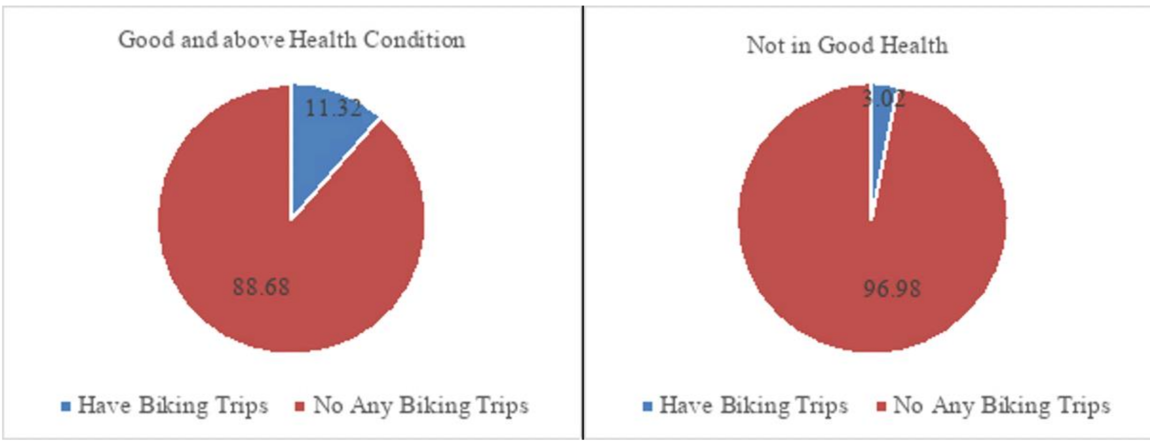

Figure 1. Chart showing biking usage as a mode of transportation among healthy people and people not in good health.

According to the data results (Figure 2), people with physical activity, have had more biking trips (19.3%) compared to the people not physically active (6.33%).

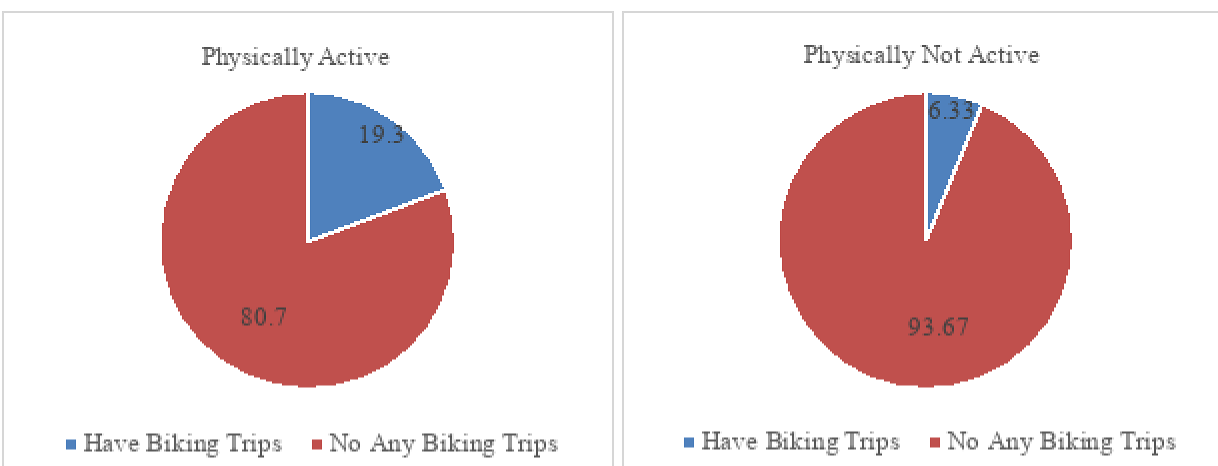

Figure 2. Chart showing biking usage as a mode of transportation among physically active people and people physically not active.

Figure 3 shows that a higher percentage of male individuals (13.59%) have used biking as a mode of transportation, compared to a lower percentage of female individuals (8.27%).

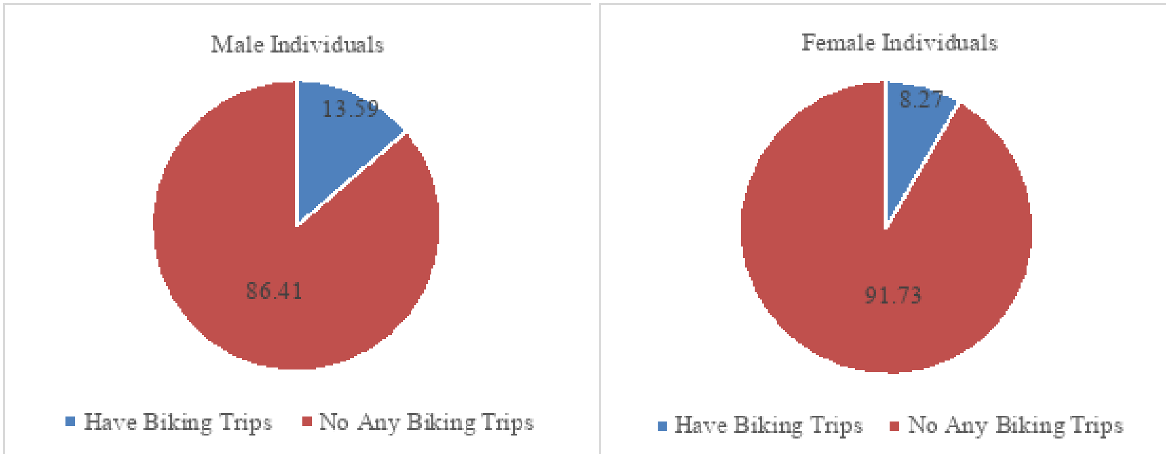

Figure 3. Chart showing biking usage as a mode of transportation among male individuals and female individuals.

Figure 4 shows the comparison of the percentage for biking usage among white people (10.72%), Asian people (10.28%), Black people (9.08%) and Other categories (13.96%) for biking as a mode of transportation.

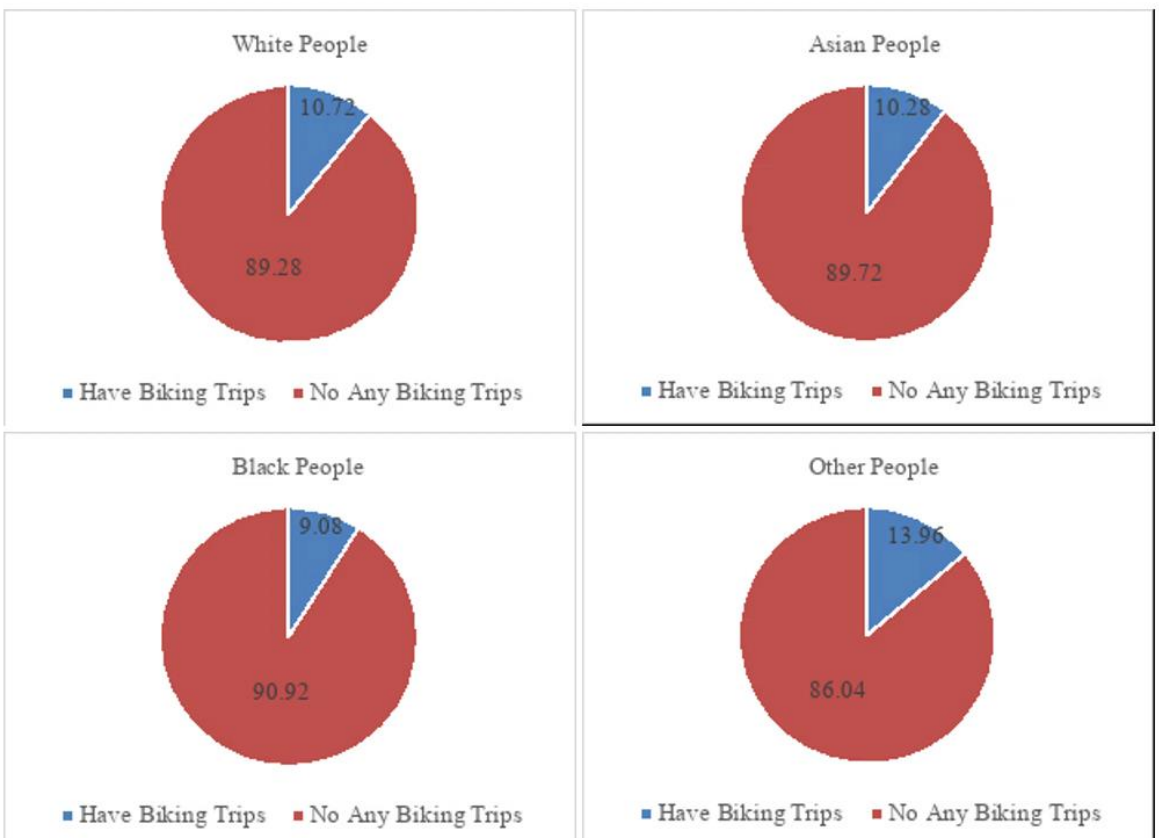

Figure 4. Chart showing biking usage as a mode of transportation among White, Asian, Black and Other People.

The statistical analysis involves a regression model, which considers variables such as Gender, Health, Race, and Physical Activity. The outcomes of this regression model can be observed in Table 1.

One of the variables investigated in this study is Health. The number of trips was measured as an independent variable versus the health level as a dependent variable. Table 2 shows the results of this data investigation.

TABLE 2. Biking Trips Based on Level of Health

Health Category	Average # of People	Having Any Bike Trips
Excellent	76557	13821
Very Good	95045	9219
Good	64668	3717
Fair	21716	713
Poor	5992	125

The number of biking trips as a dependent variable was measured versus two categories of physically active or not active is shown on Table 3.

TABLE 3. Baking Trips Based on Physical Activity Level

Physically Active Category	Average # of People	Having Any Bike Trips
Active	73115	14115
Not Active	3381	214

Biking trip results as a dependent variable have been investigated versus two independent variables of Gender and Race, and the results are shown in Table 4 and Table 5.

TABLE 4. Baking Trips Based on Gender

Age Category	Average # of People	Having Any Bike Trips
Female	139200	11517
Male	124576	16932

TABLE 5. Baking Trips Based on Race

Race Category	Average # of People	Having Any Bike Trips
White	214080	22957
Black	19415	1763
Asian	12043	1239
Other	14677	2050

RESULTS AND DISCUSSION

The regression analysis aimed to unravel the intricate relationships between the number of biking trips and key demographic and lifestyle variables. The findings, summarized in Table 1, offer significant insights into the factors shaping biking behavior. The intercept, indicating the baseline number of biking trips when all variables are zero, was statistically significant (p-value = 2.99135E-86), emphasizing the existence of a fundamental expectation for biking activity.

Health exhibited a negative relationship with biking trips (coefficient = -0.11724, p-value = 5.3067E-248), implying that as health improves, the frequency of biking tends to decrease. Similarly, gender showed a negative impact (coefficient = -0.16840, p-value = 4.6799E-154), suggesting variations in biking habits based on gender. These findings underscore the need for targeted interventions to encourage biking among healthier individuals and address potential gender-based disparities in biking engagement. Race with a positive coefficient of 0.00116 (p-value = 2.2202E-06), indicating that certain racial groups are associated with an increase in biking trips. These results prompt further exploration into the cultural and social aspects influencing biking preferences among different racial communities. Physical activity demonstrated a robust positive effect on biking, with a substantial coefficient of 0.24221 and a highly significant p-value of 0. This highlights the pivotal role of physical activity in fostering a biking-friendly lifestyle. Encouraging individuals to adopt more active lifestyles may consequently contribute to a higher frequency of biking trips.

The study found that a higher percentage of healthy individuals (11.32%) used biking as a mode of transportation compared to an individual with fair or poor health condition (3.02%). The results also indicate that physically active individuals have a higher frequency of biking trips (19.3%) compared to individuals who are not physically active (6.33%). The data suggest that a higher physically active is associated with a greater likelihood of engaging in bike riding as a means of transportation. These findings suggest that physical activity plays a significant role in determining an individual’s likelihood to use biking as a mode of transportation and that may be a more significant factor than health in determining the number of biking trips an individual takes. Specifically, the study found that the difference between healthy individuals (11.32%) and fair and poor health individuals (3.02%) was smaller compared to the difference between physically active (19.3%) and not physically active (6.33%). The study’s results reveal a notable disparity in the utilization of biking as a mode of transportation between male and female individuals. The data indicate that a higher percentage of males (13.59%) have chosen biking as a means of transportation compared to a lower percentage of females (8.27%). Possible explanations for this discrepancy include differences in perceived safety, social norms, and accessibility to cycling infrastructure. Personal preferences, cultural factors, and socialization may also contribute to the variation in bike riding participation between genders. Further research and analysis are necessary to investigate the underlying reasons for these gender-based variations in bike riding as a transportation mode. Understanding these factors can help guide the development of targeted interventions and initiatives to promote equitable and inclusive bike riding opportunities for individuals of all genders. The study’s results also include a comparison of biking usage percentages among different racial groups. The data reveals that among the participants, white individuals had a biking usage rate of 10.72%, while Asian individuals had a slightly lower biking usage rate of 10.28% as a mode of transportation; however, the analysis shows that the relationship between race and the frequency of individuals biking trip is not significant.

SUMMARY AND CONCLUSION

In this study, we have investigated the correlations between a biker's gender, level of health, race, and physical activity concerning the frequency of their trips using a bike for transportation.

It is essential to acknowledge that these four factors are just a few that can influence an individual's decision to use a bike for transportation. Moreover, correlations between these factors and biking habits may differ based on various other aspects, such as age, geographic location, and access to infrastructure. For instance, younger individuals might be more inclined to use bikes for transportation than older individuals, regardless of their healthily attainment. Therefore, when interpreting the results, it is crucial to consider the interplay of multiple factors in shaping biking behavior. According to the study's findings, the level of health, physical activity, gender and race are important factors influencing individuals' decisions to use bikes as a means of transportation.

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On the Impact of Bus Dwelling on Macroscopic Fundamental Diagrams

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ABSTRACT

Network macroscopic fundamental diagrams (MFDs) have recently been shown to exist in real-world urban traffic networks. When present, MFDs can be used to model traffic dynamics within an urban network by dividing the network into a set of spatially compact homogeneous regions and tracking the average level of congestion in each region. Existing analytical methods to estimate MFD mostly focus on the behavior of a single type of vehicle and do not capture the patterns of mixed traffic (e.g., cars and buses). The existence of buses matters since a bus will block the movements of other vehicles when it dwells at the bus stop. This paper proposes an analytical method to estimate the impact of bus dwelling on a network's MFD based on the network's geometric features, traffic control strategies, and bus operation parameters, and validates the performance of the proposed method using simulations based on microscopic traffic models. Comparisons of the analytical and simulation results show that the proposed analytical method can generally provide a good estimate of the lower bound and upper bound of the network's MFD.

INTRODUCTION

Empirical data in Yokohama (Geroliminis & Daganzo, 2008) shows that a well-defined relationship between space-mean flow and density emerges after spatially aggregating the highly scattered plots of flow vs. density from individual loop detectors. Such relationships are commonly referred to as network Macroscopic Fundamental Diagrams or MFDs. When present, MFDs can be used to model traffic dynamics within an urban network by dividing the network into a set of spatially compact homogeneous regions and tracking the average level of congestion in each region (Daganzo, 2007). A variety of regional traffic control studies have been developed using this MFD-based representation of urban traffic networks. Recent relevant examples in the literature include perimeter metering control (Haddad & Zheng, 2020; Keyvan-Ekbatani et al., 2019; Sirmatel & Geroliminis, 2021), pricing (Genser & Kouvelas, 2022; Loder et al., 2022; Yang et al., 2019), and street network design (Deprator et al., 2017; Xu & Gayah, 2023).

While most literature about MFDs focused on behavior of a single vehicle type, a few studies extended the models to incorporate a mixed stream of cars and buses (or a bi-modal system). MFDs of bi-modal systems have been first studied using empirical data. (Dakic & Menendez, 2018) proposed Lagrangian estimation methods for the space-mean speed based on loop detector data or floating car data which account for the configuration of the public transport system. (Liu & Szeto, 2020) proposed a data-driven and nonparametric analytical approach to estimate the stochastic MFD in a bi-modal transportation system composed of cars and public transit. However, these methods provided limited insight into how input parameters (bus operation parameters, signal timings, block length) affect the functional form of the network MFD.

Some work has also been done to estimate the functional form of an MFD given the network properties (Daganzo & Geroliminis, 2008; Daganzo & Lehe, 2016; Xu et al., 2020).The first attempt abstracted a roadway network into a ring road and applied variational theory (VT) to estimate the underlying flow-density relationship on the ring as a function of block length, signal cycle properties, and fundamental diagram of individual links (Daganzo & Geroliminis, 2008). However, most analytical methods to estimate MFD focus on the behavior of a single vehicle type. Only a few efforts were made to extend the VT to analytically estimate MFDs of networks with the type of temporary bottlenecks that might be introduced by multimodal traffic (Daganzo & Knoop, 2016; Hans et al., 2015). (Dakic et al., 2020) first extended the existing VT approach by introducing a stochastic shortest path algorithm to analytically estimate the MFD for bi-modal urban corridors. This method could capture the effects of stochastic moving bus bottlenecks and the correlation of bus arrival times. However, the validation in this paper did not show if the method can well capture the variation of MFD due to buses.

In light of this, this paper proposes an analytical method to estimate impact of bus dwelling on a network's MFD based on its geometric features, traffic control strategies, and bus operation parameters, and validates the performance of the method using microscopic simulations. This method builds on method in (Laval & Castrillón, 2015) that estimates MFD with stochastic network features by applying the renewal theory to the method of cuts (Daganzo & Geroliminis, 2008). As will be shown here, dwelling buses serve as temporary bottlenecks affecting the paths of moving observers in the method of cuts. An algorithm to consider all possible paths in the method of cuts affected by the stochastic bus arrival (and dwelling) at the bus stops is then proposed that allows the implementation of the stochastic method of cuts for MFD estimation.

The remainder of this paper is organized as follows. First, we propose an analytical method to estimate the MFD when buses are present. Then, the validation of the proposed analytical method via microscopic simulations is shown. Next, we investigate the impact of the variation of bus dwell time on the MFD. Finally, some discussion and concluding remarks are provided.

METHODOLOGY

Assumptions

In this section, we consider a network of one-way streets consisting of blocks with the same length L. Traffic on the roads is assumed to obey a triangular fundamental diagram with a common free flow speed v_f [mile/hour], capacity Q_m [veh/(hour.lane)] and jam density k_j [veh/(mile.lane)]. For simplicity, all intersections are set to be signalized with a cycle length of C, a red time of R, a green time of G, and a signal offset of O.

Assume that bus stops are located either immediately upstream or downstream of each signalized intersection; such a situation is common as bus stops tend to be placed at or near intersections for maximum bus user accessibility. Additionally, compared to a mid-block bus stop, a far-side bus stop has the advantage of minimizing conflicts between right-turning vehicles and buses and minimizing sight distance problems on approaches to the intersection. A near-side stop has the advantage of minimizing interferences when traffic is heavy on the far side of the intersection and resulting in the width of the intersection being available for the driver to pull away from curbs (Transit Cooperative Research Program (TCRP), 1996).

Regardless of whether placed at the far- or near-side, buses can arrive at the bus stops only during the green phase of a cycle. For simplicity, we assume that buses travel at the same speed as passenger cars so buses will not serve as moving bottlenecks. This assumption is reasonable in urban traffic networks as all vehicles have to follow a comparatively low speed limit. An example of this can be found in (Dakic et al., 2020) where no evidence of moving bus bottlenecks was found on a bi-modal corridor in Zurich, Switzerland. Moreover, it is also assumed that buses arrive at each stop with some average headway, n_b, expressed in the number of signal cycles. Finally, bus dwell time (T_d) at the bus stops is assumed to be fixed. This latter assumption is used to facilitate the analytical estimation process; however, the estimated MFDs hold remarkably well in the case where this assumption is relaxed, as will be demonstrated in the numerical results section.

Alternative Path for A Single-lane Network

Families of Moving Observers

In this paper, we expand the stochastic method of cuts (Laval & Castrillón, 2015) to account for the impact of stochastic bus arrival. This method relies on estimating the travel time (Y) of moving observers and the number of vehicles passing a set of observers (X) as they travel through a corridor between departures at the start of a green signal period. Three families of moving observers (Daganzo & Geroliminis, 2008) are used to find the bounding cuts for the MFD. (a) Family 1: Observers of family 1 are stationary observers that start and stay at a given intersection. (b) Family 2: Moving observers of family 2 move forward with free flow speed v_f until being stopped by a signal red phase. (c) Family 3: Moving observers of family 3 travel backward with backward wave speed w until being stopped by a signal red phase.

Type of Alternative Paths

Moving observers of each family set out from the beginning of a green phase at an intersection, travel forward/stay stationary/travel backward until being stopped by a red phase at an intersection, and stay there until the end of this red phase. This path, starting from the beginning of a green phase and ending at the end of a red phase, is called an "alternative path" in this paper. There are multiple alternative paths even if moving observers of the same family start from the same intersection at the same time. Take moving observer of family 2 as an example:

<u>Type 1: travel until being stopped by an intersection red phase</u>

This is the basic path type in which a moving observer will not stop until encountering a red phase at a downstream intersection.

<u>Type 2: travel until being stopped by an extended red phase of an intersection</u>

In this path type, the moving observer is stopped by an artificially extended red time at some intersection for the purpose of evaluating the maximum passing rate (Daganzo & Geroliminis, 2008). Note that there are two alternative paths belonging to this type in the given time-space diagram in Figure 1a, but only one is illustrated.

<u>Type 3: temporarily stopped by a dwelling bus</u>

For paths of type 1 and type 2, moving observers are not impacted by the dwelling buses at the bus stop. For type 3, a moving observer stops behind a dwelling bus, travels forward again when the bus leaves the bus stop, and is finally stopped by a red phase at a downstream intersection.

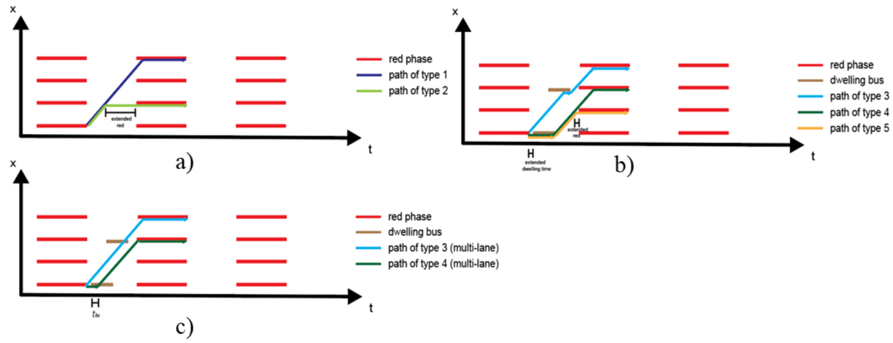


Figure 1. a) paths without a bus involved; b) paths with a bus involved; c) change of path in a multi-lane network.

Type 4: temporarily stopped by the extended dwell time of a bus

In type 4, a moving observer is stopped by artificially extended bus dwell time (imagine a bus arrives early and dwells longer) and then travels forward again as soon as the bus leaves until being stopped by a red phase of an intersection. Note that if a moving observer is first stopped by the extended bus dwell time at the intersection where he sets out, and then stopped by the extended red phase, this moving observer is same as family 1 in (Daganzo & Geroliminis, 2008).

Type 5: combination

Type 5 is a combination of path types 2, 3, and 4.

Observed Flow Along Alternative Path

Once all possible alternative paths are identified, we can then determine the travel time (Y_i) and the number of vehicles (X_i) passing the observer taking each path i. This information can be further used to determine the flow-density relationship (cut) provided by each path i. According to (Laval & Castrillón, 2015), the MFD bound $q_i\ (k)$ generated by an alternative path i is given by:

$$q_i(k) = \frac{X_i}{Y_i} = \begin{cases} \frac{Q_m.G_r}{C} & , i \text{ is a stationary path} \\ \frac{Q_m.G_r + L.k}{Y_i} & , i \text{ is a forward path} \\ \frac{Q_m.G_r + L.(k_j - k)}{Y_i} & , i \text{ is a backward path} \end{cases} \quad (1)$$

where G_r is the total remaining green (sum of all extended red and extended bus dwell time) and L is the total distance traveled by the moving observer.

Alternative Path for A Multi-lane Network

Differences from A Single-lane Network

In this section, we consider a network composed of roads with N lanes. Assume the sum of all lanes has a capacity of Q_m and jam density of k_j. When a bus dwells at a bus stop, it will temporarily block one lane and create a bottleneck with a maximum passing rate of $\frac{(N-1)}{N}.Q_m$. In order to estimate the MFD of such a multi-lane network, some modifications are needed for path type 3 and path type 4 discussed in the previous section.

In a one-lane network, a moving observer will stop behind a dwelling bus and travel forward again when the bus leaves the bus stop. In a multi-lane network, a moving observer stopped by a dwelling bus can leave the bus stop at any time and does not have to wait until the bus leaves. For example, the moving observer following path 3 in Figure 1c may leave the bus stop immediately after it arrives, and by doing so it would observe fewer vehicles than the moving observer following path 3 in Figure 1b. This is because, in a multi-lane network, when the moving observer following path 3 in Figure 1b stops at the bus stop, it will observe vehicles passing through it using the lanes without dwelling buses. As a result, the path in Figure 1c will provide a tighter bound in the MFD estimation due to same duration Y_i but lower cost X_i. Similarly, the moving observer following path 4 in Figure 1c only stops at the bus stop for a small amount of time (denoted by t_{bs}) and will observe $\frac{(N-1)}{N}.Q_m.(T_d - t_{bs})$ vehicles less than the moving observer following path 4 in Figure 1b. Therefore, the moving observer following path 4 in Figure 1c provides a tighter bound. Seeing this, we modify type 3 and 4 of the alternative paths as follows:

In type 3, a moving observer stays behind a dwelling bus, travel forward again after any amount of time $t_{bs} \in [0, T_d]$, and is finally stopped by a red phase at a downstream intersection.

In type 4, a moving observer is stopped by artificially extended bus dwell time and then travels forward again after any amount of time $t_{bs} \in [0, T_d]$ until being stopped by a red phase of an intersection.

Flow of Alternative Path

In a multi-lane network, when a moving observer stops at a bus stop, it will still observe vehicles passing it with a maximum rate of $\frac{(N-1)}{N}.Q_m$. Therefore, Equation 1 is modified as follows:

$$q_i(k) = \frac{X_i}{Y_i} = \begin{cases} \dfrac{Q_m.G_r + \frac{(N-1)}{N}.Q_m.t_{bs}}{C} & ,i\ is\ a\ stationary\ path \\ \dfrac{Q_m.G_r + \frac{(N-1)}{N}.Q_m.t_{bs} + L.k}{Y_i} & ,i\ is\ a\ forward\ path \\ \dfrac{Q_m.G_r + \frac{(N-1)}{N}.Q_m.t_{bs} + L.(k_j - k)}{Y_i} & ,i\ is\ a\ backward\ path \end{cases} \quad (2)$$

where N is the number of lanes and t_{bs} is the time that a moving observer stays at a bus stop (shown in Figure 1c). Note that the unit of Q_m and k_j are capacity and jam density of the entire road instead of one lane.

Minimum Cut for Each Family

Average Minimum Cut

If buses are not considered, then we can simply use Equation 1 and Equation 2 to find the path that has the minimum flow for each family, which we call the shortest path. This is the minimum cut associated with that family, which is the same as in (Daganzo & Geroliminis, 2008). However, when buses are considered, different locations of buses in the time-space diagram will generate different cases. For example, in a single-lane network, though the bus arrives at different times, Figure 2a is considered to be equivalent to Figure 2b since they have the same number and type of alternative paths. However, Figure 2a is considered to be different from Figure 2c as there is a total of four alternative paths in Figure 2a but only two in Figure 2c. Figure 2c is different from Figure 2d as a moving observer can travel maximum of two blocks in Figure 2c but only 1 in Figure 2d. We need to consider different cases respectively as they have different shortest paths.

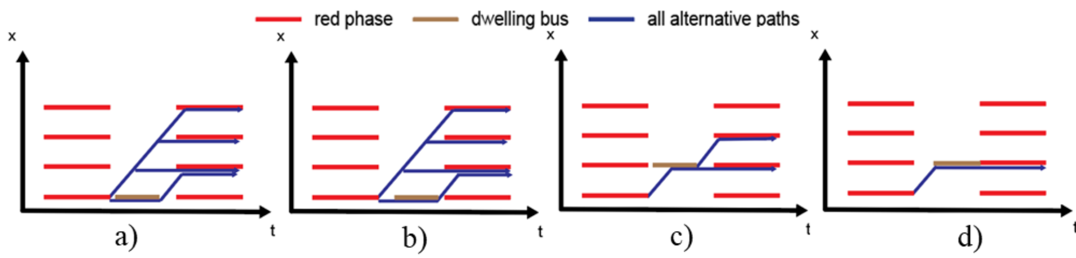


Figure 2. Four Example cases

When all cases are found, the cuts generated by each alternative path i in each case m can be calculated directly using Equation 1. Then the shortest path and the corresponding minimum cut in each case j ($q_{min_j}(k)$) can be determined by:

$$q_{min_m}(k) = \min_{i \in I_m} q_i(k) \tag{3}$$

where I_m is the set of all alternative paths in case m.

Note that since the bus headway is uniformly distributed in the green phase, the remaining green time G_r will follow a uniform distribution and so is $q_i(k)$ since $q_i(k)$ is linearly related to G_r according to Equation 1. Therefore, for the same case m in which G_r may be different but the number of alternative paths does not change (e.g., Figure 2a and Figure 2b), $q_i(k)$ is given by:

$$q_i(k) = \frac{q_i(k, G_{r_{min}}) + q_i(k, G_{r_{max}})}{2} \tag{4}$$

where $G_{r_{min}}$ and $G_{r_{max}}$ are the minimum and maximum values that G_r can take in case m, $q_i(k, G_{r_{min}})$, and $q_i(k, G_{r_{max}})$ are the corresponding flow calculated from Equation 1 using $G_{r_{min}}$ and $G_{r_{max}}$, respectively.

Finally, the average minimum cut $\overline{q_f}(k)$ and variance $var_{q_f(k)}$ of the minimum for family f is given by:

$$\overline{q_f}(k) = \sum_{m \in M} p_m \cdot q_{min_m}(k) \tag{5}$$

$$var_{q_f(k)} = \sum_{m \in M} p_m \cdot \left(q_{min_m}(k) - \overline{q_f}(k)\right)^2 \tag{6}$$

where M is the set of all cases in family f.

Algorithm to Find All Cases for Family 2 and Family 3

Here we provide a general algorithm to find all different cases under a given setting by considering all locations of the bus in the time-space diagram that results in different numbers and types of alternative paths. Take family 2 (forward observer) in a single-lane network as an example:

To begin with, we calculate the number of maximum blocks that a moving observer can travel if no bus is involved (n_{fmax}) by:

$$n_{fmax} = min\{n_f : \frac{n_f.l}{v_f.C} - \frac{n_f.O}{C} - \left\lfloor \frac{n_f.l}{v_f.C} - \frac{n_f.O}{C} \right\rfloor \geq \frac{G}{C}\} \tag{7}$$

Then calculate flow q^0 of the shortest path if no bus is involved (case 0)

$$q^0 = \min_{i \in I_0} \frac{Q_m.G_{r_i} + n_i l.k}{Y_i} \tag{8}$$

where I_0 is the set of all alternative paths in case 0.

Then let Y^0 be the duration of the shortest path. Here we only consider maximum of 1 bus:

$$p_1 = p.(1-p)^{n_{fmax}-1} \tag{9}$$

$$p_0 = (1-p)^{n_{fmax}} \approx 1 - n_{fmax}.p_1 \tag{10}$$

where p_0 is the probability for the case when no bus is involved, p_1 is the probability for the case when the bus is located at intersection n ($n = 1,2,\dots,n_{fmax}$), and $p = 1/n_b$ is the probability of bus arrival at an intersection since we assume that buses arrive every n_b cycles on average. An approximation is made in Equation 10 since we only consider maximum of one bus.

Then, the following steps are taken. Let n denote the number of intersections away from the intersection that a moving observer set out. We start at intersection $n = 0$:

<u>Step 1:</u>

If $n = n_{fmax} - 1$, go to step 4; otherwise, set case $m = 1$. In this step, we consider the cases when a bus is present but has no effect on the moving observer (type 1 and type 2 may exist). The probability of this case and the corresponding minimum flow of all alternative paths are:

$$p_m^n = p_1.\frac{\max\{0, n.l/v_f - n.O - T_d\}}{G} \tag{11}$$

$$q_m^n = q_0 \tag{12}$$

The associated duration Y_m^n is simply Y^0.

Step 2:

Set case $m = 2$. In this step, we consider cases when moving observers can be stopped by the bus (type 2 and type 3 may exist). Let t_{bg} denote the time of the beginning of bus dwelling with respect to the beginning of the green time. Set $t_{bg} = \max\{0, n.l/v_f - n.O - T_d\}$ (time when bus starts to affect the moving observer)

Step 2-1: Find the minimum time Δt that t_{bg} needs to increase before one case switches to the next case:

$$\Delta t = \begin{cases} G - t_{bg}, & if\ t_{bg} \geq G - T_d \\ \min\{\Delta t: |n_1(t_{bg} + \Delta t) - n_1(t_{bg})| > 0\}, & otherwise \end{cases} \tag{13}$$

where $n_1(t)$ is a function given by:

$$n_1(t) = \min\{n_f: \frac{n_f.l/v_f - n_f.O + (t_{bg} + T_d - n.l/v_f + n_f.O)}{C} - \left\lfloor \frac{n_f.l/v_f - n_f.O + (t_{bg} + T_d - n.l/v_f + n_f.O)}{C} \right\rfloor \geq \frac{G}{C}\} \tag{14}$$

Step 2-2: Calculate the probability of this case m and the corresponding minimum flow of all alternative paths:

$$p_m^n = p_1.\frac{\Delta t}{G} \tag{15}$$

$$q_m^n = \min_{i \in I_m^n} \frac{Q_m.G_{r_i} + n_i l.k}{Y_i} \tag{16}$$

where I_m^n is the set of all alternative paths in case m at intersection n assuming the beginning of bus dwelling is $\frac{t_{bg} + (t_{bg} + \Delta t)}{2}$.

Let Y_m^n be the duration of the shortest path in case m at intersection n.

Step 2-3: Set $m = m + 1$ and $t_{bg} = t_{bg} + \Delta t$. Check if all cases at the current intersection are considered: if $t_{bg} \geq G$, set $n = n + 1$, return to step 1; otherwise, check if all cases involving being stopped by bus are considered: if $t_{bg} \geq n.\frac{l}{v_f} - n.O$, go to step 3; otherwise, return to step 2-1.

Step 3:

In this step, we consider cases when moving observers can be stopped by the extended bus dwell time (type 1, type 2, type 4, and type 5 may exist).

Step 3-1: same as step 2-1.

Step 3-2: same as step 2-2 except that the set I_m^n contains different types of paths.

Step 3-3: Set $m = m + 1$ and $t_{bg} = t_{bg} + \Delta t$. Check if all cases at current intersection are considered: if $t_{bg} \geq G$, set $n = n + 1$, return to step 1; otherwise, return to step 3-1.

Step 4:

Finally, apply Equation 5 and Equation 6 to calculate the average minimum cut $\overline{q_f}(k)$ of this family f and the corresponding variance $var_{q_f}(k)$:

$$\overline{q_f}(k) = \sum_{n=0}^{n_{fmax}} \sum_m p_m^n . q_m^n \tag{17}$$

$$var_{q_f}(k) = \sum_{n=0}^{n_{fmax}} \sum_m p_m^n . \left(q_m^n - \overline{q_f}(k)\right)^2 \tag{18}$$

And the average duration of shortest paths of all cases $\bar{Y}(k)$ is given by:

$$\bar{Y}_f(k) = \sum_{n=0}^{n_{fmax}} \sum_m p_m^n . Y_m^n \tag{19}$$

Cuts to MFD

From above, we know that the minimum cut (flow of the shortest path) for each family follows some distribution with mean $\overline{q_f}(k)$ and variance $var_{q_f(k)}$. If a moving observer always takes the shortest path, set out again at the end of the shortest path (end of a red phase), and travels for a long time T, this process is a renewal process and can be used to calculate the lower bound for the cuts of each family. From (Laval & Castrillón, 2015), the distribution $F_f(q)$ of $q_f(k)$ is normal with mean $\overline{q_f}(k)$ and variance $var_{q_f(k)}/t$, where $q_f(k)$ is the average minimum cut for family f, $var_{q_f(k)}$ is the variance of minimum cut for family f, and t the aggregation interval (time interval for the calculation of network density and flow). Finally, the flow at a given density k is given by the minimum of the family minimum cuts. Therefore, the cdf of the network flow is given by:

$$F_{q(k)}(q) = 1 - (1 - F_1(q))\,(1 - F_2(q))\,(1 - F_3(q)) \tag{20}$$

where $F_1(q)$, $F_2(q)$, and $F_3(q)$ are the cdf of cut for family 1, family 2, and family 3.

SIMULATION VALIDATION

Comparison of Analytical and Simulation Results

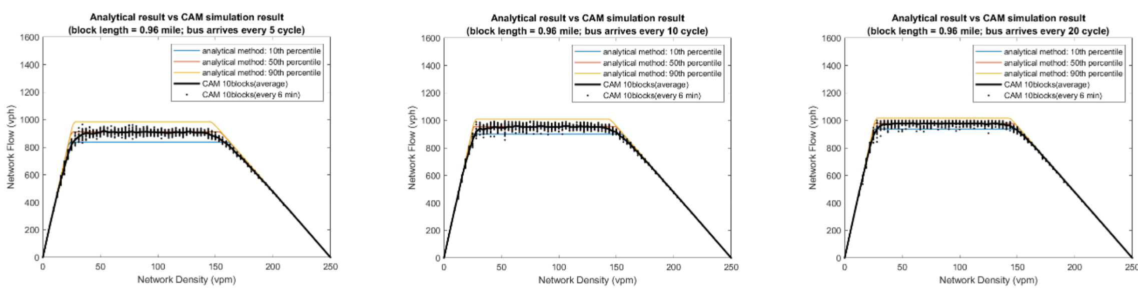
Single-lane Network

In this section, the analytical results of a single-lane network are compared with the cellular automata model (CAM) simulation results of a 10-block ring network. Each block is 0.96 mile in length and has one travel lane on which traffic is assumed to obey a triangular fundamental diagram with a free flow speed (40 mile/hour), capacity (2000 vehicle/hour), and jam density (250 vehicle/mile). Each block is separated with a signalized intersection that has a cycle length of 90 sec, green time of 45 sec, and no offset.

Figure 3 shows the analytically obtained MFDs of a single-lane network and the simulated flow-density relationships of a single-lane network for various bus headways. In each figure, the

10th, 50th, and 90th percentile values of the analytically derived MFD are compared to the observed flow-density relationship obtained from the CAM simulations. In all cases shown and tested, the observed flow-density pairs generally fall between the 10th and 90th percent confidence interval values except for the “near-capacity” regimes, which indicates good consistency between the analytical model and simulation results. For the left and right “near-capacity” regimes, the observed flow is lower than the analytical flow because vehicles are unevenly distributed across the streets due to stochastic bus arrivals. When the network is approaching capacity, some streets are in free flow while some streets are at capacity. As a result, the average flow is lower than the flow when vehicles are evenly distributed. Likewise, when the network starts to get congested, some streets are congested while some streets are at capacity, leading to a lower average flow.

In addition, the average of the observed flow-density pairs (black curve) overlaps well with the 50th percentile curve (orange curve), especially for cases with lower bus headways. This is due to the assumption that a moving observer will encounter at most 1 bus in an alternative path in the analytical methodology, which holds more often when bus arrivals are less frequent.



a) **b)** **c)**

Figure 3. MFD of a single-lane network with buses arriving: a) every 5 cycle; b) every 10 cycle; c) every 20 cycle.

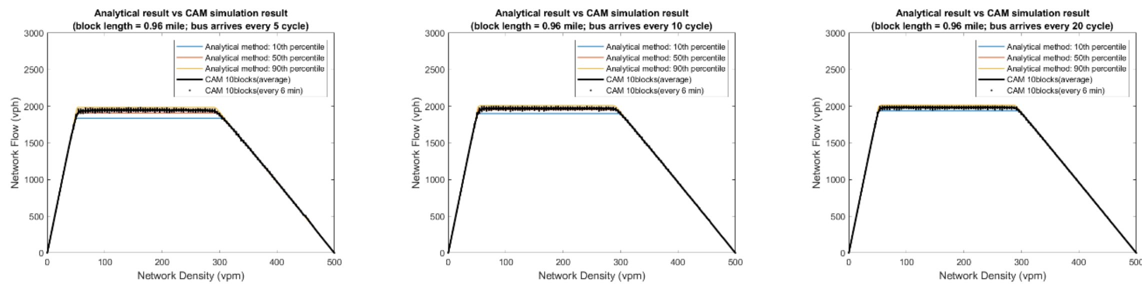
Multi-lane Network

The analytically derived MFD of a 2-lane network is also compared with the MFD obtained using CAM simulations. The same network as in the previous section is simulated except that each block now has two lanes. When a bus dwells at the bus stop, it will temporarily block one lane and reduce the capacity of the street to half.

Figure 4 shows the analytically obtained MFDs and the simulated flow-density relationships for various bus headways. Similar to the results of a single-lane network, the observed flow-density pairs generally fall between the 10th and 90th percent confidence interval values except for the “near-capacity” regimes, which indicates good consistency between the analytical model and simulation results. Moreover, as buses arrive less frequently, MFD from simulations matches more with the 50th percentile curve developed from the analytical method.

Impact of Bus Dwell Time Variation

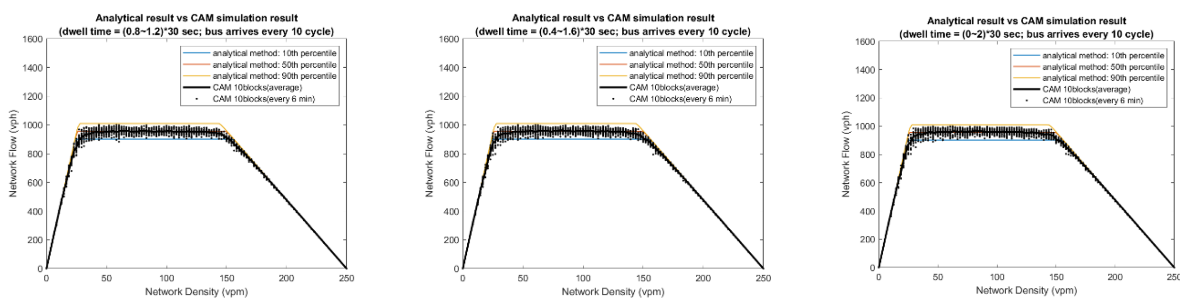
The proposed methodology assumes that the bus dwell time is fixed. In this section, we demonstrate that this assumption does not greatly affect the accuracy of the analytically estimated MFD even when bus dwell time varies, even if it does so quite considerably.



a) b) c)

Figure 4. MFD of a two-lane network with buses arriving: a) every 5 cycle; b) every 10 cycle; c) every 20 cycle.

Figure 5 compares the MFDs analytically obtained assuming fixed dwell time (T_d) and the simulated flow-density relationships assuming that the bus dwell time follows a uniform distribution with a mean of $T_d = 30$ sec but different ranges. Comparison of the flow-density pairs from simulations with different dwell time ranges in Figure 5 shows that when the mean of the dwell time is fixed, the analytically estimates always match the observed MFD very well.



a) b) c)

Figure 5. MFD of a single-lane network with bus dwell time varying from: a) 80% to 120%; b) 40% to 160%; c) 0% to 200%.

CONCLUDING REMARKS

This paper provides an analytical method to estimate impacts of bus dwelling on the functional form of the Macroscopic Fundamental Diagram. This analytical method treats dwell buses as bottlenecks and considers the impact of these stochastic bottlenecks on the paths of the moving observers of different families in (Daganzo & Geroliminis, 2008). Then, the stochastic method of cut (Laval & Castrillón, 2015) is used to estimate the MFD. Two types of networks are considered. The first type is composed of single-lane roads, which will be entirely blocked by a dwelling bus. In this network, moving observers cannot pass through a dwell bus but must stay at the bus stop until the dwelling bus leaves. The second type is composed of multiple-lane roads, the capacity of which will be temporarily reduced due to a dwelling bus. In this network, moving observers can either directly pass through a dwelling bus or stay behind the dwelling bus for any amount of time.

MFD estimates obtained from the proposed analytical methods are compared with the observed flow-density relationship obtained from microscopic simulations of a 10-block ring network. Results show that the analytical method can generally provide good estimates of the lower bound and upper bound of the network's MFD.The simulations also demonstrate that variation of bus dwell time has little impact on the MFD.

The proposed method in this paper has many potential real-world applications. For instance, this method can estimate MFD under different signal settings and thus can be used for signal timing optimization and for transit signal priority design (Geroliminis et al., 2014; Wu & Guler, 2018; Yu et al., 2020). Moreover, by analyzing impacts of bus on MFD, this method can provide insights into the necessity of dedicated bus lanes. Future work should continue to develop analytical methods to understand how bus stop locations affect the shape of the MFD. Additional work is also needed to consider the potential hysteresis pattern (Gayah & Daganzo, 2011; Saberi et al., 2014; Xu et al., 2023) in the MFD when bus demand varies greatly over time.

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Equivalence and Comprehensive Guidance for Vertical Curves on Railroads

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ABSTRACT

This paper aims to resolve confusion among track professionals regarding the shape of vertical curves on railroads, specifically whether they should be considered parabolic or circular. Through mathematical, geometric demonstrations and CAD drawing, the paper establishes the equivalence between parabolic and circular vertical curves on railroads. It derives a general formula for vertical curves that serves as the foundational source for existing formulas in reputable literature, such as the Transit Cooperative Research Program (TCRP) report and the American Railway Engineering and Maintenance-of-Way Association (AREMA) manual. The paper reviews these vertical curve formulas and recommends a maximum acceptable value for vertical acceleration. It also provides installation criterion of a vertical curve. The minimum radius required to ensure stability of a vertical curve under thermal load under unloaded condition is analyzed; this important safety aspect is ignored in literature. The paper then suggests the absolute minimum values for the radius of a vertical curve on both ballasted and direct fixation track. By addressing these aspects, the paper aims to offer a comprehensive guidance for professionals involved in designing and implementing vertical curves on railroads, ensuring safety and efficient operation of the rail network.

INTRODUCTION

Whenever two different gradients meet, an angle is formed at the junction forming crest (summit) or sag. The angle at the junction is smoothened by providing a curve in the vertical plane called “vertical curve”. Vertical curves are essential components in railroad design to ensure smooth transitions between two grades on a track. The change in gradient would cause bunching of vehicles in sags and variation in the tension of couplings in summit, resulting in train parting and bad riding.

The debate regarding whether vertical curves should be parabolic or circular in shape has led to confusion among track professionals. This paper aims to resolve this confusion by demonstrating the equivalence between parabolic and circular vertical curves on railroads. By providing a comprehensive analysis of vertical curves, this paper seeks to offer clear guidelines and recommendations for designing and implementing these curves to ensure the safety and efficiency of rail networks.

The paper presents a generalized formula for vertical curves that serves as the foundational source for all existing vertical curve formulas in reputable literature, including Transit Cooperative Research Program (TCRP) and American Railway Engineering and Maintenance-of-Way Association (AREMA). The derivation of this formula helps establish a unified approach to vertical curve design and analysis.

Through mathematical, geometric demonstrations, and CAD Drawing the paper proves that practically, parabolic curves on railroads can be considered equivalent to circular curves. This equivalence ensures that both parabolic and circular curve designs yield similar results in terms of the smoothness of the transition between grades.

The paper reviews and evaluates vertical curve formulas from reputable sources such as AREMA and TCRP. By comparing and contrasting these formulas, the paper seeks to provide a comprehensive overview of the existing approaches to vertical curve design.

Vertical acceleration is a critical factor in ensuring passenger comfort and safety during train operations. The paper recommends a maximum acceptable value for vertical acceleration to prevent discomfort and potential hazards to passengers and crew.

The paper proposes a criterion that can be used to determine when the installation of a vertical curve is necessary. The criterion considers examples from real world and ride comfort.

Considering both ballasted and direct fixation track systems, the paper suggests an absolute minimum value for the radius of vertical curves. This recommendation ensures the safe and efficient operation of trains on different types of track systems.

By addressing these aspects, the paper aims to provide comprehensive guidance for professionals involved in designing and implementing vertical curves on railroads, ensuring safety, and efficient operation of the rail network.

DERIVATION OF VERTICAL CURVE FORMULA

The derivation of vertical curve formula is done to remove the confusion among track professionals if the vertical curve is circular or parabolic.

A vertical curve is shown in Fig 1.

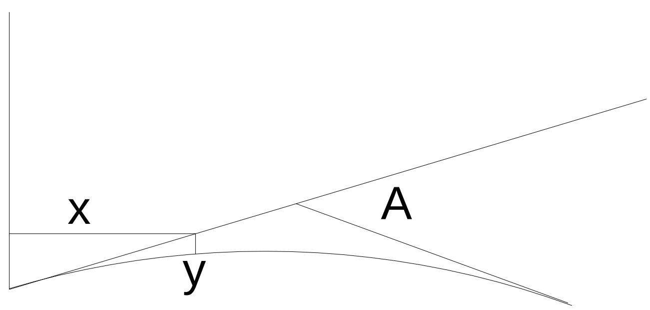

Fig 1. Vertical curve

The equation of a parabolic vertical curve is given by

$$y = kx^2 \tag{1}$$

where k is a parabolic constant.

Differentiating Eq. (1) twice:

$$\frac{d^2y}{dx^2} = 2k \tag{2}$$

By definition, the curvature at any point of a curve i.e., inverse of radius at any point is given by:

$$\frac{1}{r} = \frac{\frac{d^2y}{dx^2}}{\left(1+\left(\frac{dy}{dx}\right)^2\right)^{3/2}} \tag{3}$$

dy/dx is the slope at any point on a parabolic vertical curve. For railroad vertical curves, be it on light rail transit or heavy haul, slope would be significantly less than unity, square of the slope would be even more less than unity. Thus, the denominator in Eq. (3) would be practically unity and it can be expressed as:

$$\frac{1}{r} = \frac{d^2y}{dx^2} \tag{4}$$

If the vertical curve is designed as a circular curve instead of a parabolic curve, the radius must be large for the relation to hold under Eq. (4).

The following equation is applicable *only* on a circular curve:

$$L = \alpha \times R = \frac{A}{100} \times R \tag{5}$$

in which

α algebraic difference in gradient expressed in radian;
A algebraic difference in grade (using the % grade as whole number e.g., 2 for 2%),
R radius of a circular curve

The railway curve definition, used for conventional railways, including commuter rail systems, is defined as a circular arc described by its central angle that is subtended by a 100 foot (30.48 metre) chord. It should be noted that railway curves indexed by degree of curvature and measured in 100 foot chords are not generally utilized in light and heavy rail transit systems which instead utilize the Highway curve definition, measured in 100 foot arc (30.48 metre) and with their severity indexed by the radius (Ahlf 2003). As such, the relation between $\alpha\ (deg)$ and $R(m)$ is given by $\alpha = 1746/R$. The relation between $\alpha(deg)$ and $R(ft)$ is given by $\alpha = 5730/R$.

From Eq. (5)

$$\frac{1}{R} = \frac{A}{100L} \tag{6}$$

From Eqs. (2), (4) and (6):

$$k = \frac{1}{2R} \tag{7}$$

The equation of a parabolic curve would be

$$y = \frac{x^2}{2R} \tag{8}$$

Thus, a parabolic curve with a constant given by Eq. (7) would be practically a circular curve with radius R (ref: Eq. (8)). TCRP labels the radius as an equivalent radius (TCRP 2012). Eq. (8) is used to set out a parabolic curve in the field by tangential offset method (ref: Fig 1). To

Incorporating $x = vt$ in Eq. (1) and differentiating twice:

$$\frac{d^2y}{dt^2} = 2kv^2 \tag{9}$$

Incorporating Eq. (7) in Eq. (9):

$$a_v = \frac{Av^2}{100L} \tag{10}$$

$$L = \frac{Av^2}{100a_v} \tag{11}$$

in which

v speed [ft/s, m/s]

a_v vertical acceleration [ft/s/s, m/s/s]

L length [ft, m]

A algebraic difference in grade (using the % grade as whole number e.g., 2%=2)

Eq. (11) is the source of all vertical curve formulas in literature.

Changing unit of speed from ft/s to mph, Eq. (11) would be

$$L = \frac{2.15AV^2}{100a_v} = \frac{AV^2}{46.5a_v} \tag{12}$$

in which

V speed [mph]

Changing unit of speed from m/s to kmph, Eq. (11) would be

$$L = \frac{AV^2}{1296a_v} \tag{13}$$

in which

V speed [kmph]

Most formulas available in current handbook, manual etc. are in the form of

$$L = \frac{AV^2}{N} \tag{14}$$

in which N depends on the value of vertical acceleration.

From the value of N one can decipher the value of vertical acceleration by the following:

$$a_v(ft/s/s) = N/46.5 \tag{15}$$

$$a_v(m/s/s) = N/1296 \tag{16}$$

EQUIVALENCY OF PARABOLIC AND CIRCULAR VERTICAL CURVE: GEOMETRIC ANALYSIS

The formula in the form given by Eq. (14) implies that the vertical curve is designed as circular curve (ref: Eq. (5)). Parabolic curves are, for all practical purposes, equivalent to circular curves for LRT design, but parabolic curves are easier to calculate and are thus preferable for this purpose (TCRP 2012). Parabolic curves are easier to compute but circular curves are not difficult to compute, it is done later here in Eq. (24). However, currently software takes care of computation. TCRP and AREMA suggest formulas in the form of Eq. (14) which are essentially circular curves. Parabolic curves are more equivalent to circular curves for heavy haul as the grade/slope on heavy haul is milder than that on a LRT track (cf. 1% vs. 7%). The circular curve ensures a uniform rate of change of grade which controls the rotational acceleration. The following geometric analysis demonstrate the equivalency of parabolic and circular curves too.

A vertical curve is shown in Fig 2.

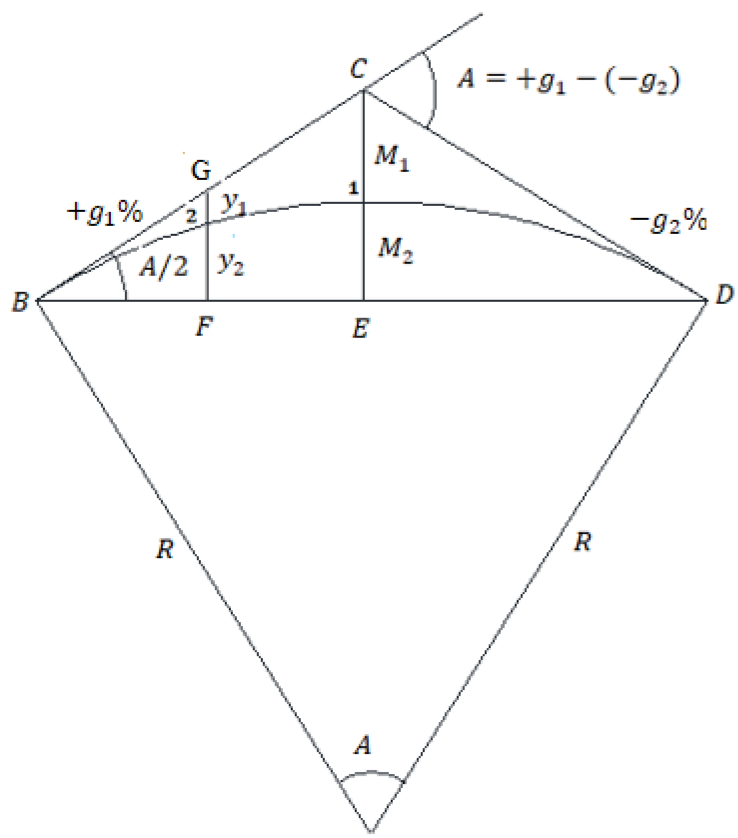

Fig 2. A vertical curve

Considering the angle $A/2$ in radian and $BE = L/2$:

$$M_1 + M_2 = \frac{A}{200} \times \frac{L}{2} = \frac{100L}{200R} \times \frac{L}{2} = \frac{L^2}{4R} \tag{17}$$

Assuming the curve in Fig 2 is a parabolic curve (ref: Eq. (8)):

$$M_1 = \frac{1}{2R}x^2 = \frac{1}{2R}\left(\frac{L}{2}\right)^2 = \frac{L^2}{8R} \tag{18}$$

Assuming the curve in Fig 2 is a circular curve:

$$M_2 = \frac{L^2}{8R} \tag{19}$$

From Eq.(17)

$$M_1 = \frac{L^2}{4R} - M_2 = \frac{L^2}{4R} - \frac{L^2}{8R} = \frac{L^2}{8R} \tag{20}$$

M_1 is computed by Eq. (20) by considering M_2 which comes from consideration of circular curve (ref: Eq. (19)) and M_1 in Eq.(20) is same as given by Eq.(18) which is based on the assumption of parabolic curve. Thus, the elevation of point **1** is same under consideration of either circular or parabolic curve.

Considering the angle $A/2$ in radian and $BF = L/4$:

$$y_1 + y_2 = \frac{A}{200} \times \frac{L}{4} = \frac{100L}{200R} \times \frac{L}{4} = \frac{L^2}{8R} \tag{21}$$

Assuming the curve in Fig 2 is a parabolic curve (re: Eq. (8)):

$$y_1 = \frac{1}{2R} \times \frac{L^2}{16} = \frac{L^2}{32R} \tag{22}$$

Assuming the curve in Fig 2 is a circular curve:

$$y_2 = \frac{L}{4} \times \frac{3L}{4} \times \frac{1}{2R} = \frac{3L^2}{32R} \tag{23}$$

$$y_1 = \frac{L^2}{8R} - y_2 = \frac{L^2}{8R} - \frac{3L^2}{32R} = \frac{L^2}{32R} \tag{24}$$

y_1 is computed by Eq. (24) by considering y_2 which comes from consideration of circular curve (ref: Eq. (23)) and y_1 in Eq. (24) is same as given by Eq.(22) which is based on the assumption of parabolic curve. Thus, the elevation of point **2** is same under consideration of either circular or parabolic curve. Similarly, this can be shown that elevation of all points on the curve are same if the curve is considered to be circular or parabolic. Thus, for all practical purposes circular and parabolic curves are equivalent. This is interesting to note that only at the point of junction, here in Fig 2 at C, $M_1 = M_2$; elsewhere they are not equal e.g., $y_1 \neq y_2$.

y_1, M_1 are correction values to compute elevation at points 2, 1 on a parabolic curve from elevation of G, C respectively on a tangent e.g., elevation at point 1 is elevation at C minus M_1. The corrections values come from the equation of a parabola, $y = kx^2 = x^2/2R$ (ref; Eq. (1,8). Thus, the correction values for any point on a vertical curve is proportional to the square of its distance from B or D to C. In the event of rail break on a curve, lateral offset of rail end is given by the correction value i.e., Eq. (8) where $x = a$ $(a, spacing\ of\ tie)$ if the rail is not pre-bent.

Slow speed curves, such as hump crests, should, however be designed with consideration for **vertical clearance** rather than using the formula given by AREMA (here it is cited by Eq. (29)). One such form of vertical curve is developed as follows: (AREMA 2023, pp. 5-3-27).

M_1 correction in elevation at C

When vertical curve is concave downwards-

$$M_1 = \frac{(elev\ at\ C \times 2) - (elev\ at\ B + elev\ at\ D)}{4} \tag{25}$$

From Fig 1

$$M_1 + M_2 = 2M_1 = elev\ at\ C - elev\ at\ E \tag{26}$$

$$2M_1 = elev\ at\ C - \left(\frac{elev\ at\ B + elev\ at\ D}{2}\right) \tag{27}$$

Eq. (27) derived from Fig 2 is same as Eq. (25) given by AREMA which is in parabolic form practically equivalent to a circular curve. Thus, the AREMA formula given by Eq. (25) looks different from the other AREMA formula but they are all parabolic curve and equivalent to circular one.

EQUIVALENCY OF PARABOLIC AND CIRCULAR VERTICAL CURVE: DRAWING OF VERTICAL CURVE ON CIVIL 3D

There are three type of curves that can be selected in Civil 3D: parabolic, circular and asymmetric. Usually, most designers select parabolic curve. The procedure is to first to determine PVI and first and second tangent, and then to select either curve length or K value.

The software would tell if the input parameter were not solvable; the CAD designers would change the input values.

K is the distance required to achieve one percent change in grade and is given by

$$K = \frac{L}{A} \tag{28}$$

in which

L length of curve,

A algebraic difference in grade (using the % grade as whole number e.g., 2 for 2%).

The relation between radius, R and K can be expressed as

$$R = 100K \tag{29}$$

Thus, if a minimum radius of 2000 m is chosen then the CAD designer is advised that the K-value must be ≥ 20 (ref: Eq. (29)).

On Civil 3D a parabolic curve is drawn with the following inputs:

The data in Table 1 gives the following output:

Profile curve length	100 m
K value	20
Curve radius	2000.00 m

On Civil 3D a circular curve is drawn with the same inputs as in Table 1. The output is:
Profile curve length 99.965 m
K value 19.993
Curve radius 2000.00 m
These is almost n o difference between the curves drawn as parabolic and circular.

Table 1. Inputs to draw a vertical crest curve

PVI station	PVI Elev.	Grade in	Grade out	A	Curve type
25+223.000 m	185.406 m		3%		
25+406.092 m	190.839 m	3%	-2%	5%	Crest
25+710.613 m	184.749 m	-2%			

REVIEW OF AREMA FORMULA

The *minimum* length of the vertical curve for both sags and crest curve is given by the following formula (AREMA 2023):

$$L = \frac{KAV^2}{a_v} \tag{30}$$

in which
L = curve length in feet,
V = speed in mph,
A = algebraic difference in grade expressed in radian,
K = 2.15 conversion factor,
a_v = vertical acceleration in ft/sec/sec .

In original AREMA (2023) formula, D is used in place of A and A is used in place of a_v. In this paper, the notation is changed to maintain consistency. Eq. (30) is same as derived Eq. (12).

Manual of Railway Engineering (MRE) recommends a vertical acceleration of 0.1 ft/s/s (=0.003g) for freight train for both crest (summit) and sag curve (AREMA 2023). Thus, Eq.(11) renders the following formula for freight train:

$$L = \frac{AV^2}{4.65} \tag{31}$$

in which
A algebraic difference in grade (using the % grade as whole number e.g., 2%=2)
From Eq. (31) the minimum radius on a freight track is given by

$$R_{min} = \frac{100}{4.65} \times V^2 \tag{32}$$

For a speed of 50 mph, the minimum radius would be 16, 390 ft (=5000 m).

Manual of Railway Engineering (MRE) recommends a vertical acceleration of 0.6 ft/s/s (=0.018g) for passenger train for both crest (summit) and sag curve (AREMA 2023). Thus, Eq.(11) renders the following formula for passenger train:

$$L = \frac{AV^2}{27.9} \tag{33}$$

in which

A algebraic difference in grade (using the % grade as whole number e.g., 2 for 2%)

From Eq. (33) the minimum radius on a passenger track is given by

$$R_{min} = \frac{100}{27.9} \times V^2 \tag{34}$$

For a speed of 60 mph, the minimum radius would be 12, 900 ft (=4000 m).

REVIEW OF TCRP FORMULAS

For Light Rail Transit (LRT), Transit Cooperative Research Program (TCRP 2000) suggests different lengths for Crest and Sag curve. The **absolute minimum** lengths are given by:
for crest curve,

$$L = \frac{AV^2}{215} \tag{35}$$

Using Eq. (16):

$$a_v = 215/1296 = 0.17\, m/s/s = 0.015g$$

Assuming a maximum speed of 100 kmph for transit, the absolute minimum radius for crest curve comes out to be 5245 m (rounding to nearest 5 m).

For Sag,

$$L = \frac{AV^2}{387} \tag{36}$$

Using Eq. (16):

$$a_v = 387/1296 = 0.3\, m/s/s = 0.03g$$

TCRP suggests half of vertical acceleration for crest curve compared with sag curve (cf. 0.015g, o.03g). This requirement might come from the fact that upward acceleration is more easily perceived than downward acceleration but this requirement only applies in the case of high speeds (for example the TGV) (Esveld 2001). AREMA recommends a single value of vertical acceleration for both crest and sag curve. Thus, a single radius for both crest and sag curve may also be acceptable.

The **desirable minimum length** is given by (TCRP 2000)

$$LVC = 60A \tag{37}$$

From simple geometry of a circular curve,

$$LVC = R \times \frac{A}{100} \quad (38)$$

Equating Eqs, (37, 38), **desirable minimum radius** is:

$$R_{desired} = 6000\ m$$

The **acceptable minimum length** is given by (TCRP 2000)

$$LVC = 30A \quad (39)$$

Equating Eqs. (38, 39), the **acceptable minimum radius** is given by

$$R_{accp\ min} = 3000\ m$$

The minimum value of radius and maximum value of vertical acceleration are computed from the TCRP formulas for the length of vertical curve and summarized in Table 2.

Table 2. Minimum value of radius and maximum value of vertical acceleration

Parameter	Desirable minimum	Acceptable minimum	Absolute minimum
Radius (m)	6000	3000	5245 Crest **2620** Sag
Parameter	Desirable maximum	Acceptable maximum	Absolute maximum
Vertical acceleration (m/s/s)	0.012g	0.025g	0.015g Crest **0.030g** Sag

Note: A speed of 100 kmph is considered for transit.

From analysis of AREMA formula, for a speed of 100 kmph the acceptable minimum radius is **4000 m** (ref: Eq. (34)).

LIMITING VALUE OF VERTICAL ACCELERATION

Discomfort is felt by a person subjected to rapid changes in vertical acceleration. To minimize such discomfort when passing from one grade to another it is usual to limit the vertical acceleration generated on a vertical curve.

The US rail industry standard for **lateral** acceleration for a long time has been 0.1g (g=acceleration due to gravity). The standard used by railroads and transit properties in the US is based on research conducted 50 years ago and was applicable to all types of cars including dining cars where a smooth ride was essential (AREMA 2023). Today, several European countries allow higher rates, SNCF (French National Railway) uses 0.15g for **lateral** acceleration for its railroads including the high speed TGV system. This has been a suggested acceptable level by others in the US but does not appear to have been implemented (AREMA 2023).

The perception of acceleration depends on various factors, including individual sensitivity and context. However, in general, people tend to be more sensitive to vertical acceleration (acceleration in the up and down direction) than horizontal acceleration (acceleration in the side-to-side direction). The reason for this is related to our anatomy and how our bodies are built. Our vestibular system, located in the inner ear, is responsible for detecting motion, acceleration, and orientation. It contains fluid-filled canals that are more sensitive to changes in vertical motion. This sensitivity allows us to perceive changes in vertical acceleration more acutely, such as when we go up or down in an elevator, experience turbulence during a flight, or ride a roller coaster.

On the other hand, our bodies are less sensitive to horizontal acceleration because we are generally accustomed to experiencing horizontal movements in daily activities like walking or driving, and our vestibular system is better adapted to detect changes in the vertical plane. So, experiencing the same magnitude of acceleration in both the horizontal and vertical directions, *one might feel the vertical acceleration more intensely*. Thus, a vertical acceleration less than 0.1g might be acceptable.

The computed maximum values of vertical acceleration from TCRP formulas for length of vertical curve as shown in Table 1 seem to be low; the desirable minimum value being 0.012g and the absolute maximum value is 0.03g.

AREMA recommends a maximum value of 0.018g for passenger train.

ISO 2631-1:1997 limits the vertical acceleration to 0.04g for continuous exposure and 0.1g for transient exposure (ISO 1997).

As per design handbook RT/CE/S/049 the maximum design value of vertical accelerations are 0.04g and 0.0325g for crest and sag curve respectively. As per design handbook RT/CE/S/049 exceptional design value of vertical acceleration is 0.045g.

Subjective experiments of ride comfort on curves were judges as “noticeable lateral acceleration” at 0.1g and “strongly noticeable but **not uncomfortable**” at 0.15 g (AREMA 2023). An unbalanced superelevation of 75 mm is applicable for any vehicle without qualification test (FRA 2022). Seventy five (75) mm unbalanced superelevation is equivalent to 0.05g uncompensated lateral acceleration.

To minimize discomfort when passing from one grade to another it is usual to limit the vertical acceleration generated on a vertical curve to a value less than 0.05g where g is the acceleration due to gravity (DOT 2002).

Most high speed trains use a vertical acceleration of 0.04g and some use even 0.06g, 0.07g etc. e.g. on NBS-Frankfurt/Main-Koln line opened in 2002, the maximum vertical acceleration is 0.07g.

Thus, a maximum value of 0.05g (1.6 ft/s/s, 0.5 m/s/s) may be accepted for passenger train without any qualification test of a vehicle.

CRITERION TO INSTALL VERTICAL CURVE

Currently, there is no criteria that warrants a vertical curve. On Indian railway, vertical curves are provided only at the junction of the grade where algebraic difference between the grades is equal to or more than 4 mm per meter or 0.4% (Agarwal 2002). This is equivalent to a deflection angle of 0.004 radian.

Australian Rail Track Corporation Ltd. (ARTC) eliminates the horizontal curve if the deflection angle is 10 minutes or less. So, a horizontal deflection angle of ten minutes (= 0.003

radian) would not cause discomfort in absence of horizontal curve. Horizontal curve would be needed if the deflection angle exceeds 0.003 radian.

AREMA allows a vertical misalignment of 0.04 of an inch over 18 inch in a joint which is equivalent to 0.003 radian.

In context with above references, vertical curve may be eliminated if the algebraic difference in grade is less than or equal to 0.3%.

MINIMUM RADIUS OF A VERTICAL CURVE

Bottom friction contributes to 45 –50% of the total resistance of a tie (Lichtberger 2005). In summer a lifted track of a crest curve due to compressive thermal load in the track is more likely to buckle horizontally because of reduced lateral resistance of ballast by around 50%. A buckled track is a real threat for traffic safety.

The weight of a track in a crest curve must offset the upward load due to thermal effect. Thus, to determine the **absolute minimum** radius in a track thermal stability under unloaded condition must be checked. This work is done in an earlier paper by the author (Hasan 2014). For a track buckling load of 2000 kN, the threshold radius of a vertical (crest) curve on a concrete tie track would be **320 m**. For a buckling load of 2000 kN, the threshold radius of a vertical (crest) curve on a wood tie track would be 1779 m, say **1800 m**. If the radius is below the threshold value, thermal load would initiate lifting of the track and tie resistance will be dropped to around 50% causing horizontal buckling at a temperature differential lower than the critical temperature differential (Hasan 2014). In the winter due to temperature drop, track will be lifted up in a sag curve and ballast resistance would be dropped to around 50%. The rail break gap would be increased by about 50% jeopardizing rail traffic safety. Moreover, in winter a lifted track over a sag curve due to tensile thermal load is likely to cause ballast degradation under repeated wheel loads of a passing train. It appears that the absolute minimum radius of 320 m for ballasted track on concrete tie, 1800 m for ballasted track on wood tie, and 1800 m for DF track are acceptable.

On a direct fixation track, the absolute minimum radius with a factor of safety (F.S.) is given by:

$$R_{min} = \frac{Max\ thermal\ load}{w} \times F.S. \tag{40}$$

The following conservative data is used for a direct fixation (DF) track on a concrete invert:

Rail	115 RE
ΔT	(+/-) 50°C
w	1.2 kN/m for DF track (weight of two rail only)
F.S.	1.1

$$R_{min} = 1800\ m$$

Under 1800 m radius, rails would be lifted up on a crest curve in summer and on a sag curve in winter which are not desirable as the rail creep resistance would be less due to lifting of rail. Due to reduced rail creep resistance, rail break gap would be more which might exceed the acceptable limit.

A vertical curve of radius 2000 m must be considered as an absolute minimum (Esveld 2001).

Common figures stipulated by car builders for high-floor LRVs for the minimum equivalent radius of curvature for vertical curves located in tangent track are **250 meters** (820 feet) for crest and 350 meters (1150 feet) for sags. The track alignment designer must therefore evaluate whether a particular parabolic vertical curve meets the car builder's criteria (TCRP 2000). When extremely constrained site conditions dictate, combined curves should generally not be more severe than an 82 feet [25 m] radius horizontal combined with a 820 feet [**250 meter**] equivalent radius vertical crest curve. These parameters must be conformed to the vehicle design specification (TCRP 2000).

From the above stability analysis, it appears that car builder's criteria is not the final choice to determine the minimum radius; thermal stability of a continuously welded ballasted track must be analyzed . For an embedded track car builder's criteria may be applied where track is restrained adequately from uplift.

TCRP guideline to pre-curve rail vertically for curve radii below 230 and 300 m for standard carbon (SC) and high strength (HS) rail respectively (TCRP 2000) might confuse readers about the minimum acceptable radius of a vertical curve. This is always a good idea to pre-curve rail of vertical curve with radii from 320 m to 400 m for all grade of rail steel (as the bending force is same for SC and HS steel) to eliminate the bending force that helps to uplift the track/rail.

As per track design handbook RT/CE/S/049 the minimum radius for exceptional design for speed up to 100 mph is 500 m.

The absolute minimum value of radius computed from TCRP formulas for the absolute minimum length of vertical curve is 5245 m for crest and 2620 m for sag curve as shown in Table 2.

For a speed of 60 mph, the minimum radius is 4000 m as per AREMA (ref: Eq. ((35).

As per track design handbook RT/CE/S/049 the minimum radius for normal design and for all new construction is 2000 m. As per track design handbook RT/CE/S/049 the minimum radius for exceptional design for speed up to 100 mph is 500 m.

Thus, a minimum radius of 2000 m is acceptable for all forms of track. The minimum radius stipulated by AREMA and TCRP as analyzed is greater than 2000 m and hence, would require more maintenance efforts.

MINIMUM CURVE LENGTH

Using the suggested criterion of 0.003 radian for algebraic difference in grade for installation of a vertical curve and a minimum radius of 2000 m, the minimum curve length is computed to be 60 m. The length of 60 m satisfies the ride comfort criterion of 2 secs ride under a speed of 100 kmph; thus, for a transit 60 m should be the minimum length. The minimum length of a vertical curve shall be the maximum of 60 m or 2 secs ride length.

CONCLUSION

Suggestion of a blanket value of vertical acceleration is not a good idea because site condition would dictate the length or radius of a curve. Higher value of vertical acceleration should go with the higher speed as vertical acceleration is proportional to the square of the speed. A limiting (maximum) value of vertical acceleration of 0.05g is suggested. The absolute minimum radius of 320 m for ballasted track on concrete tie, 1800 m for ballasted track on wood tie, and 1800 m for DF track are suggested. The desirable minimum radius of 500 m for ballasted track on concrete tie, 2000 m for ballasted track on wood tie, and 2000 m for DF track are suggested. A minimum radius of 2000 m is acceptable for all forms of track. The minimum curve length should be maximum of 60 m or 2 secs ride. Pre-curving of rail for vertical curve is suggested for radii between 320 –400 m for all grades of steel to reduce uplift by free bending force and too ensure thermal stability.

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AI-Assisted LiDAR System's Performance Assessment for Automatic Track Geometry Monitoring

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ABSTRACT

Shortlines are smaller railroads operating on shorter, light-density rail lines with marginal track conditions. With insufficient revenue and declining employees, shortlines depend on labor-intensive yet timely inspections to ensure their infrastructure remains safe and effective to operate. To increase track geometry inspection efficiency, research efforts have focused on developing automatic and effective rail extraction methods using LiDAR and artificial intelligence (AI), so that track geometry can be measured based on the extracted 3D rail model. However, many rail extraction methods have specific data collection settings or algorithm assumptions, lacking adaptability for deployment on shortlines with variable conditions. One recent study developed an AI-assisted rail extraction method, using publicly available Federal Railroad Administration grade crossing datasets, intended for shortlines without needing human interaction. However, this method has not yet undergone testing and validation with actual shortline data. This research collects additional LiDAR point cloud data from a shortline track to validate performance of the AI-assisted rail extraction method. The results show the method generates equally good extraction on single straight tracks and improved extraction on single curve tracks compared to the original study. This confirms the robust extraction performance of the method across different track types and sensor configuration and confirms that the method proposed by the original study is, indeed, independent of sensor property and configuration.

INTRODUCTION

The nation's 600 shortlines are small railroad businesses and can be found in 48 states servicing over 10,000 rural customers (ASLRRA 2023a). Collectively shortlines in the U.S. operate about 50,000 miles of track, accounting 1/3 of the national railroad network (UP 2023). Shortlines contribute significantly to the economy of the U.S. by connecting shippers in small towns and local business to the large nation's rail network. They are all identified as Class II and

Class III railroads by the Surface Transportation Board, and all considered as small business, yet they are critically important to the U.S. economy. They are preserving 17,800 local railroad jobs (ASLRRA 2023b) and focusing on providing flexible services to their local customers, and most often their customers are also small local rural businesses. Shortlines connect those small businesses to the national rail network and provide those local shippers a more economic shipping solution than trucks. Every year, shortlines divert about 20% heavy goods and congestion from the public owned nation's aging highway to avert deterioration of highway infrastructure.

However, all the shortlines are responsible for ensuring their tracks are safe to operate. Most shortlines must invest at least 25% of their annual revenues in regular maintenance and rehabilitation. The majority of the shortlines are created by entrepreneurs who purchased or leased low-density lines from Class I railroads because they are marginal or even unprofitable. Thus, the tracks that inherited by shortlines had experienced years of deferred maintenance from the previous Class I owners (Ren et. al., 2021). To succeed in the business, shortlines must compete aggressively and efficiently utilize their infrastructures to operate. Efficient and cost-effective service, and maintenance are the keys to allow shortlines to save light-density branch lines rather than abandon them. As regulated by the Federal Railroad Administration (FRA), tracks need to be inspected on a weekly basis which could pose challenges to shortlines considering their stringent budgets and workforce resources.

To meet regulation requirement, railroads depend heavily on manual visual inspection that demands considerable engineering experience and time. In the literature, various inspection technologies have been widely investigated and researched to increase the inspection accuracy and to improve the manual inspection efficiency. Machine vision techniques, employing high-speed video cameras or infrared thermal imaging cameras along with advanced image processing methods, have gained popularity for inspecting rail infrastructure. However, these methods are typically used in stationary applications for inspecting rolling stock, as video camera can be sensitive to unfavorable lighting and weather conditions and thermal imaging cameras result extreme temperature readings by moisture factor (Vaghefi et. al., 2011). In recent years, there has been a growing adoption of mobile LiDAR sensors for railroad inspections due to their exceptional capability for precise geometry measurements (Gézero and Antunes, 2019; Ai and Tsai, 2016), and their resilience to varying lighting conditions. Recent research efforts have primarily centered around the automation of rail extraction (Gézero and Antunes, 2019; Yang and Fang, 2014) which serves as the foundational step for comprehensive rail inspection and geometry measurement. Nevertheless, a significant portion of the existing studies are developed targeting class I railroads, and heavily rely on high-density point cloud datasets with well-documented sensor characteristics and configurations. Shortlines will have technical challenges to adopt those methods because most often shortlines only have low-density point cloud data with poor quality and unknow sensing specifications.

With recent research attention drawn more on cost-effective automatic track extraction method targeting for shortlines, one research recently published claimed that their automatic extraction method does not rely on any sensor specifications and works well with low-density point cloud data (Ren et. al., 2022). Ren et. al. (2022) utilized 25 public FRA LiDAR datasets with average density of 293 points/m^2 to develop an AI-assisted coarse-fine data extraction framework, the authors selected 3 out of the 25 datasets to validate the performance of the method and claimed that the method has average completeness of 96.97%, correctness of 99.71%, and quality of 96.67%. The three selected datasets covered three types of tracks: single straight tracks, single curve tracks, and double straight tracks. The research shed light on improving efficiency and effectiveness on track condition monitoring targeting on shortlines. However, how the method performs when it applies to different datasets remains unknown. This study is aimed to answer that question by collecting a different set of LiDAR point cloud data covering a shortline's track infrastructure. Such data will be used to evaluate the robustness and accuracy of the method developed by Ren et. al. (2022). Track types tested in Ren's study (Ren et. al. 2022) are also intended to be included in this study to perform a comparative evaluation.

The rest of the paper is organized in the following sections: the next section introduces the overall methodology that the researcher will use in this study followed by the data collection section which describes in greater detail on the data collection settings, collecting sensor specifications, and the data characteristics that this research collected. The next section discusses the comparative evaluation results, findings, and comparative results. The last section concludes the paper and its future research directions.

METHODOLOGY

Ren et.al. (2022) developed a coarse-fine automatic data extraction framework targeting shortlines for LiDAR data with low-density and incomplete/missing collecting sensor information characteristics. The method is designed to automatically extract rail data points from raw LiDAR point clouds without any human interventions. The method contains two primary sequential steps designed to filter out noise data points step by step. Figure 1 shows the overflow of the algorithm.

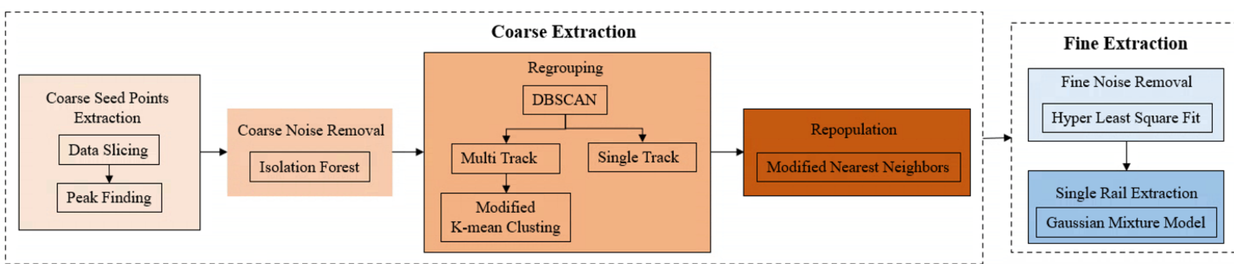

Figure 1. Overflow of the Method

As indicated in Figure 1, the coarse extraction, including methods such as isolation forest, DBSCAN, K-mean clustering, and nearest neighbors, is designed to remove noise, extract potential rail points, and regroup rail track pairs. The fine extraction is designed to further refine the extracted rail pairs by verifying and removing noise points and separating individual rail from the rail track pairs. For details of the methodology development and scientific theories of each methodology, please refer to Ren et. al. (2022).

As we mentioned before, the proposed method was developed and tested using FRA grade crossing inventory collected by SICK LMS511 LiDAR sensors (FRA 2015) with a point density of approximately 293 pts/m^2. However, its performance on datasets collected by different LiDAR sensors with distinct characteristics remains unknown. As a result, this study will utilize datasets collected by the Riegl VMZ2000 mobile LiDAR sensor, which captures point cloud data with entirely different characteristics, to validate the extraction framework introduced by Ren et al. (2022). For this validation process, we will employ a single straight track and a single curved track, which are the same track types used by Ren et al. (2022) in their original study. As we'd love to, but we could not validate the performance for a double straight track scenario because the tracks that we are collecting over do not have a double straight track. Note, shortline railroads usually operate on single-track rather than double track for reasons of cost.

DATA COLLECTION

In order to perform validation and evaluation of the method, the research team collected LiDAR point cloud data targeting the railhead over a shortline's infrastructure. The research team installed our LiDAR sensor system including GPS, camera, LiDAR and IMU on the top of a HiRail vehicle, 2017 Chevrolet 3500 Double Cab equipped with steel rail wheels. All the devices in the LiDAR system, along with a laptop for controlling sensor settings and data collection, can access power and continue to collect data while HiRail is on track.

Figure 2. Data Collection Sensors and Settings

Red River Valley and Western (RRVW) has served North Dakota and Minnesota with over 540 miles of track since July 1987. RRVW is critically important to the local community and business with their shipping, storage, and transload services (NDDOT 2007). It handled 48,103 carloads in North Dakota in 2009, where farm product shipments comprised more than 62% of its diversified traffic compared to other shortlines in North Dakota. Figure 3 shows the areas that RRVW serves, and the research team collected data over the primary areas of interest, which are represented by blue rail lines in the Figure, covering approximately 200 miles of track. Geometry issues such as warp, profile, gauge, and alignment are the focus of the inspection, and the data extraction method is the first step to assist engineers to identify areas that are highly likely to have abnormality. Various scanning angles of the LiDAR sensor and driving speeds of the HiRail vehicle are used to collect high-density and high-resolution datasets. During the data collection process, the scanning angle is set between 25° to 28° to ensure high point density of the collected dataset which differs from the data that used in Ren et al. (2022). The driving speeds vary between 10 mph to 30 mph to introduce speed variations. The scanning angle determines the vertical field of view of the LiDAR sensor as it rotates and scans. This means that at any moment, while the LiDAR sensor is rotating, the LiDAR sensor captures data points in a vertical slice between 25° to 28° of its surroundings. This relatively narrowed vertical field of view allows the LiDAR sensor to capture a high density and high-resolution data points within this defined vertical field of view to distinguish the low-density data used in the study of Ren et al. (2022). The resulting datasets have a point density of around 10,000 pts/m^2, which is distinctly different from the FRA datasets used in the study of Ren et al. (2022) with point density around 293 pts/m^2.

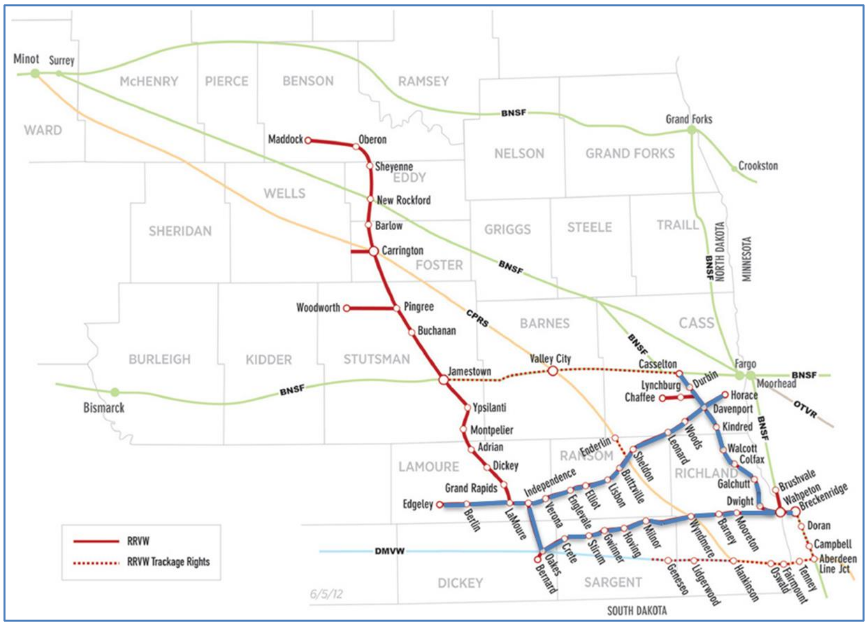

Figure 3. The Location of RRVW Rail Network and Collected Rail Line

RESULTS AND DISCUSSIONS

To evaluate the extraction result of the method proposed by Ren et. al. (2022), the research randomly selected a single straight track and a single curve track, for the validation and evaluation process. This choice was made mainly for two reasons: 1) to conduct comparative study and 2) to validate the performance of the method under various track geometry. However, double straight track that were used in Ren et. al. (2022) was not included in this study because this specific track type was not available. The single straight track and single curve track have a length of around 196 and 129 meters respectively. Both datasets are collected at around 10 mph, and the scanning angle is set to be between 25-28 degree. Figure 4 shows the location of the varication datasets.

The same evaluation method used by Ren et al. (2022) was employed in this study. Reference rails points were manually extracted from the dataset to serve as the reference rail. A regression line was then calculated for the manually extracted reference rail. Both the reference rail and the extracted rail were projected onto the same regression line to measure the length and evaluate the performance of the method. Additionally, the same evaluation metrics used in Ren et al. (2022) were employed in this study. These metrics include *Completeness*, also known as recall, which measures the quantity of the positive points that are successfully extracted; *Correctness*, also known as precision, which assesses the accuracy of the successfully extracted positive rail points; and *Quality*, which measures the overall performance of the extraction result by considering both the completeness and correctness. Higher completeness (recall) means that the algorithm returns most of the relevant points whether or not irrelevant points are also returned. On the other hand, higher correctness (precision) means that the algorithm returns more relevant points than irrelevant points. The equations of these three metrics are shown below.

$$Completeness = L_{tp}/L_r \tag{1}$$

$$Correctness = L_{tp}/L_e \tag{2}$$

$$Quality = L_{tp}/(L_e + L_{fn}) \tag{3}$$

L_r is the length of the reference rail, while L_e is the length of the extracted rail, including noise, L_{tp} is the minimum length between the extracted rail that matches the reference rail and the reference rail that matches the extracted rail. L_{fn} are length of gaps in the extracted rail and the portion of the reference rail that the method failed to extract. Figure 5 shows the visualization of the validation result.

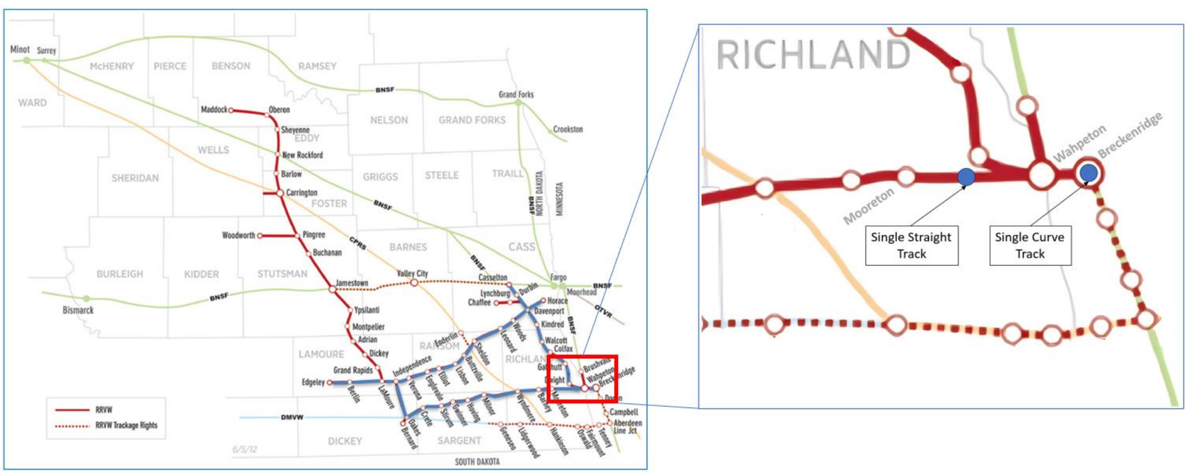

Figure 4. The Location of Varication Datasets

Figure 5a and 5c show the extraction result of Ren et al. (2022), while figure 5b and 5d show the validation result of this study. In the figures, FN represents the rail points that the method failed to extract, while FP represents the noise points that the method wrongly extracted. Rails are color-coded using blue and green to demonstrate the method's capability in terms of extracting each single rail line separately. Noise points are colored in red. Table 1 shows a comparison of the quantified extraction results between Ren et al. (2022) and this study.

Table 1 indicates that for single curve track, the method proposed by Ren et. al. (2022) can extract single curve track with 94.56% completeness, 100% correctness, and 94.56% quality in their original study. In contrast, when applied to the new validation dataset, the extraction result shows a 98.97% completeness, 99.78% correctness, and 98.74% quality. Compared to the result in the original study, the validation result shows a significant improvement, 4.41% increase in completeness, 0.22% reduction in correctness, and 4.18% increase in quality. This result complies with the statement made by the original study that the performance of the method proposed by Ren et. al. (2022) is expected to be better with higher density datasets, since more data points are expected to lay on the rails which will result in better continuity and cause more rail points to be recovered in the Modified Nearest Neighbor step. The slightly lower correctness is mainly caused by the small ground structures, such as bolts, that are close to the track, since the validation dataset has a much higher density and resolution; therefore, these small ground structures are misclassified as rail points. Figure 5a and 5b show the visualization of the extraction result on a single curve track for both the original study and the current study.

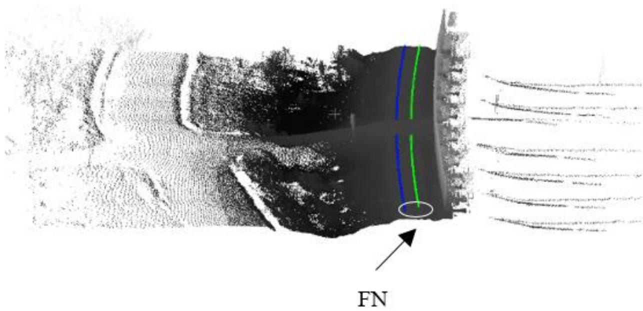

Figure 5a. Original Result of Single Curve Track

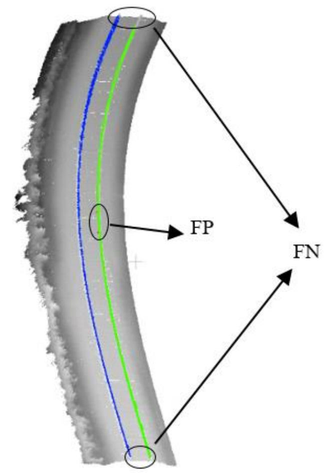

Figure 5b. Validation Result of Single Curve Track

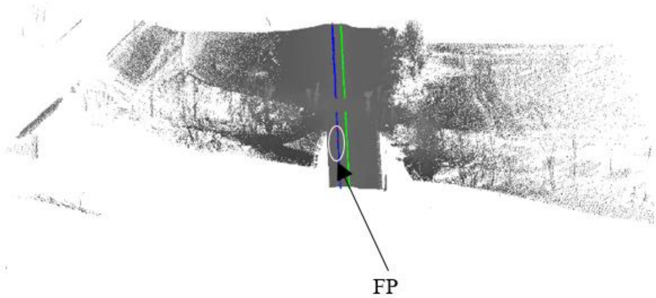

Figure 5c. Original Result of Single Straight Track

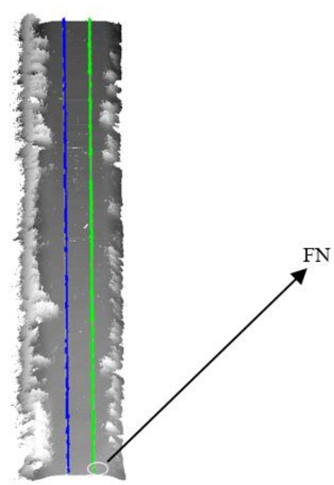

Figure 5d. Validation Result of Single Straight Track

Table 1 indicates that the method proposed by Ren et. al. (2022) can extract straight track with 99.97% completeness, 99.12% correctness, and 99.08% quality for single straight track in their original study. When applied to our collected dataset with completely different point density and resolution, the proposed method achieved 99.94% completeness, 100.00% correctness, and 99.86% quality. Compared to the results in the original study, the correctness and quality increased by 0.88% and 0.78%, respectively, with a slight decrease of 0.04% for completeness. The validation result shows that the extraction performance is about the same level (all above 99%) when compared to the original study. The validation shows a slightly lower completeness mostly because the validation used a much longer dataset. This caused Isolation Forest to misclassify some of the rail points that are further away from the majority data points as non-rail points. Additionally, the improvement of the method proposed by Ren et. al. (2022), on single straight track, is less significant compared to the single curve track. This is mostly because the proposed method had a close-to-perfect performance on single straight track, leaving little room for further improvement. Figure 5c and 5d show the visualization of the extraction result on a single straight track for both the original study and the current study.

Table 1. Performance results

Validation Result				
Track Type	**Length**	**Completeness**	**Correctness**	**Quality**
Single Curve	129 m	98.97% (↑4.41%)	99.78% (↓0.22%)	98.74% (↑4.18%)
Single Straight	196 m	99.94% (↓0.04%)	100.00% (↑0.88%)	99.86% (↑0.78%)
Original Result				
Track Type	**Length**	**Completeness**	**Correctness**	**Quality**
Single Curve	120 m	94.56%	100%	94.56%
Single Straight	115 m	99.97%	99.12%	99.08%

Furthermore, this study successfully extracted each individual rail from the track pairs, as indicated by the blue and green colors. This confirms that the proposed algorithm has the ability to extract each single rail separately. This is critically important because such extracted individual rails can be readily for further geometry measurement calculations.

Finally, in the validation process, only the X, Y, and Z coordinates are used, which validate that the method proposed in the original study is, indeed, independent of sensor configuration and property information.

CONCLUSION

This study validated the automated rail extraction method proposed by Ren et al. (2022) using a new dataset collected from a shortline railroad in North Dakota. A LiDAR sensor with completely different property and configuration is used to collect datasets that are distinctly different from the original study. The result shows that the method generated an extraction result that is equally good compared to the original study on single straight track and an improved extraction result on single curve track. This result confirmed the extraction performance of the method proposed by Ren et al. (2022). It also confirmed that the method proposed by the original study is, indeed, independent of sensor property and configuration. Other than that, this study also validated the capability of the method, proposed by Ren et al. (2022), to extract each individual rail line separately. Finally, the overall improved extraction performance on the newly collected dataset with high density and resolution also confirmed that the tested method performs better on high density datasets since more data points are expected to lay on the rails.

While this study focused on single straight and single curve track, future works could focus on evaluating the extraction performance on double straight tracks which is not included in the newly collected dataset. A more comprehensive evaluation of the original study could help establish the robustness of the method and enable its application in shortline railroads with limited resources and qualified personnel. With accurately extracted rails, future studies could also focus on developing critical inspection methods, such as geometry measurements and rail 3D profile measurements, to identify potential rail defects and areas requiring maintenance.

In addition, since the datasets are collected using various inspection speed and scanning angle, as a result the research team will further explore impacts of these scanning parameters on the final extraction result and develop accurate and robust geometry inspection methods. Additionally, by purposefully reducing the point density and resolution with various strategy, the research team is confident to identify the most cost-effective and efficient point density and resolution that are optimal to conduct fully automated low-cost LiDAR-based full scale rail inspection.

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Challenges in Implementing Emerging Technologies to Existing Rail Transit Infrastructure

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ABSTRACT

The implementation of emerging technologies is shaping the future across various aspects of society. Engineers face significant challenges in implementing these technologies to improve existing infrastructure systems as well as associated services. A key component for engineers is the continuous innovation and upgrading of aging infrastructure like water sewage, electric power, transportation, and communication systems, while considering both current and future technology landscapes. In addition to the advanced hardware and instruments like LiDAR (light detection and ranging), GPS (global positioning system), wireless transponders, or camera sensors, the introduction of enhanced database-integrated information, Internet of Things (IoT), digitization techniques, and building information modeling (BIM) are a few examples of emerging software technologies. Amid current design practices adhering to codes, regulations, and standards, engineers encounter difficulties in fully integrating these emerging technologies. This article explores the realm of current and future technologies as well as the complexities associated with improving rail transit infrastructure systems. This article further extends the introduction and challenges of implementing autonomous intelligence (AI), machine learning, and communications-based train control (CBTC) in the rail transit environment, enhancing the efficiency and safety of rail transit systems. This article also discusses the value engineering analysis which may sometimes necessitate a complete overhaul or replacement of intended improvement.

INTRODUCTION

Building rail transit infrastructure in today's modern society facilitates seamless accessibility to rail transit, fostering vital connections for efficient transportation. Overcoming challenges associated with accessibility provides valuable insights into the system, guiding improvements in areas that may be lacking. Rail Transit innovation is being transpired in numerous ways, whether it be the track system, station improvements, facility maintenance, ticketing, and transactions, etc. The extensive rail transit is far from being a basic, one-size-fits-all model, instead, it comprises many intricacies that help the system run efficiently and frequently. The ultimate objective of any transit organization is to deliver safe and reliable service to its users. As all new and existing technologies consist of the regulations they must undergo, for capacity and testing, they provide us with substantial solutions to modern problems and the challenges they face. This article discusses many facets of these technologies and the pros and cons.

RAIL TRANSIT INFRASTRUCTURE

Over time, rail transit infrastructures have advanced numerous stages from its conception to its modern world presence. Although rail transit systems have varying degrees of advancement, they all share a common baseline infrastructure. These infrastructures encompass diverse elements, including track systems such as above-ground elevated railways, subways, tunnels, and bridges; utilities like water systems, electricity networks, signals, and communication systems; and auxiliary support structures such as substations, fan plants, control centers, terminals, and maintenance facilities [1].

A train needs a path, an energy source, and a destination to function. Railway planning and urban planning go hand in hand when conceiving the track system. In developing a new transit rail system, extensive land is acquired with a planned route with destinations and geographical features to ensure optimal paths. This involves the construction of railway tracks and addressing the need to create tunnels or bridges to bypass specific geographical obstacles. Along the rail's path, signals and communications must be set up to control the traversal of trains which comes with the need for electricity supplied by the electrical grid or substation. Electricity is needed to supply power to all the utilities along the track and power the overhead catenary for passenger trains. Other facilities require power to run such as stations, terminals, control centers, maintenance shops, and the utilities associated with them [2].

Given the expansive nature of rail transit infrastructures, there is a focus on maintaining all rolling stock, structures, and utilities within the system. Once a product has aged enough, a repair or replacement is to be issued to keep the integrity of the system. In the era of rapid technological advancement, innovation occurs swiftly and frequently, often resulting in the obsolescence of previous utilities and technologies. Improving existing rail transit infrastructures invariably involves finding a balance between repairing the old and implementing the new.

EXISTING TECHNOLOGIES

Rail transit infrastructure contains a monumental number of technologies both on and beneath the surface. The rolling stock, a technology marvel, requires continuous modernization to enhance efficient passenger transportation. The technologies within train infrastructure encompass both hardware and software components, including communication systems, radio, radar, GPS, brake systems, positive train control, HVAC (heating, ventilation, and air conditioning) lighting, doors, and signals. On the tracks themselves, various components include overhead catenaries, charged rails, switch boxes, signal lights, relays, and railroad switches. Stations, while varying in design, share baseline requirements such as signals and communications to facilitate displays showing the arrival times of the next trains. Underground stations necessitate additional features such as HVAC systems, water pumps, fan plants, Wi-Fi network, sensors, and other auxiliary equipment. Ensuring accessibility for disabled customers involves the installation and maintenance of escalators and elevators. These integrated technologies collectively contribute to the safe and efficient operation of rail transit systems. Technologies employed in train maintenance facilities encompass sensors and robotics, contributing to overall maintenance efficiency.

Among the ongoing modernization efforts, existing rail transit systems that rely on analog signal controls are undergoing replacement with modern signaling control systems. The use of analogous systems has been historically reliable and straightforward. However, these methods have been in use for an extended period, and they have surpassed their expected lifespan. The analog signal systems are generally robust, they are susceptible to signal glitches and delays within the Rail Transit system. Consequently, there is an urgent need for upgrades to modernize this system, ensuring it meets current technological standards and can continue to operate efficiently and effectively in the evolving landscape of rail transit.

Software and hardware are equally crucial components of the rail transit system. The software aspect spans a spectrum from transit apps and training simulators to Computer-Aided Design and Drafting (CADD) software. Software, like any technology, often necessitates periodic updates through new versions to improve performance and enhance the quality of life for users. For passenger trains, apps play a significant role, especially in ticketing and providing real-time train status updates. These apps are intricately connected to communication systems to ensure the delivery of accurate and timely information to passengers.

LITERATURE REVIEW

Innovation will always be at the forefront when change is needed. Individuals, companies, and/or agencies will initiate the development and implementation of new technologies. By taking existing technology or systems, a critical determination needs to be made whether it is possible to advance it any further with new ideas. In certain scenarios, innovations can only be brought to life if preceding technologies are refined. To the core, various fields can always use improvement. However, new improvements and implementation are associated with risks and challenges. Follow-up questions need to be answered as to whether implementing new changes are justifiable and plausible without being detrimental to the current infrastructure. Figure 1 shows the different paths technology and challenges take when implementing new technologies into the rail transit infrastructure. Articles and research have been listed and explored to show upcoming and emerging technologies that are making strides in the rail transit world. Furthermore, the challenges will be discussed to show what needs to be considered when implementing new technologies.

EMERGING TECHNOLOGIES

Any metropolitan city's commuter rail transit system is considered the backbone of commuters such as New York City Subway or Boston MBTA in the USA, London Underground in the UK, Berlin U-Bahn in Germany, Tokyo Metro in Japan, and Paris Metro in France. Periodically, these transit organizations upgrade their railcars, enabling the use of modern equipment, enhancing mobility, and incorporating advanced technologies. For example, based on the available information, New York City Transit's new railcars are stated to have wider doors, security cameras throughout the train, digital screens in each car, and additional accessibility features [5]. These new railcars are part of the ongoing modernization plans for the extensive scope of the Metropolitan Transit Authority (MTA), aimed at providing more reliable, fast, and clean service throughout the New York Metro area. Japan is very progressive in its rail transit systems as it was one of the first to start the fast bullet train travel back in 1964 (Shinkansen) [4]. They produce some of the fastest trains in the world and are on their way to implementing one of the fastest commercial railways yet. The new science behind one of the fastest trains in the world comes from the obscure shape of the nose of these new bullet trains. Per the article, its explained how the pressure gradient changes with the shape of the nose when entering and exiting the tunnel [12]. This was needed because of hazards and problems with old designs that were affecting homes nearby, namely the piston effect. The process by which a train going through a tunnel pushes air through the tunnel, creating pressure waves that have had some disastrous effects. 1970's the Shinkansen had created cracks in windows of the nearby homes and sonic booms that could be heard a quarter mile away. This new nose shape design helped alleviate the pressure drops of this recurring issue. The flatter the nose of the train the faster the pressure builds.

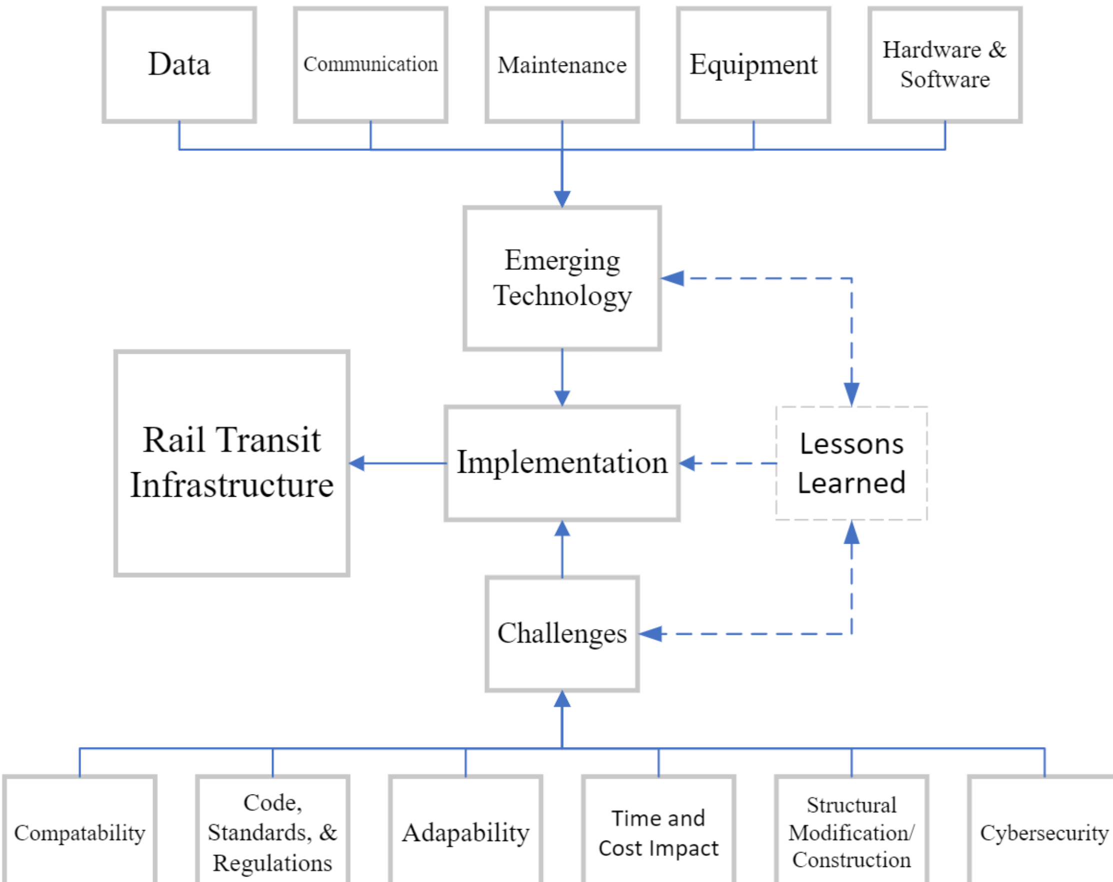

Figure 1. Implementing Technologies and Challenges in Rail Transit Infrastructure

The incorporation of emerging technologies is being addressed across various domains of infrastructural enhancement, and is articulated as follows:

Infrastructure construction/monitoring related: The use of drones is gradually becoming a staple related to construction, surveying, monitoring, and inspection due to their ability to provide valuable information from a bird's eye view of an entire project area. Its capabilities can extend from being used for surveying to data monitoring for rail transit project completion. There are more capabilities as drones are versatile, and the objective of the drone depends on the defined scope. The upfront cost for drones is massive but can reduce inspection costs while speeding up the process, allowing for real-time immersive monitoring with improved safety [8].

Maglev System and Bullet Train: Rail Transit systems around the world are showing extraordinary feats in the engineering world. Japan with its Maglev trains are airborne which is the future of railway technology. In Maglev lines, they use coils that are sanctioned in the walls linear to the path of the train. While the magnets are already within, the trains are now being pushed by these coils causing the levitation (10cm in the air) and advancement of the train (speeds of up to 603 km/h) [3].

The challenge faced with creating a new shape design for the Shinkansen was how to make the most plausible design, while also retrofitting the driver area of the train car [12]. Changing the design and trying to test these methods at the same time is very challenging without the benefits of Computational Fluid Dynamics (CFD). With CFD it is simpler to simply test out the design of each scenario to help narrow down costs and labor for final physical tests.

Train Safety/Communication and system integration: PTC (Positive Train Control) is another useful technology to help the safety aspects of railway transit workers and any bystanders or obstructions on the track. This type of sensor technology automatically stops a train to prevent certain types of human-caused accidents and make rail transit safer [7]. Metrolink is working on PTC using GPS-based safety technology that can help reduce the number of train-to-train collisions [13]. They even have automated releases for brakes if the locomotive engineer does not respond to the onboard display warning.

The future of communication-based train control (CBTC) is primarily focused on the communication between rail cars on tracks, mostly parallel tracks on moving block systems as opposed to a fixed block system. Figure 2 shows the advantage of CBTC signals, as they can provide more accurate information about the trains' location, direction of travel, and speed [17]. This decisiveness allows trains to move more frequently and efficiently. The limitations of fixed block signaling are that there are no precise locations of train cars ahead and no speed control, and the fixed block system in its complexity is difficult to maintain. These limitations are what CBTC can absolve and provide the information needed to run effectively, while PTC helps run these signals to provide better safety.

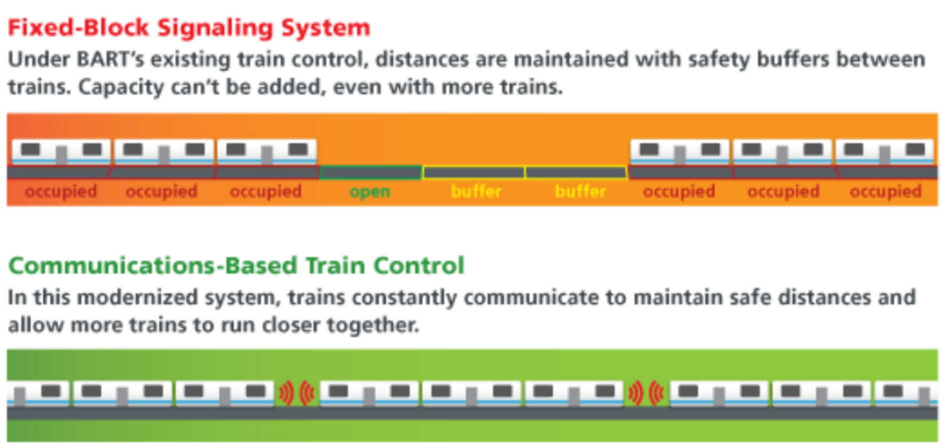

Figure 2. Fixed Block Signaling vs. Moving Block (CBTC) Diagram (Source: BART [17])

As shown in Figure 3, as a schematic, these are the conditions for PTC to operate efficiently and effectively. Computer dispatch uses code to send necessary restrictions for speed zones, track geometry, and signal trafficking for work zones and caution zones. This is then picked up by the onboard system, which monitors and controls train movement when the engineer is not responsive. They also consider wayside signals in the monitoring of train movement, tied into a system that is processed on the onboard system. All by using modern GPS-based signals that provide an approximate representation of the data [13]. Metrolink is one of the companies that produces the PTC system around the southern California Rail region for developing, installing, testing and deploying PTC to solidify its expansion of the technology.

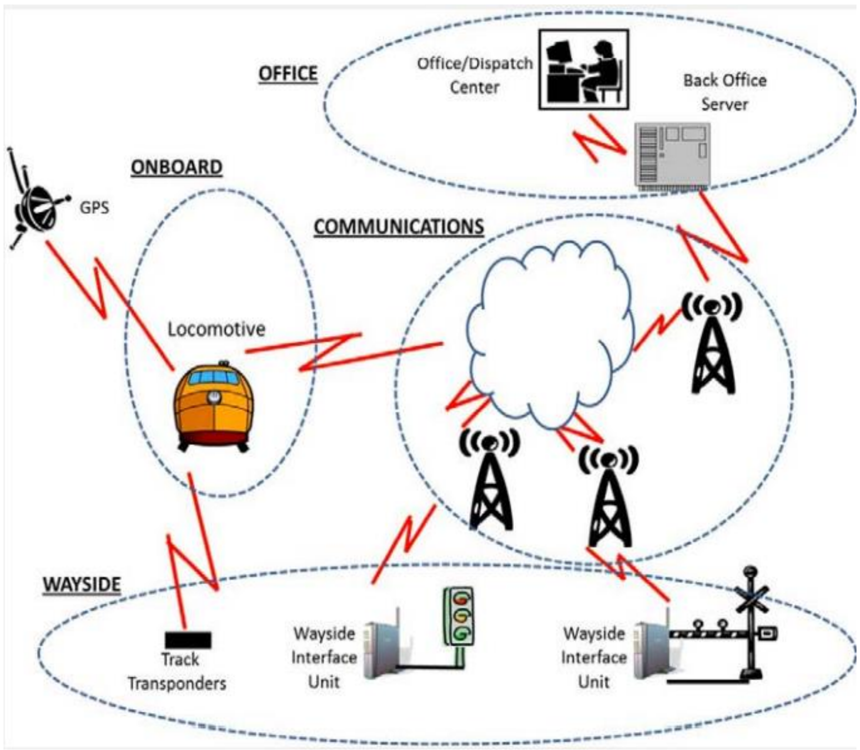

Figure 3. PTC Diagram of System Architecture (Source: DOT FRA [18])

As previously mentioned, much software is in a constant state of being updated and many new software are emerging to keep up with the new technology. The software innovation is leading the railroad industry to start using autonomous technology for freight and passenger fleets. Automatic Train Control (ATC) and Automatic Train Operation (ATO) were the initial strides to ensure safety and efficiency. The International Association of Public Transport has created a standard for automation known as the four (4) Grades of Automation (GoA)[9].

With innovations in major European and Asian countries such as China, Singapore, and Germany, they have conducted pilot programs for driverless (GoA3) trains where only door closer and operation in the event of disruption is performed by personnel. Due to the well-being and safety of the public, the train operator and train personnel were onboard during the pilot programs. With enough advances in A.I. software and the collaborative assistance of data collection systems, GoA4 is nearly attainable where the entire train operation is unmanned but public safety will always be a concern.

Consistency, train/system maintenance, and asset management: Using sensors, GPS, and Wi-Fi signals, the benefits of the Internet of Things (IoT) can be deployed. It is essential when transferring from analog controls to digital controls. For example, there are 3 types of controls in a proposed solution by Marco Ronchetti, named: low-level, intermediate-level, and high-level commands [15]. These commands can drive controls such as train mobility, train routing, signaling, and operations. With big data, IOT can enhance train consistency and maintenance of train cars and track repairs with information that can be analyzed and utilized. A variety of innovations are making themselves more known across the railway industry, such as new infrared sensors to protect the longevity of train rail wheels [6]. There have been investments in acoustic monitoring and laser technology to help benefit the overall life cycle of the railcars and maintenance to make it easier to monitor any state of repairs.

Rail transit utilizes sensors such as LiDAR, vibration sensors, noise sensors, etc. for various projects and maintenance. Over time, these sensors become more user-friendly, physically compact, and can be used in more difficult situations. For example, vibration and noise monitoring has become an integral part of the construction of rail transit systems. Trains will always cause mass amounts of vibration and noise which the public will receive negatively. To ensure proper maintenance, deployable and remote equipment is essential; equipment from Sigicom has shown this innovation with their INFRA C22 [16]. This is an upgrade from previous models since the C22 can be used wirelessly, uses GPS, and doesn't require a powered connection. LiDAR sensors use light to measure and generate detailed maps of its surrounding location. In comparison to cameras, LiDAR technologies can work in most environmental conditions with high levels of accuracy. These technologies will elevate the way surveys are conducted and provide quicker and more accurate spatial data.

Introduction of Artificial Intelligence (AI): AI can be used for data collecting instead of just controlling trains. For example, agencies have been tackling fare evasion via monitoring through AI-powered surveillance systems [10]. In addition, AI surveillance systems will improve public security. With AI progression, computers will be able to self-analyze data and situations by integrating deep learning. Deep learning is a way to teach AI how to behave similarly to human instincts [14]. The article also explored the adaptation of deep learning with drone usage on construction projects. The goal is to limit and reduce construction accidents and injuries while seamlessly introducing new technology to the well-established methodology of construction work. Deep learning: and AI in general, can be further used for train car repairs. Using IOT and sensors, information can be gathered and sent to the AI model to evaluate the issue and actuate a solution by repairing damages.

Real-time data management and display: With the mass movement of information and data between server to server and to the cloud, communication systems need to be on par with input and output needed. Fiber optics is the leading development in connection communications across the board. Since fiber optics is an expensive investment, they can be used purely within cars and systems but not for system-to-system communication. Wireless connections are recommended to drive the cost lower by using Wi-Fi, WiMAX, and short-range communication nodes (DSRC) [16]. Higher frequency bands are being developed to allow higher levels of communication without bottlenecks. As for in-system communication, fiber optics can be used to allocate information received via wireless communication and displayed on screens on platforms or information displayed in trains.

CHALLENGES IMPLEMENTING TECHNOLOGIES

Implementing new technologies will always be associated with challenges to overcome. Given the broad size of rail transit infrastructures, these challenges can come in all shapes or forms. Rail transit systems that have severely outdated infrastructure may have to deal with the lagging implementation of technology. The following could be highlighted or categorized as challenges:

Compatibility: Compatibility plays a huge role when considering implementing new technologies into the existing infrastructure. The rail transit ecosystem relies on components being able to communicate and feed information to each other. As new technologies are invented, they need to have the ability to be seamlessly incorporated so all parts of the system can keep communicating without interference.

Future considerations: These technologies must be configurable to allow futureproofing when the system is inevitably upgraded again.

Time and cost impact: In certain rail transit infrastructure, compatibility comes at the cost of improving old infrastructure not meant for upgrades which can become a huge monetary loss depending on the size of the improvements needed. For example, added technology will drive the electricity demand. New substations or green-energy methods will need to be implemented to reduce strain on the electrical grid. Time is another important factor for monetary loss as it will take time to upgrade and knowing the speed of innovation, an inevitable technological chase can begin where a system will always be lagging.

Adaptation: With new technologies, comes the need for personnel handling these technologies along with training to maintain them. Some individuals are naturally resistant to adapting and changing to new environments which could potentially lead to safety risks or a longer time to train. Adaptability can impact the riders and users as well depending on where changes were made. If the physical environment, schedule, or ticketing systems change, it will be a shock to the riders or users. Younger riders may be able to adapt quicker to the change compared to older riders; in which older riders may begin to express their dissatisfaction.

Safety and security (cybersecurity): Construction sites are typically dangerous environments where full attention is needed by workers. For example, utilizing drones, if they are deployed onto a site, they can be considered a distraction to workers as they will be making noise, and they can serve as a visual distraction [11]. This could inevitably lead to accidents occurring, furthermore, if the drones interfere with machinery. If the drones are piloted by humans, there will always be room for human error and if the drones are piloted via computer, the signal can be intercepted by a cyberattack. Furthermore, with the increased load of data collection and data analysis, this information needs to be protected. Agencies and companies that run rail transit infrastructures need to be aware of cyber-attacks and data leaks that might be associated with the compilation of user data. Cybersecurity is a battle of tug-of-war in which security measures must always be under surveillance and routinely updated to ensure maximum protection.

Error in data processing: Taking the data and interpolating it could lead to human error when post-processing. It is necessary for the information (e.g., survey) to be accurate to ensure smooth construction progress. Improper post-processing can lead to delays or other on-site implications.

Jurisdiction and regulations: On the topic of regulations, each country and state have its own codes and standards that need to be complied with. A new technology that worked in the Asian transportation sector may not necessarily work the same or can't be implemented in Western countries. In the construction and development of new or updated infrastructure, these codes need to be upheld. With new technology, some of these codes may still not be updated to the status quo. There will need to be a momentary pause until codes and regulations are settled for new technologies before they can be used by the public. Both the government and transportation agencies will have to update these policies which could push back projects.

Analysis, design, and test: There are always challenges involved in modifying physical shapes, geometry, or alignment concerning railcar or rail track systems. But, with analysis, design, and test verification, these challenges can be resolved. For example, the benefit of performing Computational Fluid Dynamics (CFD) by utilizing tunnel ventilation.

Accessibility: As infrastructure continues to upgrade, disability accessibility codes and specifications, such as ADA (Americans with Disabilities Act), need to be updated to comply with future advancements. Most stations and rail-transit infrastructures must consist of elevators and escalators to allow ease of mobility for disabled users. Communication systems need to properly announce and display information for people with sight or hearing impairments. Platforms and walking areas should include tactile paving to further improve safety for the visually impaired. In addition, the trains need to be attuned to disabled users, for example, by having wider doors and a proper distance between the platform and the train for wheelchairs.

CONCLUSION

Certainly, Rail Transit Infrastructure inherently presents challenges that may be difficult to implement in systems around the world due to various circumstances. Whether it is scheduling, funding, engineering analysis, time, codes, or standard and practicality, these are common hurdles when introducing new technologies. Examples include Maglev trains in the US and the complexity of integrating AI technology into rail infrastructure. An approach that considers the lessons learned from projects related to infrastructure is instrumental in overcoming the challenges associated with implementing emerging technologies. Agencies need to consider the details of how each technology is incorporated into the system.

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Built Environment and the Safety of Vulnerable Road Users near Commuter Rail Transit Stations

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ABSTRACT

Recently, there has been an increase in public transportation ridership in the United States. The transit users tend to walk or bike to the transit stations. As such, more pedestrian and bicycle crashes have been reported near transit stations. Thus, understanding the pedestrian and bicycle crash characteristics may help to improve their safety near transit stations. This study evaluated the safety of pedestrians and bicyclists near commuter rail transit (CRT) stations in South Florida. The study used five years of pedestrian and bicycle crashes in South Florida. The negative binomial and zero-inflated model were used to identify factors that contribute to the crashes in the census block group (CBGs) near the CRT station. The results indicated that the residential density, distance to the nearest CRT stop, and frequency of transit service per square mile were significantly associated with the number of crashes near the CRT stations in the nearby CBGs.

BACKGROUND

Public transportation ridership in the United States has risen by more than 20% in the last decade, touching its highest level since 1957 (FTA, 2017). A 61% increase in commuter rail and streetcar revenue miles nationwide was observed between 2006 and 2016 (Ziedan & Brakewood, 2020) As a result, several urban areas have planned, designed, and constructed rail systems and other transit systems, such as bus rapid transit (BRT) and monorail, to cater to the growing demand for public transportation. The rail system has emerged as a safe, reliable, high-capacity public transit system.

Many transit users walk to access the rail stations or other stations. People are willing to walk for 5-10 mins, or approximately 0.25 - 0.5 miles, to a transit stop (FHWA, 2017). Due to rail stations' shorter spacing and operational capacity at street level, it is compatible with pedestrians. In addition to walking, biking is also used as a transfer mode to and from transit stations. A 2-mile radius around a transit station is the average distance most people are willing to ride a bicycle (Osmonson, 2017)Evidently, travel distance is the most important influence on cycling rates for transfer trips between transit stations and home or workplace (Zhao & Li, 2017).

Public transportation ridership depends on users' safety, who are mostly pedestrians for a certain distance (i.e., 0.25 miles) from the transit station (Pulugurtha & Srirangam, 2021). A study on vehicle and pedestrian safety at light rail stops in mixed traffic indicated that 82% of safety incidents associated with streetcars were auto-pedestrian conflicts (Currie & Reynolds, 2010). Therefore, improving ridership of rail must start with promoting pedestrian and bicycle safety near stations. However, despite many efforts to evaluate the factors influencing pedestrian and bicycle crashes, only a few studies have analyzed the effects of the built environment on pedestrian and bicycle safety near rail stations.

Current research has described the "built environment" concept using the D transportation variables, which include density, diversity, design, distance to transit, and destination accessibility. Density is measured as the variable of interest per unit area, whereas diversity pertains to the number of different land uses in a given area (Ewing & Cervero, 2010). The design includes street network characteristics within an area. Destination accessibility measures the ease of access to trip attractions (Ewing & Cervero, 2010) and the distance to transit is usually measured as an average of the shortest street routes from the residences or workplaces in an area to the nearest rail station or bus stop (Ewing & Cervero, 2010).

The D variables allow agencies to understand areas that require systemic measures to improve safety. Also, they clearly show the influence of the built environment on pedestrian and bicycle safety in different dimensions. Previous studies considered some D variables in the analysis, especially density, design, and distance to transit stations. Pulugurtha and Srirangam (S. S. Pulugurtha & Srirangam, 2021)indicated that mixed-use areas, office areas, single-family residential areas, and industrial areas have a statistically significant influence on the number of pedestrian crashes at intersections near rail stations. Zahabi et al. (2011) indicated that land-use characteristics influence the injury severity of pedestrian crashes near intersections. Moreover, (Pulugurtha et al., 2011) revealed an increase in the number of bus stops within a 0.25-mile radius to be associated with pedestrian crashes.

This study evaluated the safety of pedestrians and bicyclists near the CRT stations. Specifically, the study identified the built environment attributes influencing pedestrian and bicycle safety near the transit stations. Several transportation D variables, i.e., density, design, diversity, distance to transit, and destination accessibility evaluated. The study used five years (2015-2019) of pedestrian and bicycle crashes in South Florida. The negative binomial (NB) and zero-inflated model (ZINP) were used to identify factors that contribute to the number of crashes in the census block group (CBGs) near the CRT stations.

STUDY AREA AND DATA

The study area included eighteen (18) transit stations from the three counties in South Florida (i.e., Broward, Miami-Dade, and Palm Beach counties). Figure 1 presents the locations of the commuter rail stations used in the study.

Data used in the present study include crash, transit stations, and the built-environment data from three counties in South Florida (i.e., Broward, Miami-Dade, and Palm Beach counties). The crash data involving vulnerable road users (i.e., pedestrian and bicycle crashes) in the years 2015 through 2019 were extracted from the Signal Four data analytics. The data provided information on the crash types (i.e., vehicle-vehicle, vehicle-pedestrian, vehicle-bicyclist, etc.), crash severity (i.e., fatal, injury, or no injury), and crash locations (i.e., latitude and longitude). Transit station data were obtained from the tri-rail database. The data contain information such as the location of the stations and their corresponding names.

The five D-transportation variables that describe the built environment include density (e.g., population density, employment density, etc.), diversity (e.g., employment and household entropy, etc.), design (e.g., road network density, etc.), transit access (e.g., distance to transit, etc.), and destination accessibility. These variables were extracted from the smart location database, a publicly available data product, and service provided by the U.S. EPA Smart Growth Program. Table 1 shows the selected variables for each of the D elements of the built environment, their corresponding description, and descriptive statistics. For more details on the variables, the reader can refer to the data manual (Chapman et al., 2021).

FIGURE 1. CRT stations in South Florida

METHODOLOGY

Data Processing

The geospatial analysis was conducted to identify all CBGs within the vicinity of the transit stations. It is worth mentioning that one transit station may be surrounded by more than one CBG. Since crashes are geocoded at street centerlines and street centerlines are used as CBG boundaries, a 200-ft radius was created around each CBG, and the buffer area was used to extract the number of pedestrians and bicyclists crashes within the CBG. Because the block group typically uses arterials and thorough fares as geographic boundaries, it is consistent with the characteristics of crashes that occur along the street. The 200-feet radius was considered reasonable to capture pedestrian and bicyclist crashes that occurred at the boundary of the CBG. This method was used by the previous studies (Dumbaugh & Li, 2011; Dumbaugh & Rae, 2009; Ouyang & Bejleri, 2014). Also, using CBGs provides accurate demographic information and has a relatively homogeneous design characteristic (Ouyang & Bejleri, 2014).

Table 1: Descriptive statistics of five D-variables used in the analysis

Variable	Description	Min	Mean	Max	SD
Density					
Residential density (D1a)	Housing units per acre on unprotected land	0.00	3.69	14.32	2.81
Population density (D1b)	People per acre on unprotected land	0.00	8.93	25.31	5.95
Employment density (D1c)	Jobs per acre on unprotected land	0.06	5.97	47.29	7.81
Diversity					
Employment and household entropy (D2A_EPHHM)	Land use diversity used this as a proxy by quantifying the blend of the number of jobs in different employment sectors and residential housing types	0.14	0.57	0.98	0.24
Employment mix/entropy (D2b_E8Mix)	Calculate the employment mix based on an eight-tier employment category. The employment denominator is set to observe existing employment types within each CBG	0.00	0.66	0.98	0.19
Design					
Total road network density (D3a)	Ratio of all types of facilities links by the land area	8.77	23.47	36.21	6.29
Street intersection density (D3b)	Total intersection density-weighted to emphasize pedestrian and bicycle connectivity (pedestrian-oriented facilities)	11.76	97.56	216.75	46.98
Transit access					
Distance to the nearest transit stop (D4a)	The minimum walk distance (meters) between the 2010 population-weighted CBG centroid and the nearest transit stop of any route type	0.00	482.49	1,178.84	272.48
Proportion of employment within 0.25 miles of a fixed guideway transit stop (D4b025)	Proportion of CBG employment within 0.25 mile of a fixed-guideway transit stop. Access to this type of transit services included all rail transit (metro, light rail) and some bus rapid transit with dedicated right of way	0.00	0.14	0.55	0.14
Proportion of employment within 0.5 miles of fixed guideway transit stop (D4b050)	Proportion of CBG employment within 0.5 miles of a fixed-guideway transit stop. Calculated as the ratio of the unprotected area within 0.5 miles to the unprotected area of the CBG	0.01	0.50	0.99	0.29
Aggregate frequency of transit service [D4c] per square mile (D4d)	Applies density characteristics to aggregate transit service frequency per square mile. This metric was calculated by dividing aggregate transit service frequency [D4c] by total land acre	0.52	32.88	116.85	33.58
Destination accessibility					
Proportional regional accessibility to jobs ((D5dr))	Proportional accessibility of regional destinations-transit	0.00	0.00	0.01	0.00

Note: CBG = Census block group; SD = Standard deviation.

The pedestrian crashes within walking distance of 0.25 miles were assigned to each of the transit stations. The 0.25 miles was considered sufficient walking distance for the pedestrian. For the bicycle crashes, a riding distance of a 1-mile radius from the transit stations was used to assign the bicycle crashes to the transit stations. Table 2 provides the descriptive statistics of pedestrian and bicycle crashes. There were more bicycle crashes that occurred within a mile radius of the transit stations than pedestrian crashes. The higher number of bicycle crashes may be due to the higher radius (i.e., 1 mile) from the transit rail stations compared to the pedestrian crashes (radius of 0.25 miles).

Table 2. Summary of the crash data

	Minimum	Mean	Maximum	Standard deviation
Pedestrian crash frequency				
Total crash	0.00	2.05	8.00	2.06
Fatal plus severe injury	0.00	0.39	2.00	0.62
Minor injury	0.00	1.31	6.00	1.51
No injury	0.00	0.36	2.00	0.55
Bicyclist crash frequency				
Total crash	17.00	47.53	96.00	24.17
Fatal plus severe injury	1.00	5.64	14.00	4.18
Minor injury	10.00	31.83	65.00	16.08
No injury	2.00	10.05	23.00	6.47

Negative Binomial and Zero Inflated Negative Binomial Model

This research used a generalized linear model (GLM) approach with a Negative Binomial (NB) and Zero Inflated Negative Binomial (ZINB) distribution to develop the relevant regression models. The NB models are suitable count models in cases of over-dispersed data, which means the variance of the count process is significantly larger than its mean (Washington et al., 2020). The over-dispersed crash data were modeled using the NB model, whose probability distribution is expressed as:

$$g(y_i) = Pr\left(Y = y_i \mid \mu_{i,} \alpha\right) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\, \Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha\mu_i}\right)^{\alpha^{-1}} \left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i} \quad (1)$$

where is the μ_i is the mean crash frequency at location i, α is the over-dispersion parameter, and Γ is the gamma function. The basic form of the NB model used in this study is:

$$\mu_i = exp\left(\beta_0 + \beta_k \times X_{ik}\right) \quad (2)$$

where μ_i is as defined in Equation 1, X_{ik} is the built environment attribute k of location i, β_0 is the model intercept/constant, and β_k is the model coefficient for the built environment attribute k.

The ZINB model was used to account for the CBG with zero crashes that cannot be solely explained by the Negative Binomial (NB) models. The ZINB models are applicable for count data that exhibit over-dispersion and excess zeros. The probability distribution of the ZINB random variable y_i (NCSS, 2018) is:

$$Pr(y_i = j) = \begin{cases} \pi_i + (1-\pi_i)\, g(y_i = 0), & if\ j = 0 \\ (1-\pi_i)\, g(y_i), & if\ j > 0 \end{cases} \quad (3)$$

where π_i is the proportion of true zeros that cannot be explained by the NB model, and $g(y_i)$ is the negative binomial distribution shown in Equation 1. The ZINB random variable can take two types of values presented by j in Equation 3, such that $j = 0$ represents the probability of zero crash occurrence at location i, and $j > 0$ represents the probability of at least one crash occurrence at location i. A Vuong test statistic was used to test the appropriateness of using the ZINP model over the NB model. More details on the Vuong test could be referred from Washington (2003). The regression coefficients, over-dispersion parameter, and Vuong test were estimated using the *glm* and *pscl* package in the statistical software *R*.

RESULTS AND DISCUSSION

Variable Selection

The number of pedestrian and bicycle crashes was the dependent variable of the models. The built environment variables were taken through a selection process due to the potential of existing multicollinearity between them. The selection procedure followed the steps adopted by (Xu et al., 2012). The Pearson correlation coefficient between each pair of candidate variables was calculated, and several combinations, including the maximum number of uncorrelated variables were generated. The correlation threshold value of 0.6 was used to identify highly correlated variables (Kwak & Kho, 2016). That means variables with a correlation coefficient of greater or equal to 0.6 indicated high correlation. The variable to be included in the model was selected by fitting a model with one of the correlated variables in turn and compare the Akaike Information Criteria (AIC) of each model. The model with the least AIC value was considered the best model, and its variables were selected to be used in fitting the NB and ZINB models. Figure 3 shows the correlation matrix of the selected model variables.

Pedestrian Safety

One objective of this study was to identify built environment factors that may influence pedestrian crashes near transit rail stations. The Vuong test statistic indicated that the ZINP model was a more appropriate model for fitting the pedestrian crashes within 0.25 miles of the CRT stations. The Vuong statistic between the ZINP model and the NB model was 2.3858, with a *p*-value of 0.009. Table 3 shows the results of the ZINP model of the pedestrian crashes within 0.25 miles of the CRT stations. Only the residential density, distance to the nearest transit stop, and frequency of transit service per square mile were significantly associated with the number of crashes near the CRT in the nearby CBGs. These results are consistent with the previous studies (Pulugurtha et al., 2011; Pulugurtha & Srirangam, 2021)None of the design and destination accessibility variables was significant.

The positive coefficient of residential density indicates that areas with CBGs with higher residential densities are associated with more pedestrian crashes near train stations. The distance to the nearest transit stop was positively associated with more pedestrian crashes. This result meant that the longer the distances to the nearest stop increase the pedestrian crashes near the train stations. Longer distances to the transit stop indicate that pedestrians are exposed to a higher risk of crashes than shorter distances to the stops. This result was opposite to the observation made by Ouyang (2014) that the distance to a bus stop was not significant for pedestrian crashes. The difference could be attributed to the consideration of all types of transit stops and pedestrian crashes only within 0.25 miles of the CRT station. Also, the frequency of transit service per square mile was associated with more pedestrian crashes near the CRT stations. This result was unexpected, considering that higher frequency was expected to encourage transit users from walking, hence reducing their exposure to the risk of crashes. Further analysis is required to better understand the impact of frequency of transit service on pedestrian safety.

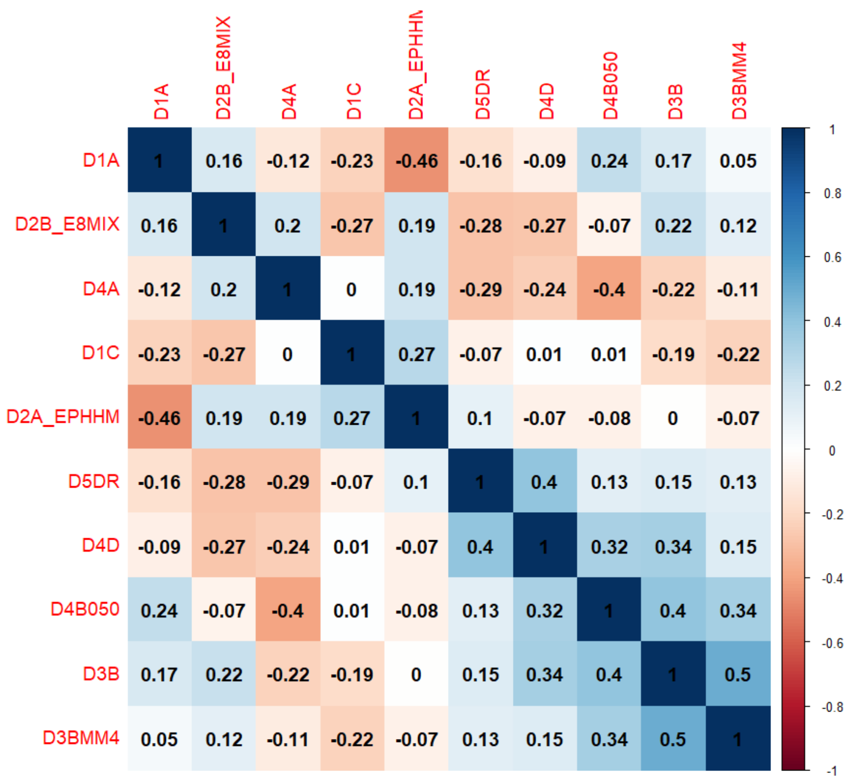

Figure 2. Correlation matrix of the selected model variables

Moreover, residential density and proportion of employment within 0.5 miles of fixed guideway were associated with the absence of pedestrian crashes within 0.25 miles of the CRT stations in the nearby CBGs. Results indicate that residential density was associated with the increased likelihood of the occurrence of pedestrian crashes near the CRT stations. As previously mentioned, higher residential density indicates more pedestrian activities and exposure. A higher proportion of employment within 0.5 miles of fixed guideway decreased the likelihood of occurrence of pedestrian crashes within 0.25 miles of the CRT station. One explanation could be that activities near CRT stations suggest that pedestrians are not compelled to walk longer and, hence, less exposed to vehicles.

Table 3. Factors associated with pedestrian crashes within 0.25 miles of CRT stations

Count model coefficients				
	Estimate	Std. Error	Z value	Pr (>|z|)
D2B_E8MIX	-0.091	0.876	-0.104	0.918
D1C	0.013	0.015	0.830	0.407
D1A	**0.116**	**0.051**	**2.300**	**0.022**
D2A_EPHHM	0.298	0.580	0.513	0.608
D4A	**0.001**	**0.000**	**2.009**	**0.045**
D5DR	0.166	0.126	1.321	0.187
D4B050	0.530	0.494	1.073	0.283
D3A	-0.026	0.022	-1.209	0.227
D4D	**0.007**	**0.004**	**1.789**	**0.074**
Intercept	0.068	0.774	0.087	0.930
Log(theta)	13.440	302.100	0.044	0.965
Zero-inflation model coefficients				
	Estimate	Std. Error	z value	Pr (>|z|)
D2B_E8MIX	-5.842	5.529	-1.057	0.291
D1C	-0.105	0.201	-0.521	0.603
D1A	**0.410**	**0.240**	**1.707**	**0.088**
D2A_EPHHM	1.360	3.332	0.408	0.683
D4A	0.001	0.002	0.502	0.616
D5DR	0.056	0.500	0.111	0.911
D4B050	**-3.446**	**2.043**	**-1.687**	**0.092**
D3A	-0.046	0.111	-0.415	0.678
D4D	0.025	0.018	1.399	0.162
Intercept	1.793	2.828	0.634	0.526

As a comparison, all pedestrian crashes in the CBGs near the CRT stations were analyzed. Considering that there were no CBGs with zero pedestrian crashes, the NB was the more appropriate model for the data. Table 4 shows the results of the NB model of all pedestrian crashes in the CBGs near the CRT stations. It is indicated that employment entropy, employment density, residential density, distance to the nearest transit stop, total road network density, street intersection density, and frequency of transit service per square mile were significantly associated with the number of crashes in the CBGs. Results indicated factors that could influence all pedestrian crashes but not within 0.25 miles of CRT stations, including employment entropy, employment density, total road network density, and street intersection density. The effect of the residential density on all pedestrian crashes was opposite to its effect on the pedestrian crashes with 0.25 miles of the CRT stations. A similar effect was observed for the frequency of transit service per square mile on the number of pedestrian crashes.

Bicyclists Safety

One objective of this study was to identify built environment factors that may influence bicyclist crashes near CRT stations. Considering that there were no CBGs with zero bicyclist crashes within a mile of CRT, the NB was the more appropriate model for the data. Only the proportional regional accessibility to jobs was significantly associated with the number of bicyclist crashes near the CRT in the nearby CBGs. None of the density, diversity, design, and transit access variables was significant. The negative coefficient of the proportional regional accessibility to jobs indicates that CBGs with higher proportional regional accessibility to jobs are associated with fewer bicyclist crashes near CRT stations. One explanation could be a better transit system decreases the number of bicyclists on the road, which reduces their exposure to crashes.

Table 4. Factors associated with all pedestrian crashes in the CBGs near the CRT stations

	Estimate	Std. Error	z value	Pr(>|z|)
D2B_E8MIX	**1.749**	**0.414**	**4.222**	**0.000**
D1C	**0.023**	**0.008**	**2.762**	**0.006**
D1A	**-0.075**	**0.029**	**-2.540**	**0.011**
D2A_EPHHM	-0.044	0.319	-0.137	0.891
D4A	**-0.001**	**0.000**	**-2.197**	**0.028**
D5DR	-0.101	0.076	-1.338	0.181
D4B050	0.003	0.259	0.011	0.991
D3A	**-0.036**	**0.013**	**-2.783**	**0.005**
D4D	**0.004**	**0.002**	**1.971**	**0.049**
Intercept	2.562	0.387	6.620	0.000

Table 5. Factors associated with bicycle crashes within 1 mile of CRT stations

	Estimate	Std. Error	Z value	Pr(>|z|)
D2B_E8MIX	0.396	0.395	1.002	0.316
D1C	0.009	0.009	0.980	0.327
D1A	-0.004	0.028	-0.142	0.887
D2A_EPHHM	-0.192	0.323	-0.595	0.552
D4A	0.000	0.000	0.048	0.962
D5DR	**-0.144**	**0.073**	**-1.979**	**0.048**
D4B050	0.347	0.257	1.350	0.177
D3A	0.012	0.013	0.873	0.383
D4D	0.001	0.002	0.355	0.723
Intercept	3.173	0.384	8.253	0.000

As a comparison, all bicycle crashes in the CBGs near the CRT stations were analyzed. Considering that there were no CBGs with zero pedestrian crashes, the NB was the more appropriate model for the data. Table 6 shows the results of the NB model of all bicycle crashes in the CBGs near the CRT stations. It is indicated that employment entropy and residential density were significantly associated with the number of bicycle crashes in the CBGs. Both of these factors were not found significant when considering the bicycle crashes within 1 mile of CRT stations. It was indicated that a higher employment mix was associated with a higher number of bicycle crashes. Also, higher residential density was associated with fewer bicyclist crashes in the CBGs near the CRT stations. This observation was similar to the one related to pedestrian crashes in the CBGs near the CRT stations.

Table 6. Factors associated with bicycle crashes in the CBGs near the CRT stations

Variable	Estimate	Std.Error	z-value	Pr(>|z|)
D2B_E8MIX	**0.628**	**0.361**	**1.742**	**0.082**
D1C	0.011	0.008	1.360	0.174
D1A	**-0.046**	**0.025**	**-1.800**	**0.072**
D2A_EPHHM	-0.209	0.298	-0.702	0.483
D4A	0.000	0.000	-0.599	0.549
D5DR	-0.041	0.066	-0.618	0.537
D4B050	-0.145	0.237	-0.609	0.542
D3A	0.004	0.012	0.312	0.755
D4D	0.000	0.002	-0.115	0.908
(Intercept)	4.514	0.351	12.871	0.000

CONCLUSIONS

Many transit users have a tendency of walking or biking to the transit stations. Ensuring pedestrian and bicycle safety could help promote transit ridership. Amongst many factors, the built environment is one of the factors that influence pedestrian and bicycle safety. The objective of this study was to identify built environment attributes that influence pedestrian and bicycle safety near the CRT stations. Specifically, the study aimed to examine the D variables of the built environment, which include density, design, diversity, distance to transit, and destination accessibility.

The study used crash data, CRT station data, and built environment data. Data containing crashes that involved pedestrians and bicyclists on non-freeway roadways in South Florida were collected from the Signal Four Data Analytics database. The collected data contained crashes that occurred from 2015 to 2019. Transit station data were obtained from the tri-rail database. The built environment data were extracted from the Smart Location Database, a publicly available data product, and service provided by the U.S. EPA Smart Growth Program.

The study objective was achieved by identifying pedestrian and bicycle crashes in the CBGs near CRT stations. The NB and ZINP were then applied to identify factors that contribute to the number of crashes in the CBGs near the CRT station. To understand whether there is a difference between all crashes and those within walking or biking distance, the study analyzed the two groups separately. Moreover, the study analyzed bicycle and pedestrian crashes separately to reveal the differences between the two groups of vulnerable road users.

The study findings revealed that the residential density, distance to the nearest transit stop, and frequency of transit service per square mile were significantly associated with the number of crashes near the CRT in the nearby CBGs. The design, diversity, and destination accessibility variables did not have a significant impact on the number of pedestrian crashes near the CRT stations. Moreover, residential density and proportion of employment within 0.5 miles of fixed guideway were associated with the absence of pedestrian crashes near the CRT stations. Only the proportional regional accessibility to jobs significantly influenced bicycle crashes near the CRT stations. In general, there is a difference between built environment factors influencing pedestrian and bicycle crashes near CRT stations.

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Safety Analysis of the Britton Highway Railroad Grade Crossing

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ABSTRACT

The number of fatal traffic accidents at railroad crossings has decreased, but concerns persist about certain locations that remain significant safety hazards. The Britton Highway Railroad Grade Crossings (HRGC) in Oklahoma City is one such perilous intersection in Oklahoma, with 24 documented highway-railroad collisions occurring over the past 25 years. This paper conducts an in-depth safety analysis of this critical intersection, leveraging data from the HRGC inventory and crash database maintained by the Federal Railroad Administration (FRA) since the 1970s, as well as the Collision database managed by the Oklahoma Department of Transportation (ODOT) since 1998. A total of 514 highway-only crashes have been reported at the Britton intersection. A considerable portion of these incidents involved motor vehicles, with a significant number transpiring during daylight hours. It was observed that the nearby ungated HRGC, situated within 500 ft, which intersects with a local road, often served as an alternative route when the Britton HRGC was temporarily closed for passing trains. This secondary intersection witnessed eight highway-railroad accidents during the same timeframe, along with 67 highway-only crashes. Consequently, an analysis was conducted to assess the influence of traffic characteristics, highway geometry design, HRGC control devices, and other factors, to gain deeper insights into the safety implications of this HRGC. The findings in this paper could underscore the potential for reducing accident occurrences by implementing effective safety measures and supporting data-driven decision-making to enhance safety and curtail accidents at this intersection.

Keywords: Highway rail grade crossing (HRGC), safety analysis

INTRODUCTION

A highway-railway grade crossing (HRGC), also known as a railroad or level crossing, is the point at which a road or highway meets a railway track. These crossings are designed to allow vehicles, pedestrians, and other traffic to safely cross railway tracks. The term "grade" refers to the elevation of the road or highway along the railway lines, implying that the road and the tracks connect at the same level. To warn road users of an approaching train, grade crossings are typically equipped with warning signs, lights, and barriers known as crossing gates. These safety treatments and technologies are critical in reducing accidents involving vehicles, people, and trains (Abioye et al., 2020) (Lenné MG, 2011). Markings on the road surface and other visual cues are frequently used to guide vehicles and pedestrians as they safely pass across railway tracks. The configuration and safety components of HRGCs can range from simple to complex, depending on factors such as the volume of highway and rail traffic, train velocity, and the unique characteristics of the crossing location.

A thorough analysis of various HRGCs across the state of Florida revealed 429 injuries and 146 fatalities between 2010 and 2019 (Singh et al., 2021). A wide range of elements were studied, including physical and operational characteristics, vehicle and train properties, geographical and environmental conditions, temporal aspects, driver behavior, and other relevant details. The results of a descriptive analysis combined with statistical tests such as the Chi-square test and a generic linear regression model with a binary logistic structure revealed critical patterns in HRGC incidents. Accidents occurred most frequently in HRGCs without lighting. Surfaces made of concrete or asphalt, as well as timber or asphalt, were linked to greater accident rates. Hazardous HRGCs frequently saw trains traveling at high speeds, with vehicles and buses passing through these crossings daily. A notable observation was the prevalence of accidents involving stalled or trapped highway users at HRGCs. Dry road conditions were noted as a common component in these instances, and many accidents occurred as users sought to bypass the crossing gates. It is vital to emphasize the importance of obeying and respecting the warning signs and equipment at these crossings to protect the safety of everyone who uses them. The primary contributing cause to accidents in the investigation of HRGC incidents has been frequently recognized as the driver's behaviors (Author et al., 2021; Vivek et al., 2021). The continuation of incidents, even in the presence of comprehensive safety infrastructure, highlights the necessity for an advanced and diverse approach that delves into the details of driver behavior to further improve HRGC safety measures.

This paper presents a comprehensive safety analysis focusing on the Britton HRGC (identified as 012080E) located in Oklahoma City, one perilous HRGC intersection with 24 documented highway-railroad collisions and 514 highway intersection crashes occurring over the past 25 years. An adjacent ungated intersection within 500 feet (012080L) is frequently used as an alternate route when the Britton HRGC is closed for upcoming trains, resulting in eight highway-railroad accidents and 67 highway-only crashes. The study was based on an extensive dataset obtained from the Federal Railroad Administration (FRA) and the Oklahoma Department of Transportation (ODOT). The dataset encompassed crash records and inventory data associated with the two HRGCs. Various factors were evaluated such as traffic characteristics, road design, control devices, and other elements to better understand safety implications. It aims to provide insights that could guide the implementation of effective safety measures and data-driven decision-making and assist the understanding of driver behaviors to reduce accidents and enhance safety at this intersection.

DATA SOURCES

As part of this study, three key data sources were employed to obtain pertinent information, including the FRA crossing inventory, the FRA crossing accident database, and the ODOT highway crashes database.

- The FRA inventory database includes information regarding the location, operating railroad (number of trains, speed limit), physical characteristics (crossing surface, lighting condition), intersecting highway characteristics (AADT, percentage of trucks), control devices (warning signs, presence of gates, gate configuration), pavement markings, etc. The FRA database maintains data sets since 1975 (FRA, 2023).
- The FRA crash data includes general accident information (date and time of accident), railroad information, environmental conditions (temperature, visibility, weather), road

condition, direction of accident, outcome of accident (fatality, injured, property damage), control devices, and other relevant information (FRA, 2023).

- The ODOT crash database (ODOT, 2023) is a tool to catalog and analyze roadway collisions in the state of Oklahoma since 1998. Reports generated by the system include maps showing locations of collisions and an analysis of when and why collisions occurred. The system can search for locations by number of collisions, and the lists included in the reports give general information on each collision.

General Information of the HRGCs

The primary Britton HRGC is an intersection of a primary BNSF railway track and four lanes of highway vehicular traffic in each direction. The crossing has the smallest angle between 60 and 90 degrees. An adjacent ungated secondary intersection within 500 feet (012080L) is located on a local street (92nd Street) within a neighborhood, which has been frequently used as an alternate route when the Britton HRGC is closed for upcoming trains. The geometry of the crossings is shown in Figure 1.

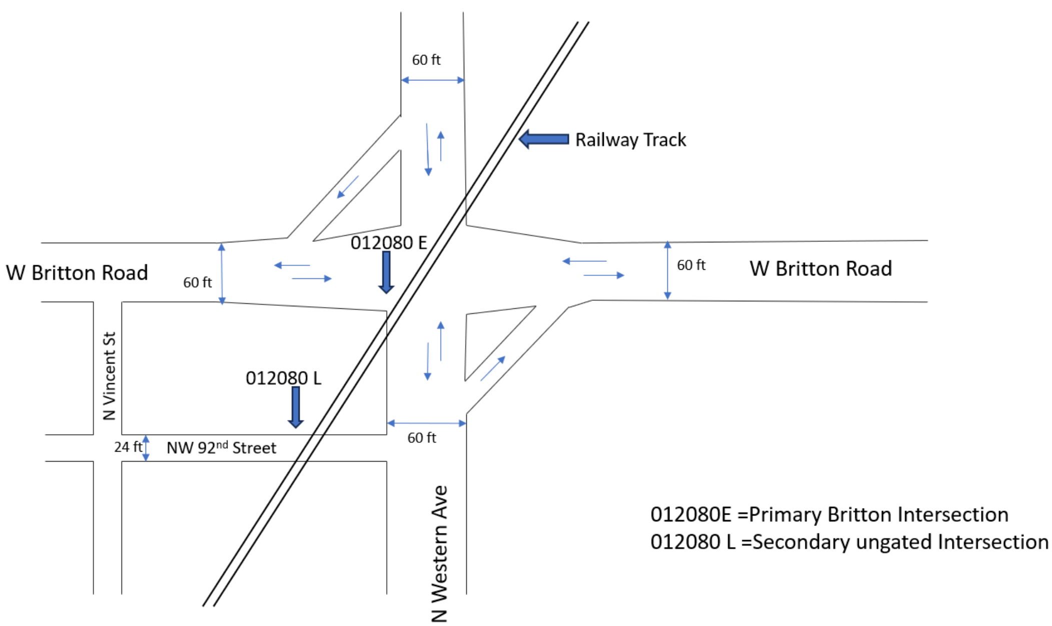


Figure 1. Geometry of Britton Intersection (not in scale)

The Britton HRGC is equipped with an extensive number of safety devices to improve the intersection's overall safety and functionality. Eight crossbucks have been placed to provide clear warnings to oncoming vehicles. Five W10-1 signs following the Manual on Uniform Traffic Control Devices (MUTCD) requirements are installed to alert traffic to the existence of a railroad crossing. At the intersection, an Emergency Notification System (ENS) sign (I-13) is displayed, serving as a communication tool in case of emergencies or unforeseen situations. Furthermore, an LED-enhanced sign displaying the critical message "Do Not Stop on Track" is in place, reinforcing the importance of not halting on the railway tracks. In addition, there are eight gate arms configured in a 2-quad gate design to physically control and regulate vehicular traffic. Four cantilever flashing lights and eight mast-mounted flashing lights provide additional visual signals to warn drivers of an oncoming train. Four bells are erected to ensure auditory alerts, contributing to the multi-sensory strategy of indicating the presence of an approaching train. However, the HRGC does not have any highway monitoring and surveillance devices. Table 1 displays the changes in the HRGC inventory. The changes of both HRGCs are provided.

Table 1. HRGC inventory changes

Crossing #	Year	HRGC Inventory Change
012080E	1988	Four bells installed, previously only one
	1988-2001	Stop lines absent
	1992	Eight gates installed
	1992	Eight Crossbucks installed
	1999	DC train detection replaced by constant warning time
	2004	4 MUTCD warnings installed
012080L	1999	Stop lines and RR Xing symbols added
	2004	Two MUTCD warnings added
	2019	DC replaced by motion detection

The railway crossing primarily serves freight trains, and the estimated Average Annual Daily Traffic (AADT) is 14,516, with approximately 6% attributed to truck traffic (USDOT 2004). Another HRGC crash exposure factor is the number of daily trains. Figure 2 displays the change in the number of day and night trains throughout the years. The total daily trains ranged from 11 in the early 1990s to 32 trains in 2010s.

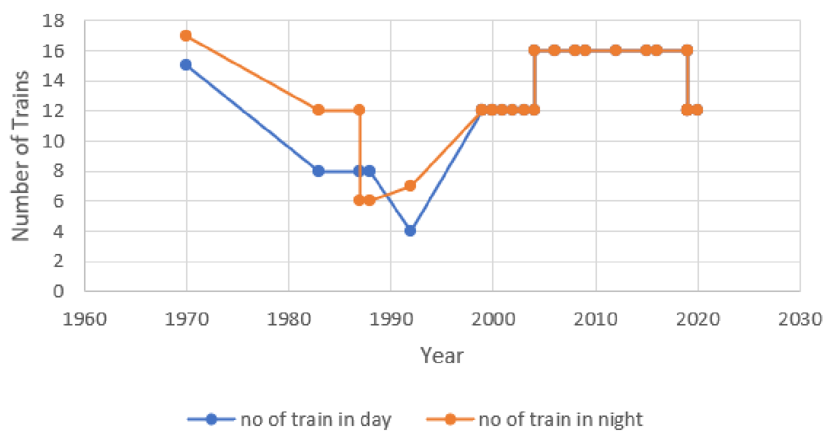


Figure 2. Number of total trains

Crash Analysis for the Primary Britton HRGC (012080E)

Highway-Rail Crashes

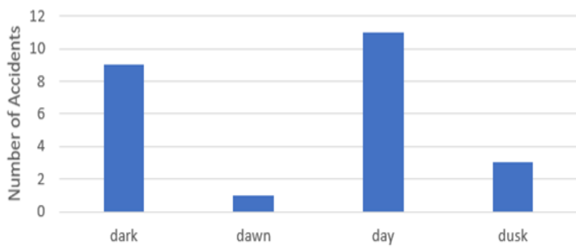
Since the 1970s, the Britton HRGC has experienced 24 highway-rail crashes. The detailed crash records are shown in Table 2.

Table 2. Primary Britton HRGC highway-rail crashes (012080E)

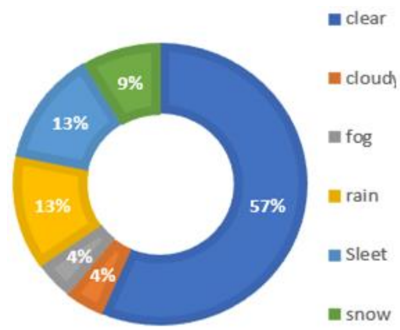
Vehicle	Date	Time	Temp (^{0}F)	Dir	Weather	Injury *	Speed (mph)	Position **	Type ***
Auto	02/14/ 2016	8:21 PM	55	N	Clear	PDO	37	Stall	Rail
Auto	08/16/ 2014	2:30 AM	80	N	Clear	PDO	40	Stall	Rail
Auto	2/4/ 2011	10:40 PM	21	W	Snow	PDO	48	Move	Rail
Auto	01/17/ 2010	1:50 am	41	E	Fog	PDO	42	Stop	Rail
Auto	04/20/ 2002	10 pm	61	S	Clear	PDO	10	Stall	Rail
Auto	1/2/ 2000	7:05 am	22	N	Sleet	PDO	38	Stop	Rail
Truck	06/19/ 1996	6:30 pm	93	S	Clear	PDO	36	Stop	Rail
Auto	07/21/ 1995	3:05 pm	94	W	Clear	K	43	Move	Rail
Auto	05/26/ 1995	11:40 am	66	W	Rain	PDO	32	Move	Rail
Truck	2/7/ 1992	9:06 am	45	W	Clear	A/B	41	Move	Rail
Auto	05/24/ 1991	3:16 pm	70	S	Clear	PDO	40	Move	Rail
Auto	12/19/ 1990	12:55 pm	55	S	Clear	A/B	35	Move	Rail
Auto	12/16/ 1990	3:30 pm	40	E	Rain	A/B	40	Move	Rail
Auto	01/17/ 1988	5:54 pm	50	N	Clear	PDO	40	Move	Rail
Auto	12/14/ 1987	12:45 pm	32	E	Sleet	PDO	40	Move	Hwy
Auto	11/13/ 1985	10:05 pm	45	E	Rain	A/B	35	Move	Rail
Auto	06/16/ 1984	11:15 am	90	E	Clear	PDO	35	Stall	Rail
Auto	6/9/ 1981	1:00 pm	90	W	Clear	PDO	25	Stall	Rail
Auto	2/8/ 1980	2:05 am	25	N	Snow	PDO	40	Stop	Rail
Auto	1/2/ 1979	7:20 pm	20	E	Sleet	A/B	40	Stop	Rail
Auto	11/21/ 1977	7:42 pm	34	W	Cloudy	A/B	45	Move	Rail
Auto	7/11/ 1977	7:25 pm	92	W	Clear	PDO	45	Move	Rail
Auto	4/5/ 1977	6:40 pm	65	E	Clear	PDO	45	Move	Rail
Auto	3/12/ 1977	6:45 am	54	E	Clear	PDO	37	Stop	Rail

Notes: * Injury type: (1) K- fatality; A/B – injury; PDO – no injury; ** Crash position: Stall - stalled or stuck on crossing; Move - moving over crossing; Stop - stopped on crossing; *** Crash circumstance type: Rail - railway equipment struck highway user; Hwy - railway equipment struck by highway user.

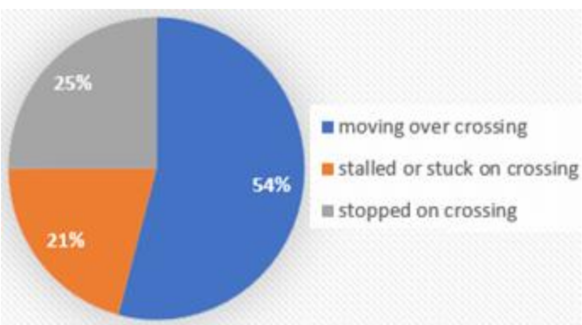
Nearly half of the reported accidents occurred during daylight hours and under clear weather conditions (Figure 3). 54% of the vehicles in the crashes were moving over the crossing, while 46% of highway traffic was either stopped or stuck on the crossing. A further field investigation (as shown in Figure 4) found that there was a significant drop-off at the Southeast corner of the intersection adjacent to the track. When drivers made a left turn with a relatively small turning radius from Britton Road to Western Avenue, it was frequently observed that drivers could head towards the drop-off areas. Additionally, the concrete surface of the rail track could also mislead the driver to follow the rail track as where the street goes, resulting in stopping or stalling on the track.



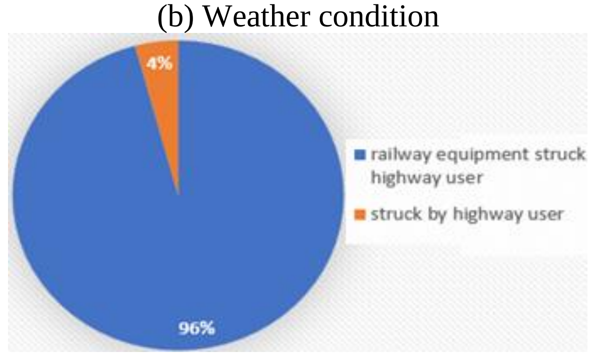
(a) Time of crash



(b) Weather condition



(c) Vehicle position



(d) Crash circumstance

Figure 3. Highway rail crossing crash distributions

Figure 4. Drop-off areas at the Southeast corner of Britton HRGC

Highway Only Related Crashes

While examining the accident data from the ODOT crash database, a total of 514 crashes were recorded at this intersection since 1998 when the data were available. Although the number of crashes fluctuated with a surge in 2001 and 2004, the level of crashes remains very high with an average of 20.8 crashes per year (Figure 5). It is also noticed that most majority of the crashes occurred in clear weather conditions, dry road surfaces, and during daylight time (Figure 6). Notably, 168 crashes took place in the presence of clouds, and 46 crashes under wet conditions, accounting for 8.95%. 123 accidents transpired in lighted conditions, which may raise questions about the adequacy of intersection lighting infrastructure to ensure it effectively contributes to safety. The accidents predominantly occurred on dry roads, which suggests that field examination may be necessary to understand whether factors like road maintenance, skid resistance, or road design may have contributed to these patterns.

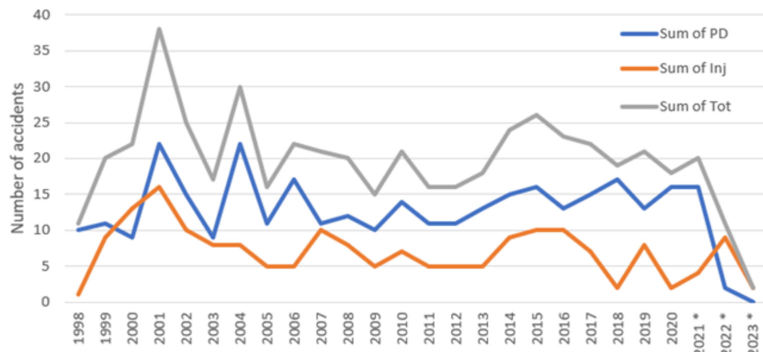
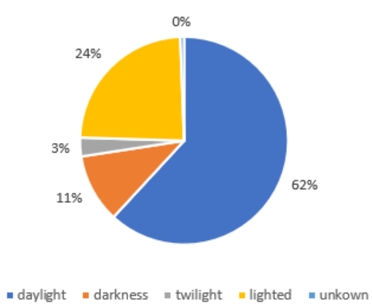
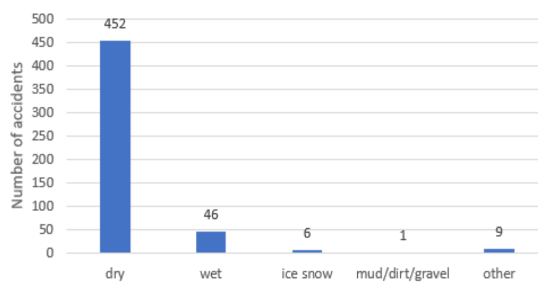


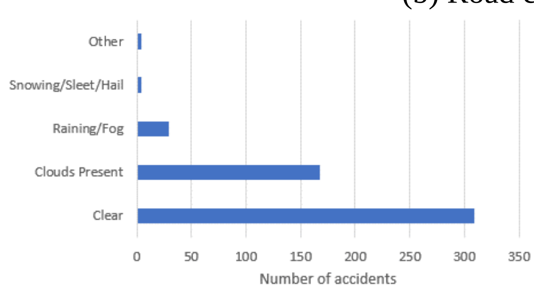
Figure 5. Number of crashes per year



(a) Time of crash



(b) Road condition



(c) Weather condition

Figure 6. Highway intersection crash distributions

The crash diagram for the Britton intersection is shown in Figure 7, and the number of crashes for the various manners of crashes is summarized in Table 3. It should be noted that not all the crashes have been mapped on the diagram due to the lack of specific information. "Turning Left, Right" (TLR), "Rear End Stopped" (RES), and "Right Angle Straight" (RAS) account for more than 85% of the crashes. It may indicate that the traffic signals, especially the change interval and red indication time, need to be revisited to eliminate the presence of possible dilemma zones. The red light running should also be investigated.

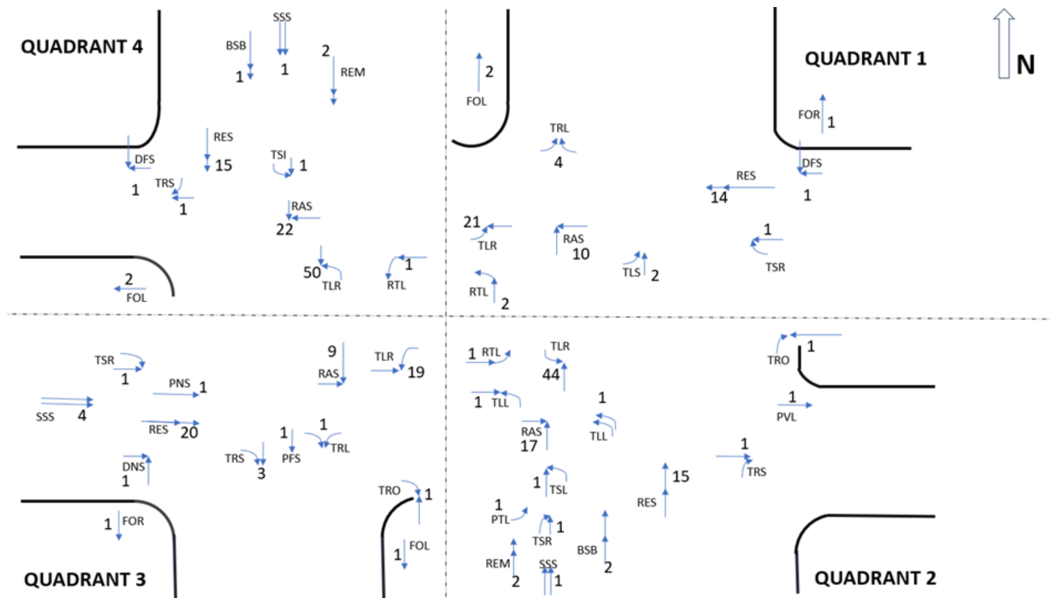
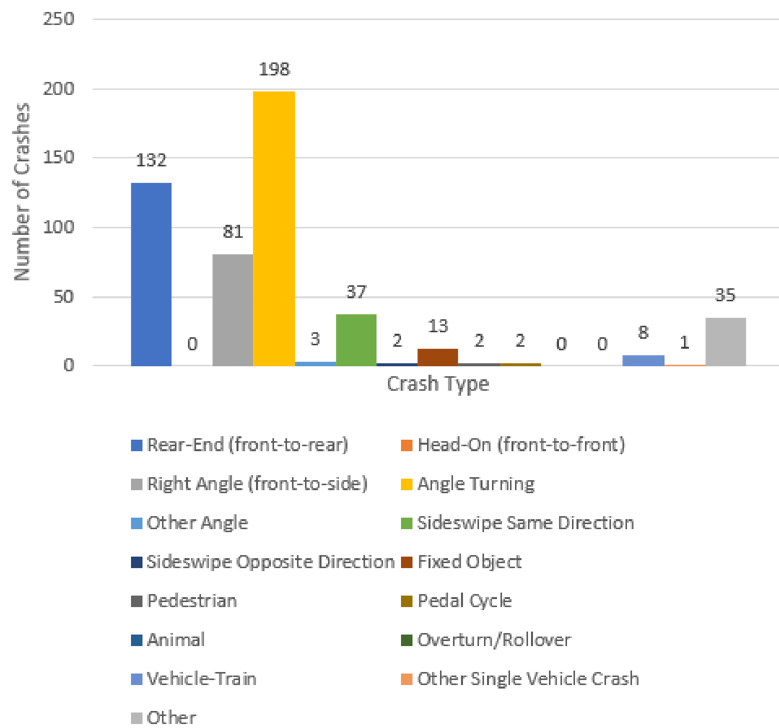


Figure 7. Crash diagram at the Britton HRGC

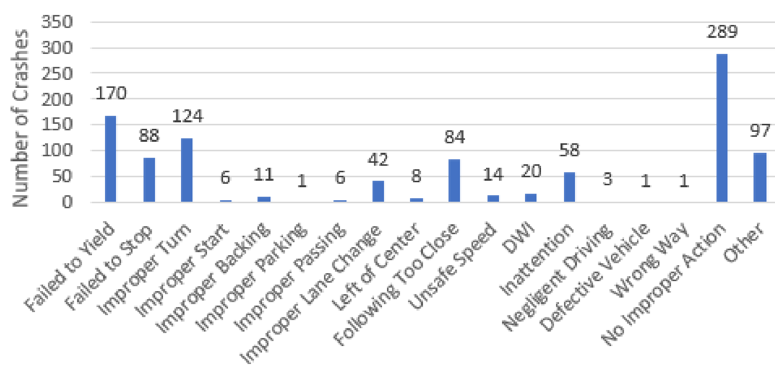
Table 3. Manner of crashes at Britton HRGC

Denotation	Manner of crash	Crashes, count	Crash, %
TLR	Turning Left, Right	144	45.7
RES	Rear End Stopped	65	20.6
RAS	Right Angle Straight	60	19.1
SSS	Side Swipe Same Direction	6	1.9
TRS	Turning Right Straight	5	1.6
FOL	Fixed Object Left	5	1.6
Others (REM - Rear End Motion; RTL - Rear End Turning Left; TLL - Turning Left, Left; TSL - Turning Straight Left; TSR - Turning Straight Right; TLS - Turning Left Straight; FOR - Fixed Object Right; PNS - Pedestrian Near Side; PFS - Pedestrian Far Side; TRO - Turning Right Opposite; BSB - Backing, Stopping, Backing; PTL - Pedestrian Turning Left; DFS - Driveaway Far Side; DNS - Driveaway Near Side; PVL - Parked Vehicle Left Side)		30 (in total, each type less than 5)	9.5

In the ODOT's database, the crash data were also recorded in terms of crash type (Figure 8(a)) and the cause of crashes (Figure 8(b)). The majority of accidents, a total of 170, were attributed to drivers' failure to yield at signalized intersections. 124 accidents resulted from improper turns. These findings underscore the importance of driver compliance with traffic signals and the significance of safe turning practices. It also highlights the need for enhanced driver education and awareness programs.



(a) Type of crash



(b) Possible cause of crash

Figure 8. Type and cause of crashes at the Britton HRGC

Crash Analysis of Secondary Ungated HRGC (01208L)

Within approximately 500 ft from the primary Britton crossing, a secondary ungated HRG intersects with 92nd Street, which has been frequently used as an alternate route when the gates of the primary Britton HRGC are closed for upcoming trains. During the same period, this HRGC intersection experienced eight highway-railroad accidents, as shown in Table 4. Although the count of FRA-recorded crashes at this alternative intersection is relatively low, the number of fatalities is comparable to the primary intersection (one fatality and three injury crashes). This highlights the critical importance of monitoring and addressing safety concerns at this alternative route. The accident conditions at this secondary intersection resemble those at the main intersection.

Table 4. Secondary Ungated HRGC highway-rail crashes (012080L)

Vehicle	Date	Time	Temp (^{0}F)	Dir	Weather	Injury *	Speed (mph)	Position **	Circumstance ***
Pickup Truck	01/28/ 2016	3:26 pm	56	N	Clear	PDO	38	Move	Rail
Auto	9/5/ 2015	11:07 am	95	E	Clear	A/B	38	Move	Rail
Auto	2/16/ 2013	2:30 am	27	E	Clear	K	35	Move	Rail
Van	10/10/ 2006	2:10 pm	75	W	Clear	PDO	40	Move	Hwy
Truck-trailer	7/12/ 1999	8:30 am	78	W	Clear	PDO	13	Stall	Rail
Auto	5/2/ 1981	2:50 am	60	-	Clear	PDO	2	Stall	Rail
Auto	2/8/ 1980	11:10 pm	20	W	Cloudy	A/B	40	Move	Hwy
Auto	1/11/ 1980	11:21 am	35	W	Clear	A/B	35	Move	Rail

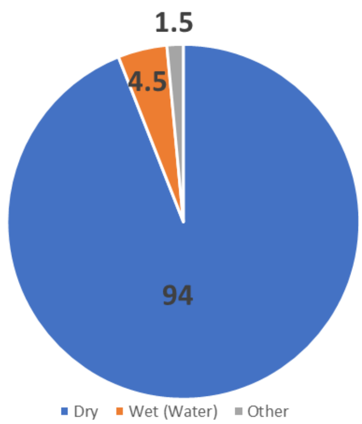
Notes: * Injury type: (1) K- fatality; A/B – injury; PDO – no injury; ** Crash position: Stall - stalled or stuck on crossing; Move - moving over crossing; Stop - stopped on crossing; *** Crash circumstance type: Rail - railway equipment struck highway user; Hwy - railway equipment struck by highway user.

Additionally, the roadway segment on 92nd Street, approximately 354 ft in length, had 67 highway-only collisions, including one fatality crash (2 people killed), 26 injury crashes (39 people injured), and 40 PDO crashes. The accidents primarily transpired in clear weather conditions on dry road surfaces, and the majority of them unfolded during daylight hours, as shown in Figure 9 (a) and (b). Moreover, the types of collisions observed primarily included right-angle (front-to-side) collisions and angle-turning accidents (Figure 9(c)), while the possible causes of crashes (Figure 9(d)) include "Failure to yield" (36.2%), "Failure to stop" (6.9%), "Improve turn" (9.2%), or a significant portion (32.3%) reported "No improper action."

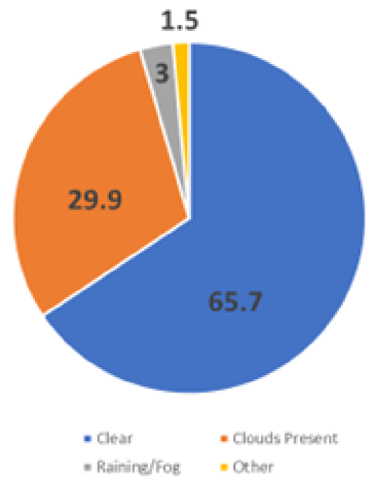
This similarity in accident conditions between the two intersections underscores the need for comprehensive monitoring and safety measures at both locations. It suggests that factors such as driver behavior and road conditions are influential in accident occurrence and should be addressed proactively. Additionally, the data highlights the importance of a broader safety strategy that takes into account the consistent patterns seen in accidents at these intersections.

FUTURE RESEARCH

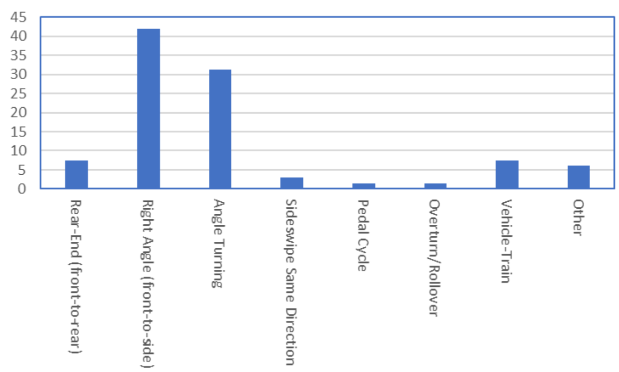
Future research on highway railway crossing safety should focus on leveraging advanced data-collection techniques to gain comprehensive insights into crash patterns and vehicle/driver behavior at these locations. This involves exploring cutting-edge technology, including various sensor technologies and machine learning algorithms, to collect and analyze data beyond conventional methods. Prioritizing the integration of vehicle telematics, meteorological conditions, and driver behavior analysis is essential to identify high-risk areas and understand contributing factors. Specifically, deploying surveillance cameras at strategic points along train crossings presents new opportunities. Real-time monitoring and data collection through these cameras can offer crucial information on vehicle and driver behavior, and traffic flow, and facilitate swift responses to safety concerns. Furthermore, future studies should aim to devise targeted safety measures and contribute to a holistic understanding of factors influencing railway crossing safety.



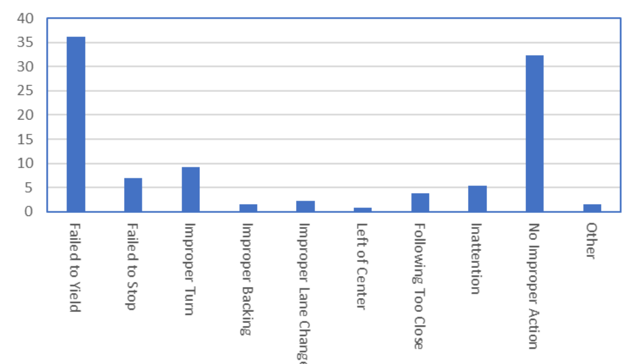
(a) Weather conditions



(b) Roadway/Lighting



(c) Type of collision



(d) Possible cause of crash

Figure 9. Type and cause of crashes at the Britton HRGC

CONCLUSIONS

An extensive safety assessment conducted on the primary Britton HRGC and the secondary ungated crossing in Oklahoma City highlighted persistent safety issues concerning highway-railroad intersections and collisions exclusive to highways. The paper analyzed various safety aspects at these two intersections. Despite the intersection having robust safety infrastructure in place, there remains a need for enhancements, particularly in highway monitoring equipment and surveillance devices aimed at understanding driver behaviors. The study underscored the critical importance of proactive safety measures, comprehensive comprehension of crash patterns, driver behaviors, and real-time monitoring. Future research endeavors should leverage advanced data collection methods and surveillance technologies to bolster safety at high-risk crossings. By addressing identified risk factors and embracing technological advancements, it is possible to establish safer crossings, thereby reducing accidents and ensuring the safety of both road and rail users.

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Investigation of Public Knowledge and Perceptions toward Railroad Trespassing in the United States

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ABSTRACT

Despite government efforts, railroad trespassing persists, largely due to widespread unawareness of its risks. To investigate public knowledge and motivations regarding this issue, we surveyed 591 people (August 2022–May 2023). Employing descriptive statistics, for example, frequency distribution, and non-parametric tests, we preliminarily analyzed the findings in this paper. Alarmingly, 90% of respondents never received rail-related safety training, 40% believed private railroad property was public, and 48% were unaware of its illegality. Notably, 52% admitted to trespassing. Regarding the reasons for trespassing, 68% of the respondents who trespassed before reported shortening a trip, an official crossing is too far away, not convenient, or a busy highway were the main reasons. For the destinations after trespassing, 32% chose hiking, walks, and walking dogs, 26% chose going to the town/city/center, restaurant, or shopping, and another 22% reported way to (from) school/work. These findings highlight significant gaps in railroad safety education in the US.

INTRODUCTION

Railroad lines and related rail property are inherently risky to trespassers that are illegally on private railroad property without permission (FRA, 2016). The efforts to reduce rail deaths at rail crossings regarding employees and passengers have been effective. However, efforts to reduce railroad trespassing and suicide rates have not been as successful (Havarneau & Topel, 2019), which may be reflected by the trend of the trespasser casualties in the past decade. At the national level, the trespasser casualties excluding highway-rail incidents increased by 41% from 765 in 2011 to 1082 in 2020; for North Carolina, the number increased by 20% from 20 in 2011 to 24 in 2020 (FRA, 2021). The lack of a sustained improvement is in stark contrast to the considerable reduction in the risks faced by railroad employees, passengers, and the public.

Understanding public perceptions and knowledge of railroad trespassing is pivotal in reducing trespassing incidents. Yet, a clear understanding of the United States' public perceptions regarding railroad trespassing and its impact on their crossing behaviors remains elusive. Although studies in Finland (Silla & Luoma, 2012) and the Czech Republic (Skládaná et al., 2019) have delved into this issue, comprehensive research within the United States context is notably lacking. This paper endeavors to bridge this gap by conducting a survey, which could facilitate formulating effective strategies for reducing railroad trespassing incidents.

METHODS

Survey Design. The survey was anonymous and had 20 questions, including questions related to the following categories:

- demographics (e.g., gender, age, education level, whether living close to rail track),
- public knowledge about railroad trespassing (e.g., whether having any rail safety training or education, whether aware of railroad property is private in the United States, and whether aware of railroad trespassing is illegal in the United States),
- trespassing behaviors (i.e., whether trespassed before taking the survey), and purposes and motivations for railroad trespassing (e.g., way to (from) work, walks, or walking dogs),
- risk perceptions toward railroad trespassing (e.g., whether feel trespassing is dangerous or having any fear when trespassing), and
- rail noise impact (e.g., do they think trains are noisy and how far away they can hear the train).

Survey Collection. The IRB (Institutional Review Board) approval for the survey from The University of North Carolina at Charlotte was obtained. Qualtrics was used to host the survey online. Social media (e.g., LinkedIn) announcements were made to recruit the participants. We also sent messages (e.g., emails) to our connected contacts, introducing the research and asking for their consent to participate in the survey. No incentives were provided. From August 2022 to May 2023, 591 surveys were collected in total.

Data Cleaning and Analysis. When conducting data cleaning, 52 survey data were removed due to the significant missing responses (90% of the survey questions were not responded). Then, a preliminary analysis of the survey results mainly using descriptive statistics (e.g., frequency distribution) and non-parametric tests (including Spearman's rank correlations, Mann-Whitney U tests for 2 independent samples, and Kruskal-Wallis H tests for 3 or more independent samples) were conducted. The Mann-Whitney U test is widely used to test whether or not two independent samples are significantly different. Kruskal–Wallis H test is a non-parametric method for testing whether samples originate from the same distribution, which is used for comparing two or more independent samples of equal or different sample sizes. Non-parametric tests were employed to address the challenges posed by data that may not follow a normal distribution. IBM SPSS 25 and R statistics were used to run the analysis in this paper.

RESULTS

Demographics. As shown in Table 1, 64% of the survey participants were male, 34% were female, and 2% preferred not to say. The average age of all the participants was 26 years old, and on average, they lived in the United States for 21 years. In addition, 33% of the survey participants were 25 years or older and 10% were high school graduates or less. Almost three quarters of the participants lived in the city area, and more than half (61%) lived close to rail track.

Public Knowledge About Railroad Trespassing. Most of the survey participants (90%) never got any rail-related safety training or education (Table 2). It is surprising to see that 40% of the participants believed the private railroad property was public and 48% did not know railroad trespassing is illegal before taking the survey.

Table 1. Demographics of the Survey Participants

Selected Questions	Responses	Count	%
Gender	Male	345	64
	Female	181	34
	Prefer not to say	13	2
Age	18-24 years	362	67
	25 years or older	175	33
Education	Graduate or professional degree	132	24
	Bachelor's degree	123	23
	Some college, or associate degree	234	43
	High school graduate (includes equivalency)	47	9
	Less than high school graduate	4	1
Do you live in city or rural area?	City	389	73
	Rural	144	27
Do you live close to rail track?	Yes	320	61
	No	208	39

Table 2. Public Knowledge About Railroad Trespassing

Selected Questions	Responses	Count	%
Have you ever taken any railroad safety related lecture, workshop, seminar, training, etc.?	Yes	56	10
	No	480	90
Do you think railroad property in US is private property or public property?	Private	317	60
	Public	211	40
Before you take this survey, do you know walking around train cars when a train is stopped, crossing rail tracks for recreational purposes (e.g., taking photos on rail tracks), or crossing rail tracks for shortcuts (e.g., for shopping or hiking), is illegal in US?	Yes	273	52
	No	256	48

Trespassing Behaviors, Purposes and Motivations for Railroad Trespassing. Based on the analysis, 52% of the survey participants trespassed before taking the survey. Regarding the reasons why people trespass, 68% of the survey participants who trespassed before reported shortening a trip, or an official crossing is too far away, not convenient or a busy highway were the main reasons, and 28% reported they did that just because everyone goes through there or a habit. In terms of their destinations after crossing rail tracks, 32% chose hiking, walks, and walking dogs, 26% chose going to the town/city/center, restaurant, or shopping, and another 22% reported way to (from) school/work, as shown in Figures 1 and 2.

Risk Perceptions toward Railroad Trespassing. We also investigated whether people feel it is dangerous to cross rail racks. Among the 251 survey participants who trespassed before, 40% did not think it was dangerous, 31% thought it was a little dangerous, but they could easily hear a train coming, and 26% thought it was dangerous, but they looked both ways and hurried across the rail tracks, as shown in Figure 3.

Survey participants were also asked the reasons for the fear if they experienced any when crossing a rail track, 52% reported fear of accidents, 13% reported fear of police, security cameras, or sketchy people near the tracks, 2% reported fear of fines, and the remaining participants reported not applicable or others.

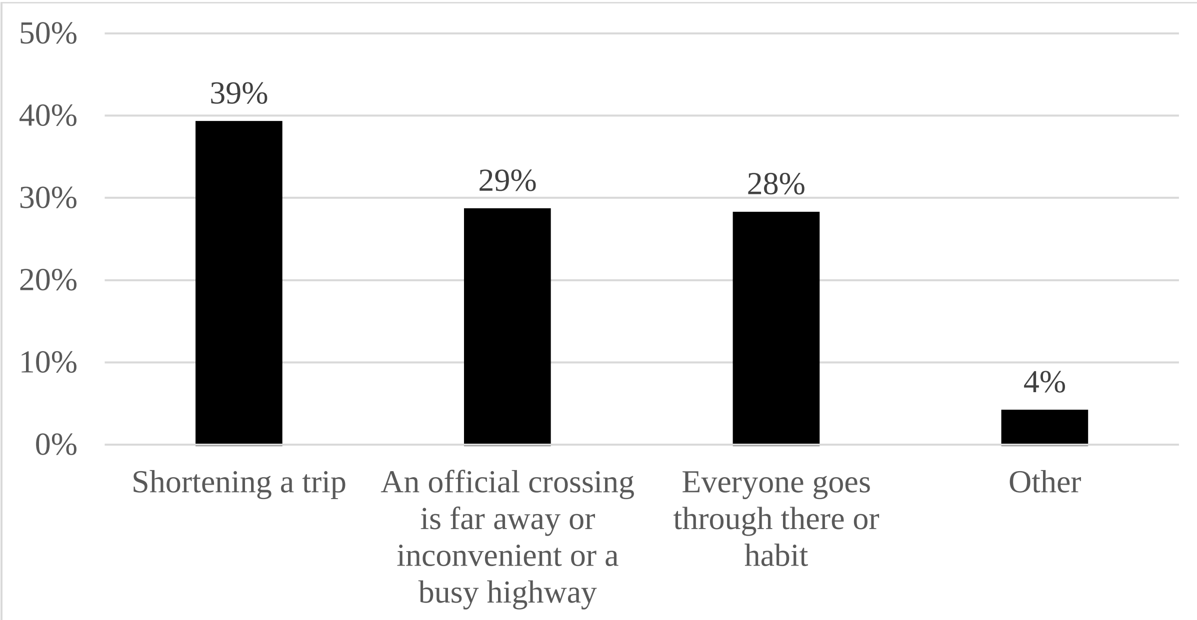

Figure 1. Why Do Pedestrians Trespass?

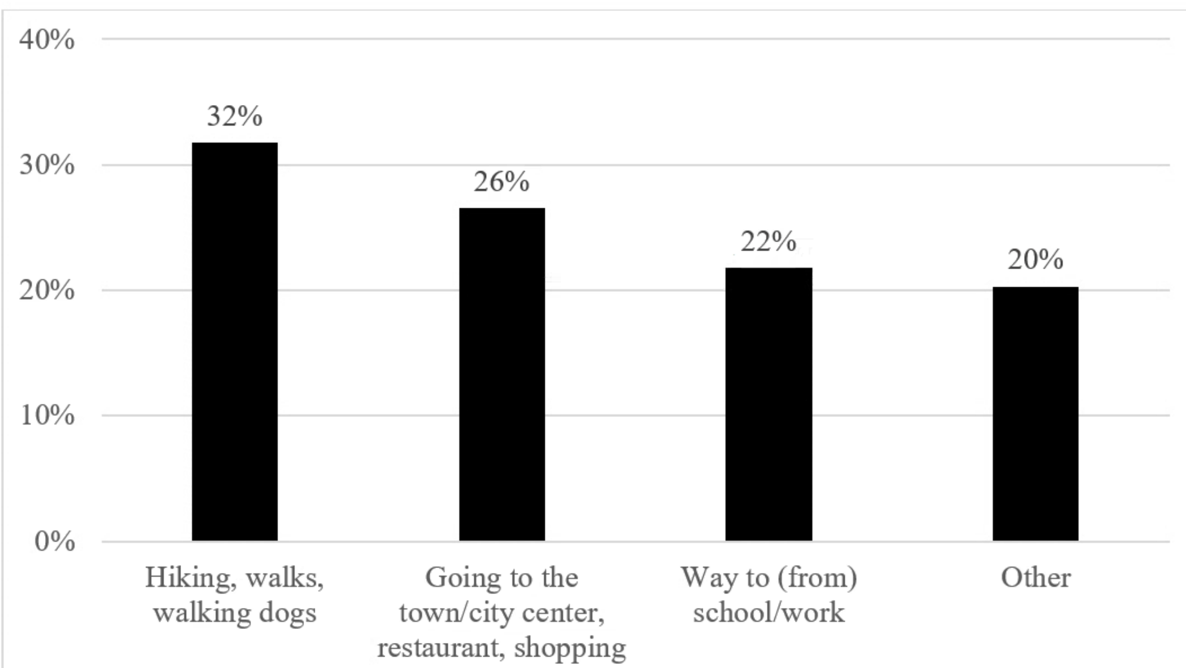

Figure 2. Destinations after Crossing Rail Tracks

Rail Noise Perceptions. Based on the analysis, 78% of the survey participants thought trains were noisy, 15% did not think trains were noisy, and 7% were not sure. In addition, participants were asked how far away they could hear a train when it is approaching, 35% reported at least half a mile (>=805 meters), 33% reported about 300 feet away (~91 meters), 19 reported a mile or more (>=1,609 meters), and 13% reported 100 feet or less (<=30 meters) (Figure 4).

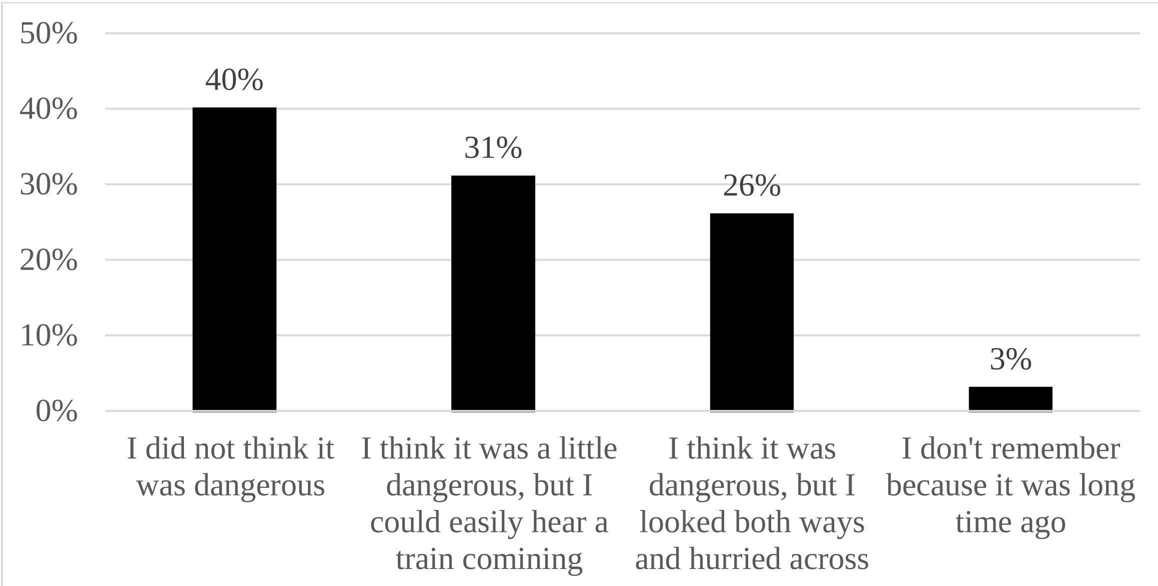

Figure 3. Risk Perceptions of Crossing Rail Tracks

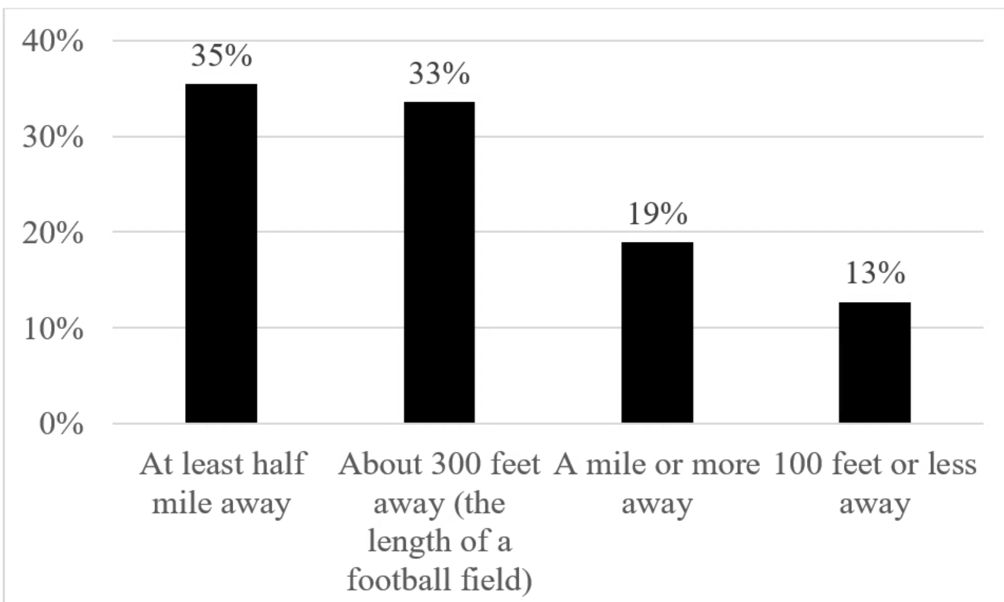

Figure 4. Distance to Hear a Train

Rail Safety Education vs. Rail Trespassing. Further, 56 (~10%) participants reported they did receive rail related safety training and education. For example, some participants reported they attended a lecture on rail safety before. A relatively higher proportion (i.e., 59%) of the participants with rail safety training and education experience reported they never crossed rail tracks, compared to those without any rail safety education experience (i.e., 47%), as shown in Figure 5. However, it is hard to draw any conclusions in terms of the effectiveness of the rail safety training on reducing the trespassing behaviors of the public with this small sample size (i.e., 56 people had rail safety and education experience) and limited information on when the survey participants took the training (i.e., before or after the trespassing behavior).

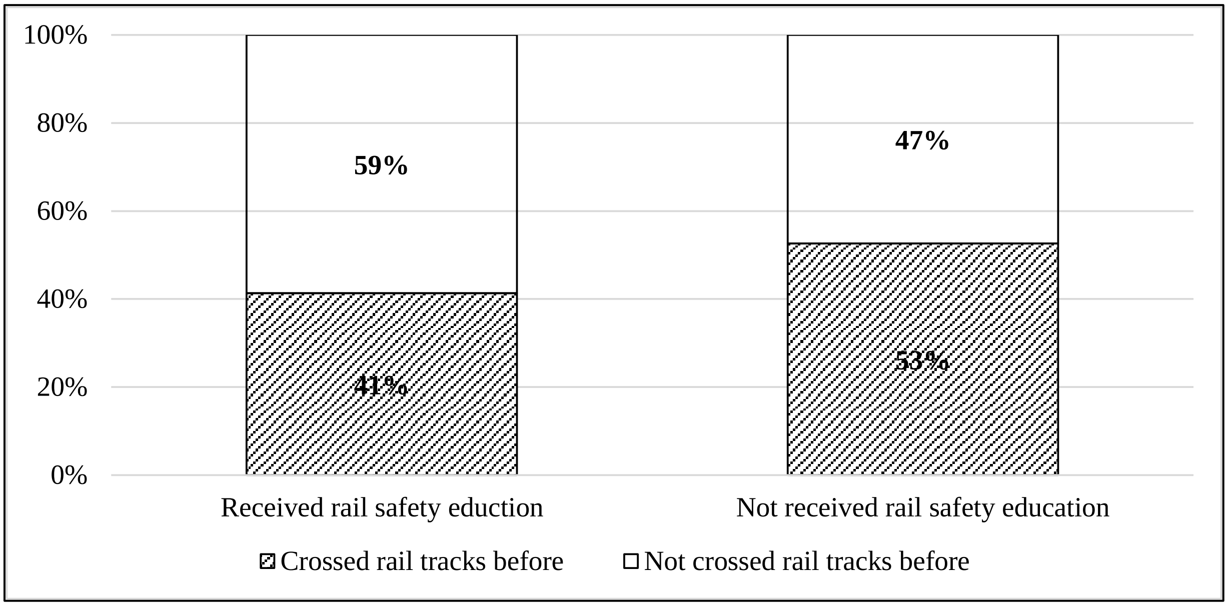

Figure 5. Rail Safety Education vs. Rail Trespassing

Non-parametric Analysis. Spearman's rank correlations (two tailed, listwise) were conducted. Some selected results are shown in Table 3. For example, we found a significant positive relationship between rail safety training and whether people know trespassing is illegal ($\boldsymbol{\rho}$=0.211, $p<0.01$), which suggests that if a person gets rail safety training, then that person tends to know railroad trespassing is illegal. We also found that more male participants knew railroad property was private ($\boldsymbol{\rho}$=0.235, $p<0.01$), and when a participant knew railroad property is private, then he/she tends to know railroad trespassing is illegal ($\boldsymbol{\rho}$=0.321, $p<0.01$). More importantly, we found a significant negative correlation between whether know railroad property is private and trespassing behavior ($\boldsymbol{\rho}$=-0.108, $p<0.05$), which suggests that if a participant knew railroad property was private, then he/she tends to not trespass.

Further, a series of Mann-Whitney U tests and Kruskal–Wallis H tests were conducted to identify factors related to trespassing behaviors. It was found that participants who lived close to rail tracks had a higher chance of trespassing (Figure 6). Education level was also found related to trespassing behaviors based on the Kruskal–Wallis H test (Figure 7). To identify which education level group has a significant difference in terms of trespassing behaviors, Mann-Whitney U tests were conducted as well. It was found that survey participants with a graduate or professional degree reported significantly fewer trespassing behaviors than those with college or associate degree or bachelor's degree. No significant difference between other groups were observed, e.g., participants with less than high school graduates vs. those with graduate or professional degrees.

Table 3. Spearman's Rank Correlations

	Gender (Male=1, female=0)	Living in city/rural area (City=1, rural=0)	Obtained rail safety training (Yes=1, no=0)	Whether know trespassing is illegal (Yes=1, no=0)	Trespassed before (Yes=1, no=0)
Whether know trespassing is illegal (Yes=1, no=0)	-	-	.211**	1	
Whether live close to rail track (Yes=1, no=0)	-	.176*	-	-	
Whether know railroad property is private (Private =1, public=0)	.235**	-	-	.321**	-0.108*

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Ranks

	Live Close to Rail Track (Yes=1, No=0)	N	Mean Rank	Sum of Ranks
Trespassed or Not (Yes=1, No=0)	0	185	227.61	42107.50
	1	300	252.49	75747.50
	Total	485		

Test Statistics[a]

	Trespassing or Not
Mann-Whitney U	24902.500
Wilcoxon W	42107.500
Z	-2.194
Asymp. Sig. (2-tailed)	.028

a. Grouping Variable: Live Close to Rail Track

Figure 6. Relationship Between Living Close to Rail Tracks and Trespassing Behaviors (Mann-Whitney U Tests)

DISCUSSION

This paper aims to investigate the public knowledge and perceptions toward railroad trespassing, and a significant effort was made to survey the public from August 2022 to May 2023. Thousands of people were exposed by the research announcement when recruiting survey participants, and eventually 591 people were surveyed.

Ranks

	Education Level	N	Mean Rank
Trespassed or Not (Yes=1, No=0)	Less than high school graduate=1	2	117.50
	High school graduate (includes equivalency)=2	46	249.29
	Some college, or associate's degree=3	210	245.68
	Bachelor's degree=4	105	269.93
	Graduate or professional degree=5	122	214.90
	Total	485	

Test Statistics[a,b]

	Trespassing or Not
Kruskal-Wallis H	14.090
df	4
Asymp. Sig.	.007

a. Kruskal Wallis Test

b. Grouping Variable: Education Level

Figure 7. Relationship Between Education Levels and Trespassing Behaviors (Kruskal–Wallis H Tests)

A Lack of Research Studies Investigating Public Perceptions toward Railroad Trespassing. Most railroad trespassing studies in the United States focused on developing trespassing crash prediction models using the FRA data. These studies mainly used statistical modelling approaches to identifying factors affecting the frequency and severity of trespassing crashes. For example, Kang et al. (2019) investigated different factors that could affect the frequency of railroad trespassing crashes at the county level, and found population density, length of rail tracks, median age, proportion of male population, and train volume affected the frequency of trespassing crashes. Wang et al. (2016) investigated the spatial effect on railroad trespassing crashes and found that pre-crash trespassing behavior and lighting conditions affected the frequency of trespassing crashes. In addition, their study also reported trespasser age, weather conditions, and land use status affected the frequency of railroad trespassing crashes. Another study, Zhang et al. (2018) proposed an artificial intelligence algorithm to detect near-miss trespassing events from surveillance footage near at-grade railway crossings. However, few studies have been conducted to investigate public knowledge and perceptions toward railroad trespassing. This research is the first study making the efforts on this issue in the United States. More research studies will be needed to explore this area.

A Significant Lack of Knowledge and Education on Railroad Trespassing. The results showed that there is a significant lack of knowledge and education about railroad trespassing in the United States. For example, almost half of the survey participants did not know railroad trespassing is illegal, and 40% did not know railroad property is private in the United States. Alarmingly, few people have had any rail safety related training or education. As a result, a significant large number of participants trespassed before taking the survey (52%). The risk perceptions of the survey participants may also explain the large percentage of the participants who trespassed. That is, 40% of the participants did not think trespassing was dangerous, and 31% thought it was a little bit dangerous, but they could easily hear a train coming. In fact, with the advancement of technology development, trains are quieter and quieter. Therefore, the 31% of the survey participants might be overconfident about whether they can hear a train. On average, a train needs at least a mile to stop, which means there is no chance to escape if a train is approaching while a person is crossing the rail track but fails to hear the train.

Education Impact and Challenge. Our analysis found that if a person knows railroad property is private, then he/she has a lower chance of trespassing. Although only a very small percentage of the survey participants had rail safety trainings (mainly work related, e.g., construction workers whose work is related to railroad), they reported fewer trespassing behaviors compared to those without safety training. We also found that participants with graduate or professional degrees reported significantly fewer trespassing behaviors compared to those with associate or bachelor's degrees. All of the above evidence may suggest a potential role education can play in reducing trespassing injuries and fatalities. We believe that leadership support from government agencies and organizations, and the partnership between different stakeholders is the key. For example, if railroad companies incorporate educating general public railroad safety knowledge into their company missions, then more people could be educated. In addition, developing railroad safety education programs cannot succeed without the support from government agencies. However, there is a lack of attention from the government authorities to railroad trespassing. For example, FRA submitted its first report in history to Congress in 2019 about the national strategy to prevent trespassing on railroad property (FRA, 2018), although trespassing fatalities and injuries always exist since the start of using railroad back to almost two hundred years ago.

Purposes and Motivations for Railroad Trespassing. Almost 40% of the survey participants reported shortening a trip was the top reason for them to cross a rail track, and 29% reported an official crossing was too far away or inconvenient, or a busy highway. Consistently, many survey participants reported they trespassed because they wanted to shorten the trip to school/work, shopping, city center, etc. This indicates the importance of urban planning and transportation planning and design in affecting the public's trespassing decisions.

Limitations and Future Work. The survey participants in this research had an average age of 26 years, and the third quartile of the age value was 28 years old. To obtain a more representative sample, diverse age groups, especially those older than 28 years old, need to be recruited for the research.

CONCLUSION

Almost 600 people were surveyed to investigate their knowledge and perceptions toward railroad trespassing from August 2022 to May 2023. Major findings from this research include: 1) There is a significant lack of education on railroad trespassing in the United States; 2) A lot of people do not know trespassing is illegal; 3) A lot of people cross rail tracks even if they know it is dangerous, and the major motivations are shortening a trip for entertaining activities and work/school; 4) Rail safety training and education have a potential to restrict public trespassing behaviors.

ACKNOLWGEMENT

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Displacement Response of a Truss-Type Steel Railroad Bridge during Train Passage

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ABSTRACT

Most railroad bridges in New England were designed and built more than a century ago with unique designs and have historic significance. The Cos Cob Bridge is one of the historic bridges of New England located in Greenwich, Connecticut. The structure is a steel truss bridge, with the members of the bridge trusses connected through gusset plates at the joints. Considering the age of the structure and its significant importance in regional transportation, it is important to understand the dynamic behavior of the bridge in response to the train loads to which it is currently subjected. This paper presents the results delineating the vertical displacement of the Cos Cob Bridge obtained from field tests, as well as that using the finite element (FE) modeling of the structure. Field test data were acquired to evaluate the vertical displacement of the bridge under several service trains passing over the bridge using the laser Doppler vibrometer. These field test results were then compared to the vertical displacement obtained from FE results performed under realistic train loading conditions using the commercial FE modeling tool, ANSYS. The FE model was developed which could depict the field test results with an accuracy of over 90%. This study aims to identify discrepancies between the field test results and the FE model analysis prediction as well as the potential areas for model refinement.

INTRODUCTION

Long-haul passenger, commuter, and freight railroads are essential to maintaining a thriving economy, especially in New England, with its many urban areas, industries, and significant national defense activities (Malla et al. 2016; Malla et al. 2017). Amtrak's Northeast Corridor (NEC) is the busiest passenger rail network in the United States, connecting Washington, D.C., to Boston, Massachusetts, serving major cities, and contributing to the region's economic fabric. Most of New England's railroad bridges are old, and they often show unusual behavior under typical service loads (Malla et al. 2017; Jacobs et al. 2021). Recognizing the significance of the railroad corridor, the US Department of Transportation and the Federal Railroad Administration have designated the NEC corridor as the highest priority line for upgrading railroad infrastructure for high-speed trains.

Cos Cob Bridge is one of the old and historic bridges in the NEC corridor, located on the Mianus River in Greenwich, Connecticut. It is a long-span open-deck bridge, built in 1904 by the

American Bridge Company and owned by the Connecticut Department of Transportation. It comprises eleven simply supported spans resting on eleven stone piers and two abutments at the ends (Figure 1). Three of the sections are deck girder, seven are deck trusses, and one is rolling lift bascule. The bridge has four tracks (Track 1, Track 2, Track 3, and Track 4), and each track sits on a separate parallel bridge. The bridge utilizes ASTM A7 steel, primarily riveted, forming I- and C- sections in the superstructure. The members are connected using gusset plates. There is no prior monitoring study for the Cos Cob Bridge, so it is important to study the dynamic behavior of the bridge.

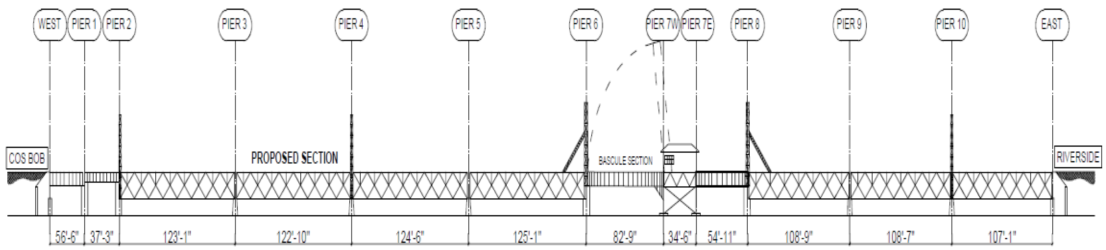


Figure 1: Cos Cob Bridge Elevation View (Malla et al. 2022).

The bridge is commonly used by passenger trains like Metro-North Railroad M8 (MTNR M8), Amtrak Regional, and Acela Express This study focuses on Track 4 of span 3 (Figure 2) because of its accessibility for field-testing equipment, especially during periods of lowered water levels affected by tides. The section is 37.2 m (122.08 ft) long between the centerlines of the piers. This work presents the comparative analysis of the vertical displacement response of the bridge, using a combination of field tests performed on the structure and detailed finite element (FE) modeling of the bridge.

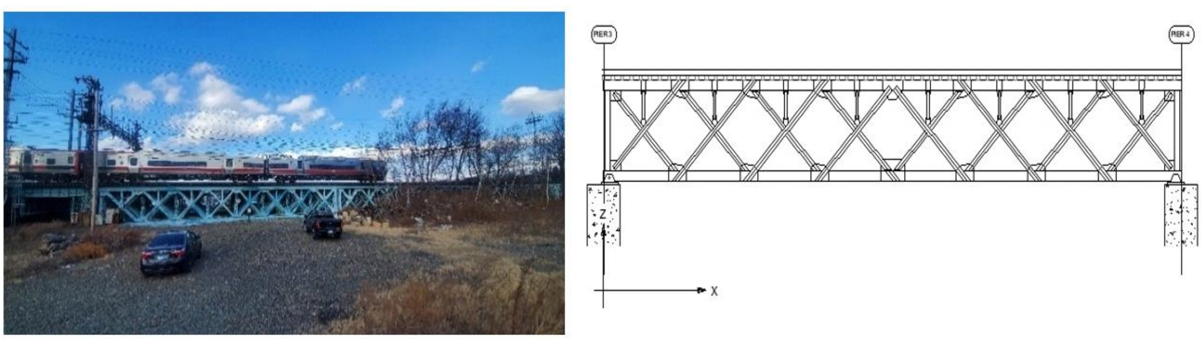


Figure 2: a) Cos Cob Bridge Span 3 b) Elevation View of Span 3 (Malla et al. 2022).

METHODOLOGY

This section presents a detailed description of the methodology used to analyze the response of the bridge using a combination of field tests and the FE model. Field test data was collected using a Laser Doppler Vibrometer (LDV). The field test results have been compared to the FE modeling results obtained using ANSYS, which helps in assessing the accuracy and reliability of the modeling approach.

Field Tests and Data Processing

Field tests were performed while passenger trains passed over the bridge using a single-point LDV. An LDV is a scientific non-contact measurement device that uses a laser beam to extract the frequency of vibration from the Doppler shift of the reflected laser beam during the vibration of the surface under observation. The output of an LDV is generally a continuous analog voltage directly proportional to the target velocity component along the direction of the laser beam (Petrescu, 2012).

Data were collected in the time domain using the Polytec PSV® and software (Polytec, 2015) and processed using MATLAB® (MATLAB, 2022), a versatile scientific computing software package. All data were collected in the time domain at a sample rate of 512 Hz. The output from the instruments, measured in terms of velocity, is assumed to be a linear function of the voltage reading obtained from LDV (Polytec, 2015). To obtain the desired values i.e. vertical displacements, pre-processing is necessary. Those operations include scaling and centering to convert the voltage to the vertical displacement and to remove the DC bias, respectively (Bro et al. 2003). The DC bias is an undesired offset of the data mean from zero and is often encountered in LDV data (Polytec, 2015).

MTNR M8 was chosen for the study as it was the most frequent train passing over the bridge. The single-point LDV was installed vertically under track 4 to record the vertical velocity during the service train operation. Figure 3 shows the experimental setup for the Cos Cob Bridge field test. After successfully recording a response from the train passage over the bridge at one node, the position of the LDV was changed to record the response of other trains on other nodes. Bridge responses were collected at three different nodes of the bridge, as shown in Figure 4. Vib 1, Vib 2, and Vib 3 represent the location of the LDV under the bridge. The responses of trains passing from New York to New Haven (West to East) were recorded.

Figure 3: LDV setup to record vertical response.

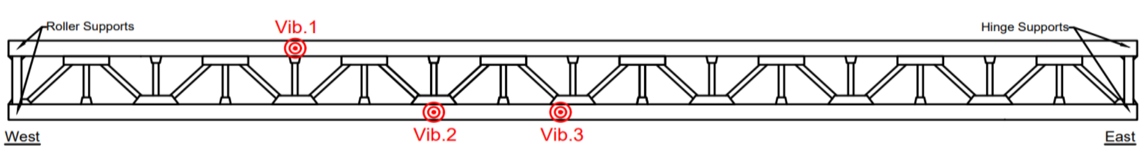
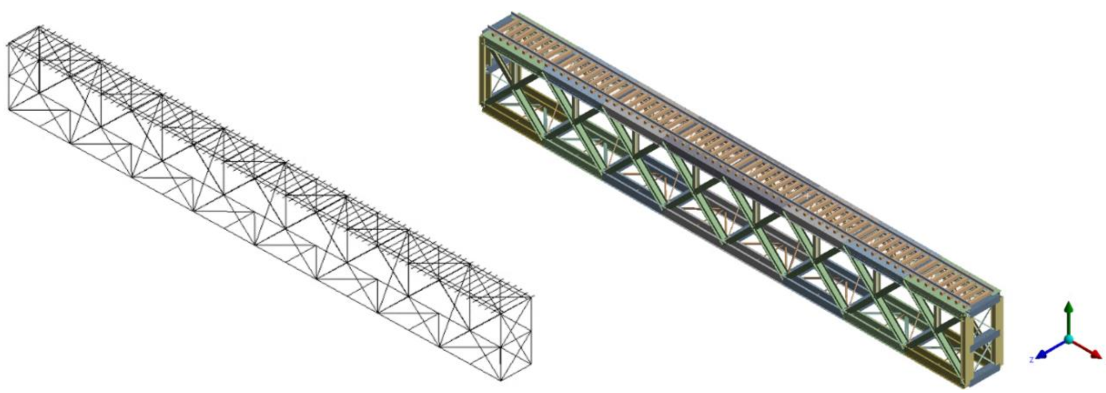


Figure 4: Cos Cob Bridge plan view (Track 4); Vib 1, Vib 2 and Vib 3 represent nodes where the responses were collected using LDV.

Finite Element Model

A finite element (FE) model of span 3 (track 4) of the Cos Cob Bridge (Figure 5) was developed to simulate the current bridge conditions under static and dynamic loads. The model was developed using the commercial finite element analysis (FEA) software package, ANSYS, and is based on an 'as-built' drawing (Under Water Construction, 1990), repair plan drawing (A.G. Lichtenstein & Associates, 1998), and load rating report (Clough, Harbour, and Associates, 2010). The model was developed using wire elements and the boundary conditions were manually defined to represent the bridge support. On the west end of the bridge, it is free on the axis, and translational movement is restrained on the y and z axes (roller support), and on the east end of the bridge, translational movement is restrained on three axes (hinge support) (Figure 4 and 5). The cross sections were assigned to the wire elements of the bridge according to the as-built drawing. The bottom chords, top chords, and two vertical members on the end of the bridge are considered beam elements while other members are assumed to be truss elements. For the ties, oak wood properties were assigned and for all other members, structural steel properties were specified. Material properties assigned in the FE model are presented in Table 1. Figure 5 shows the 3D model of span 3 of the Cos Cob Bridge.



(a) **(b)**

Figure 5: Cos Cob Bridge FE model (a) 3D wire model; (b) Rendered view.

Table 1: Bridge Material Properties used in the FE model.

Material Structural Parameters	Structural Steel	Oak Wood
Young's Modulus (N/m^2)	2×10^{11}	2.278×10^{10}
Poisson's Ratio	0.3	0.3742
Tensile Ultimate Strength (N/m^2)	4.6×10^{8}	1.467×10^{8}
Tensile Yield Strength (N/m^2)	2.5×10^{8}	4.776×10^{7}
Density (kg/m^3)	7850	935.7

This study uses a series of stepwise activated pulse loads to represent the moving axles of the vehicles. Each train's wheel load is represented as a triangular pulse load (Figure 7). The loads were moved forward from the west end of the bridge to the east end of the bridge at a total of 100 discrete steps. The loads were moved by 37.2 cm (14.7 in). The load time is defined by dividing the distance between two consecutive nodes in the FE model of the rail (d) by the desired vehicle traveling speed (v). The integration time was defined in the software using the sub-steps of the load. Figure 6 shows an example of each train's wheel load time history (force vs time) modeled as a triangular pulse load.

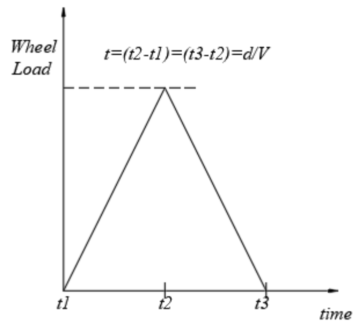


Figure 6: Triangular Step load model of force applied.

For the analysis, the MTNR M8 service loading (Figure 7) is applied in the FE model. The MTNR M8 is an electric multi-axle railroad car built by Kawasaki Rail Car, Inc., for exclusive use on the Metro-North Railroad New Haven Line and the CTrail Shoreline East. The train can reach a maximum speed of 161 km/h (100 mph) and an operational speed of 129 km/h (80 mph). The typical composition is four to five married (double) cars with the same axle load (Lochner, 2011).

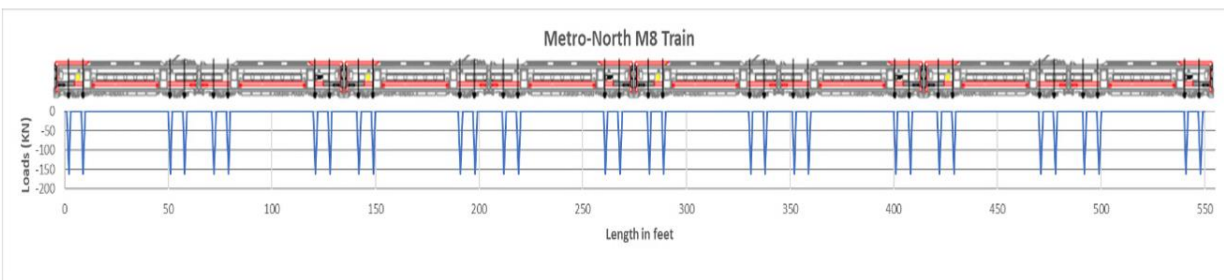


Figure 7: FE Model Axle load in triangle step load of MTNR M8 train.

RESULTS

This section presents the vertical displacement results of the Cos Cob bridge from FE model analysis using ANSYS and the field-testing results obtained using the LDV measurements under the service load of an 8-car MTNR M8 train. The results from these two methodologies have been compared to assess the accuracy of the FE modeling approach.

Field Testing

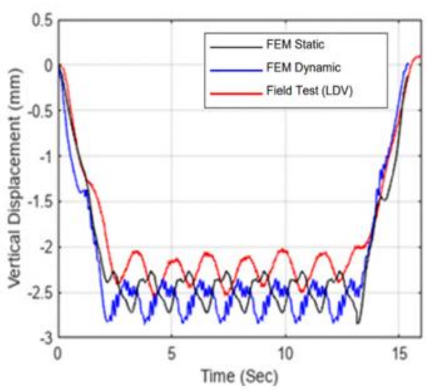
The vertical displacements of the bridge at the three different locations of the bridge (Vib 1, Vib 2 & Vib 3) obtained from the LDV measurements are shown in Figure 8. The vertical peak displacement at different locations across the bridge deck is presented in Table 2.

Finite Element Modeling

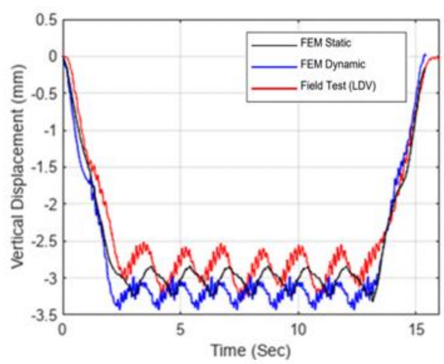
The vertical peak displacement results from the FE analysis at the corresponding locations on the bridge deck under a static train load as well as a moving train load with a speed of 40 mph are presented in Table 2:

Table 2: FE Modeling Results: Peak Static and Vertical Deflection Results at different locations of the bridge

Location	FE Static Vertical Deflection Results	FE Transient Vertical Deflection Results	Field Test Vertical Displacement Results	% Difference of FE Results with respect to the Field Test Results
Vib 1	-0.11 in (-2.81 mm)	-0.11 in (-2.81 mm)	-0.102 in (-2.61 mm), train speed: 41.93 mph	7.11%
Vib 2	-0.13 in (-3.32 mm)	-0.135 in (-3.43 mm)	-0.131 in (-3.32 mm), train speed: 37.36 mph	3.2%
Vib 3	-0.14 in (-3.58 mm)	-0.145 in (-3.69 mm)	-0.133 in (-3.38 mm), train speed: 37.85 mph	8.4%



(a)



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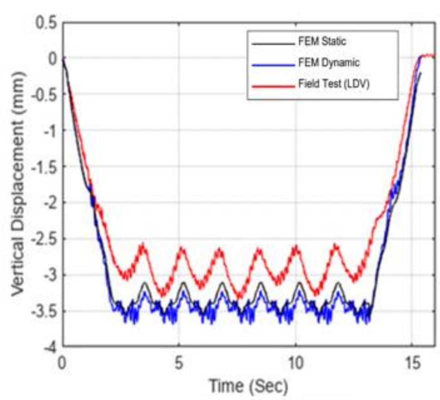

(c)

Figure 8: Comparison of vertical displacement time histories at the floor beam at different LDV locations for the Cos Cob Bridge: FE analysis prediction versus Field results. (a) Location of Vib 1; (b) Location of Vib 2; (c) Location of Vib 3

Figure 8 displays the results of the vertical displacement vs time histories of the bridge at the three different locations, obtained from the field test and the FE analysis. Although the overall trends align, the magnitude of the predicted FE analysis results is 3%-9% higher than the field test results (Table 2).

There may be various reasons for the difference in the results. The FE model may not be able to accurately replicate the complex structure of the bridge and the details of the connections between its members, resulting in larger deflections. The actual structure might be stiffer compared to the FE model. The LDV measurements might be affected by the environmental conditions. Also, there may be small variations in the actual train loading compared to the simulated load in the FE model. On the FE model, ideal train loading is considered, but the actual train loading might be less than the assumed train loading. Also, static vertical deflection and transient vertical deflection are very close to each other. The similarity of the results might be because of the short time duration used for the transient analysis.

CONCLUSIONS

This study compared the vertical displacement results of track 4 of span 3 of the Cos Cob Bridge under service train loading, obtained using FE simulations and field tests with LDV. The present work focuses on the vertical displacement of the bridge using the service load of the Metro-North M8 train. The vertical displacements predicted by the FE model were higher than those observed in the field tests, by amounts varying from 3.3% to 9.2%, depending on the location of the LDV. The difference in the displacement results indicates that the FE model needs to be refined. The refinement of the model may include detailing geometry more precisely and redefining material properties and boundary conditions of the bridge.

Both methods showed a similar deflecting trend of the bridge. The near alignment of the results demonstrates the accuracy and reliability of the FE analysis approach of the bridge to understand the dynamic response as well as the behavior of the bridge under different loading conditions. The FE model can also contribute to analyses of the individual members and their connections to ensure the long-term structural integrity and safety of the bridge.

By addressing the limitations and improving the agreement of results between the field test and the FE modeling, this research can contribute to the development of a reliable method for predicting the behavior of aging bridges. The methodology presented in the study can be utilized for bridge maintenance and safety assessments to ensure the longevity and functionality of the structures.

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Mapping Communication Patterns of Transit Agencies on Social Media

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ABSTRACT

Social media networks, like X (formerly Twitter), emerged as a revolutionary means of communication, drastically changing how information is disseminated. This study attempted to synthesize the current state of social media usage by transit agencies, accomplishing three primary tasks: (1) conducting a comprehensive review of agencies' social media practices, (2) surveying and analyzing representative United States agencies to understand their social media usage, and (3) performing text mining on selected agencies' archived tweets. Notably, the study revealed that the COVID-19 pandemic has significantly impacted information-sharing patterns among transit agencies. The text network analysis indicated that the information shared was primarily related to services, alerts, delays, detours, and promotional offers, such as free rides. However, more recent discussions have started to include evolving topics like equity and disability-related issues. By understanding these insights, agencies can better plan and develop strategies to leverage social media effectively in their operations and communication with the public.

INTRODUCTION

In the digital age, the meteoric rise of social media platforms has revolutionized how individuals and organizations connect and disseminate information across the globe. From Twitter (now titled X), Facebook, and Telegram to Instagram, TikTok, YouTube, Vimeo, and Twitch, as well as professional networking sites like LinkedIn, social media has ushered the world into a new era of interconnectedness. With its profound impact on the user community, social media has not only transformed personal interactions but also spurred companies, including transit agencies, to leverage these platforms as powerful communication channels. In recent years, transportation agencies have undergone a radical shift in their approach to social media utilization. Recognizing its potential, they actively employ social media as direct marketing and public relations channels, engaging with both existing and potential riders. Moreover, these platforms serve as valuable tools for collecting passenger data and feedback, allowing agencies to personalize their services and foster cooperation and customer-driven innovation.

The aim of our study was to examine the social media usage patterns of transit agencies in the United States and Canada. To achieve this, we embarked on three crucial tasks. Firstly, we conducted an extensive review of the existing literature on social media usage by transit agencies. Secondly, we conducted a nationwide survey to comprehensively understand how social media is employed in terms of timely updates and crisis information, public education and awareness, public engagement, transit promotion, and support in achieving organizational goals.

Finally, we collected and analyzed archived tweets (now called posts) from select case study transit agencies to gain insights into their information-sharing patterns. The findings of our study bear significant implications for policy and decision-making concerning social media usage by transit agencies. By understanding and optimizing their presence on these platforms, agencies can effectively connect with their customers, market their services and products, enhance client satisfaction, build a strong brand image, and foster equity in public transportation. In an era where online interactions are increasingly central to daily life, our research seeks to empower transit agencies in their quest for seamless communication and improved service delivery through the dynamic realm of social media.

LITERATURE REVIEW

Our primary focus was on examining recent studies regarding the utilization of social media by transit agencies. The literature review encompassed a comprehensive analysis of scientific articles and reports that shed light on best practices and lessons learned from these agencies' experiences with social media. This review not only included studies from the United States but also incorporated relevant international literature to gain a holistic understanding of social media usage in the transit sector.

Collecting Feedback and Sharing Information

Social media use in transportation agencies can take on various forms, including informational, participatory, collaborative, or interactional approaches. Liu and Ban (2017) discussed transit agencies primarily utilize social media to provide information to riders and gather feedback in the form of complaints, comments, and service requests. As a result, Choudhury (2013) emphasized a growing need to implement advanced technological strategies to collect more accurate rider information and effectively reach their target audiences. Watkins et al. (2015) suggested that transportation professionals, including policymakers, marketers, customer service managers, operations, maintenance managers, and safety and security personnel, can benefit from using customized toolkits to systematically collect customer feedback. The advancement of technologies and the widespread use of social media have led to a significant preference among riders around the world for receiving transportation information, such as fares and promotions, through these platforms. Notably, Crawford (2013) found that passengers are willing to pay more for rides booked through smartphone applications due to the time-saving convenience it offers.

Ferreira et al. (2017) proposed innovative solutions like OneRide, that have emerged to seamlessly integrate social media platforms with payment and route planning sites, further enhancing the overall user experience. Additionally, Ma et al. (2017) introduced the MOBility ANAlyzer (MOBANA) framework, designed to provide real-time integrated information from various sources, classify texts, and filter information from tweets, ensuring relevant and accurate data is delivered to riders. Beyond routine functions, the role of social media platforms for transport agencies extends to critical situations, such as disaster response. Chan and Schofer (2014) mentioned that during events like Hurricane Sandy, transit agencies in New York effectively utilized Twitter communications to disseminate vital information to users, ensuring their safety and well-being during the crisis. Furthermore, Mahmood et al. (2017) developed algorithms capable of detecting locations affected by violence and informing bus riders in real time via Twitter, showcasing the potential of social media in enhancing passenger safety and security.

Public Engagement and Transit Promotion

Schweitzer (2014) highlighted that understanding user engagement on social media is crucial for agencies as it influences rider sentiment, cognitive involvement, and communication behavior. Hanifin (2014) examined the social media practices of transit agencies, highlighting their significance as a determinant of agencies' success. Posting user status messages on popular platforms like Twitter and Facebook and engaging with them directly can naturally foster positive sentiment among users (Schweitzer, 2014; Osorio Arjona et al., 2021). Zhang et al. (2019) underlined that with user-generated metrics such as likes, comments, and shares becoming essential for measuring public engagement, sentiment analysis, topic modeling, text mining, opinion mining, and deep learning frameworks are being applied across various domains, including traffic agencies, to gather public opinions and understand patterns of thinking. Osorio Arjona et al. (2021) utilized tweet-per-topic index-based sentiment analysis to comprehend rider feedback and reasons for dissatisfaction and Haghighi et al. (2018) integrated topic modeling to combine social media analysis results with customer satisfaction surveys. El-Diraby et al. (2019) assessed user politeness, Das and Al-Zubaidi (2021) categorized tweets' sentiment as positive or negative, and Kim et al. (2019) classified feedback based on service areas such as cleanliness, mobility, or timeliness using deep learning frameworks. Additionally, Casas and Delmelle (2017) identified riders' leading concerns related to public transportation, such as transit infrastructure, safety, and fellow passenger behavior. Qi and Costin (2019) had a practical insight from sentiment analysis, which was that rider dissatisfaction increases during delays and breakdowns, revealing valuable user habits.

The extraction of information on social media behavior and engagement using advanced methods is a burgeoning field with immense potential for enhancing transit promotion. Recent studies have extensively explored rider behavior and effective communication strategies to attract more riders. For example, Shafer and Macary (2018) found that young people prefer receiving transit information through social media rather than targeted messaging. Qualitative studies indicate that younger individuals, such as millennials or those under 24 years old, favor public transportation over personal vehicles (Shafer and Macary 2018; Yang and Cherry 2016). Consequently, Delbosc and Currie (2015) noted that targeting young adults through social media can lead to increased travel frequency. Blumenberg and Taylor (2018) examined how technological and social changes influence millennials' travel behavior, with younger audiences turning to social media influencers. Abellera and Panangadan (2016) mentioned that transit agencies can identify influencers whose audiences align with their target markets and collaborate accordingly. Bregman (2012) suggested that aligning social media networks with specific transportation uses can further enhance the success of social media promotion campaigns. Additionally, Dau-Ngo et al. (2013) discussed involving the public through social networking platforms during the planning stages of transit projects can be effective, bringing together collective user voices to generate innovative ideas.

Support and Influence Organizational Goals

The integration of social media data into transit agency operations has opened up new possibilities for optimizing services, engaging with riders, and improving communication strategies. By leveraging the diverse capabilities of social media platforms, agencies can enhance their overall efficiency, customer satisfaction, and public engagement in the ever-evolving landscape of transportation. Gkiotsalitis and Stathopoulos (2016) utilized mobility data derived from social media platforms, agencies have optimized transit vehicle timings and routes and Zhang et al. (2016) extracted valuable rider information. Studies by Ni et al. (2016) and Zhang et al. (2016) introduced algorithms capable of predicting both planned traffic events, such as high passenger flow during large public gatherings based on hashtags, and unplanned events like road crashes. By tapping into crowd-based perception and social media data, two studies (Chandra et al., 2020; Imran et al., 2015) suggested that agencies can gain insights into potential riders' travel mode choices, enabling them to strategically influence and alter travel mode preferences. The effective information-sharing practices by transit agencies on social media have proven crucial for successful communication, particularly during busy traffic schedules, as exemplified during the 2014 Commonwealth Games (Cottrill et al., 2017). Kaufman (2014) emphasized the necessity of co-monitoring systems to establish a strong and rapid line of communication between transit agencies and riders.

Different social networking platforms offer transit agencies diverse tools to continuously serve and engage their users based on unique characteristics and features. Platforms like Facebook helps in building communities, directing people to the agency's website, disseminating information, and raising awareness. Bregman and Watkins (2013) highlighted that real-time messaging apps such as Twitter and Instagram facilitate interactions with existing riders and promote events. Platforms like YouTube, Vimeo, Flickr, and Pinterest enable agencies to engage more vividly with riders through rich media content. Nikolaidou and Papaioannou (2018) investigated the appropriate use of social media platforms according to their distinct features and recommended the most effective platforms for each purpose. For example, Foursquare, being a location-based service, proves useful for identifying mobility patterns and trip purposes. Transit agencies can benefit from incorporating various tools for training transit authorities. Liu et al. (2019) developed a toolbox for integrating general transit feed specification (GTFS) data and social media data to assess performance, identify areas requiring infrastructure improvements, and evaluate network effectiveness. Additionally, Weisenford et al. (2018) highlighted social media to train transit authorities for quick access to information, creating a more interactive and dynamic community of learners, and reaching a mass audience.

Existing Challenges and Future Directions for the Transit Agencies

In surveyed agencies, the management of social media pages is often divided among staff members instead of employing dedicated full-time staff. Liu et al. (2016) noted that one of the common limitations observed in these agencies is the lack of well-defined goals and metrics to effectively assess the performance of their social media endeavors. Bjerkan and Øvstedal (2020) suggested barriers to accessibility, such as the need for high-contrast texts and screen-readable websites for better comprehension and readability, must be tackled. In the realm of social media practices, transportation researchers and practitioners have provided valuable recommendations based on surveys and analysis. Howard (2019) suggested policy changes that could enhance communication with riders and, in turn, benefit the agency's reputation. The author also highlighted the efficiency of Twitter as a platform for customer service. Bregman and Watkins (2013) emphasized how social media can play a role in providing equitable information despite language barriers, accessibility challenges, and the digital divide. Stewart and Cochrane (2018) presented the benefits of digital practices adopted by Novo Rail in Sydney, showcasing their own mobile app named NovoView, which can serve as an effective strategy for other agencies.

The literature review demonstrates a significant increase in research interest in social media usage by transportation agencies in recent years. However, there is a pressing need to synthesize the most up-to-date practices, address existing challenges, and explore prospects in this domain. The current study undertakes a comprehensive approach to meet this need by identifying best practices, existing problems, and potential areas for future development in the use of social media by transportation agencies. By doing so, it aims to provide valuable insights and guidance to the transportation industry for harnessing the potential of social media effectively and efficiently.

METHODOLOGY

Survey Design

To gain a deeper understanding of how transit agencies engage with social media, we undertook the development of an online survey questionnaire that covered various crucial sections, including social media platforms, agency considerations, challenges and barriers faced, lessons learned, and future needs. Through this comprehensive survey, we aimed to gather valuable insights into the social media strategies and practices adopted by transit agencies. The survey was carefully crafted to explore the social media structure of these agencies, delving into important aspects such as the specific platforms they utilize, the amount of time and resources invested by staff members for social media usage, and the frequency at which they employ social media for different purposes. Additionally, we sought to understand how these agencies measure the outcomes of their social media programs and how their policies are designed to cater to the needs of both users and employees.

To ensure a diverse pool of respondents, we distributed the survey request via email to 75 North American and Canadian transit agencies, which were selected based on regional location and relative size or service coverage. Our efforts in curating a varied mix of respondents led to participation from 60 agencies, resulting in an impressive response rate of 80%. However, we had to exclude 13 incomplete submissions from the analysis. Ultimately, we analyzed 47 complete responses, each representing distinct transit agencies. Notably, in one case, two personnel from the same agency submitted responses, providing an even more comprehensive outlook on that agency's social media engagement. Through this robust and diverse sample, we aimed to obtain a comprehensive understanding of the social media practices, challenges, and future needs of transit agencies. The data collected from the survey will serve as a valuable resource for examining the current state of social media usage in the transit sector, identifying successful strategies, and formulating recommendations to enhance social media engagement for improved communication, service delivery, and customer satisfaction.

Twitter Mining

Twitter mining, also known as Twitter data mining or Twitter analytics, is a specialized form of text mining that focuses on extracting valuable insights and patterns from the vast amount of data generated on the Twitter platform. With millions of users posting tweets daily, Twitter serves as a valuable source of real-time information and opinions on various topics, making it a goldmine for researchers, businesses, and analysts. The process of Twitter mining involves collecting and preprocessing tweets, which may include filtering by keywords, hashtags, or user profiles of interest. NLP techniques are then employed to analyze the text.

We selected seven case study agencies for Twitter data mining. These case studies are a representative sample of ridership, agency type, and social media network size (for example, by follower counts). Table 1 provides information on some social media metrics of these agencies.

Table 1. Social Media Metrics of the Case Study Agencies

Agencies	Twitter Handle	Followers	Tweets	Retweets	Likes	Replies
San Francisco Bay Area Rapid Transit District (BART)	@SFBART	316,100[1]	36,689	169,613	559,456	49,442
Miami-Dade Transit	@iridemdt	13,900	35,388	11,079	17,177	7,040
CyRide	@cyride	2,048	1,602	805	1,448	97
Transit Authority of Northern Kentucky (TANK)	@tankbus	442	475	365	1,038	56
Central Midlands Regional Transit Authority (The COMET)	@catchthecomet	1,082	2,336	1,810	2,554	305
Capital Metro	@capmetroatx	24,900	24,906	31,772	47,897	10,276
Halifax Transit	@hfxtransit	59,100	16,901	34,935	35,780	11,152

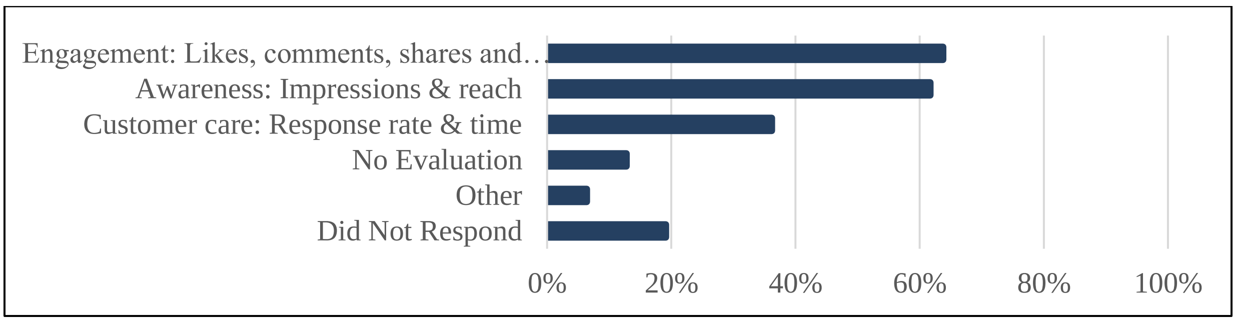
Note: [1]Tweets are collected till June 30, 2021 (from the start date of each of the Twitter handles).

RESULTS AND DISCUSSIONS

Survey Results

The survey measured how often the transit agencies used social media for sharing specific information. We found that transit agencies use social media to share real-time service information (40.43%), general service information (25.53%), and promote their agencies (10.64%) several times a day. There is a tendency among the agencies to match the type of content with the social media platforms they use. For example, 66% of the agencies share real-time service alerts through Twitter. For meeting and event notices, feature stories, and agency promotion, Facebook is preferred by transit agencies. Both Twitter and Facebook are frequently used by agencies for service information, emergency alert and crisis information, agency news and projects, press releases, and statements. Similarly, Facebook and Twitter are the most popular platforms for reaching all target segments including regular riders, occasional riders, student or young adults, seniors, people with disabilities, low-income communities, minorities, agency employees, and external stakeholders. For reaching young adults or students, most of the agencies almost equally use Facebook (59.6%), Twitter (57.4%), and Instagram (57.4%).

With regards to measuring social media metrics, our survey results indicated that more than half of the transit agencies relied on users' engagement (63.8%) estimated by likes, comments, shares, and clicks, followed by awareness (61.7%), which was measured through impressions and reach, and customer care success (38.1%), measured by response rates and time (Figure 1). Some of the survey respondents also reported engaging Facebook Insights (53.2%), Twitter Analytics (44.7%), Hootsuite (25.5%), and Sprout Social (19.2%) for analyzing their social media usage.



Note: Multiple responses were allowed. Responses are expressed as a percentage of total participating agencies (N=47).

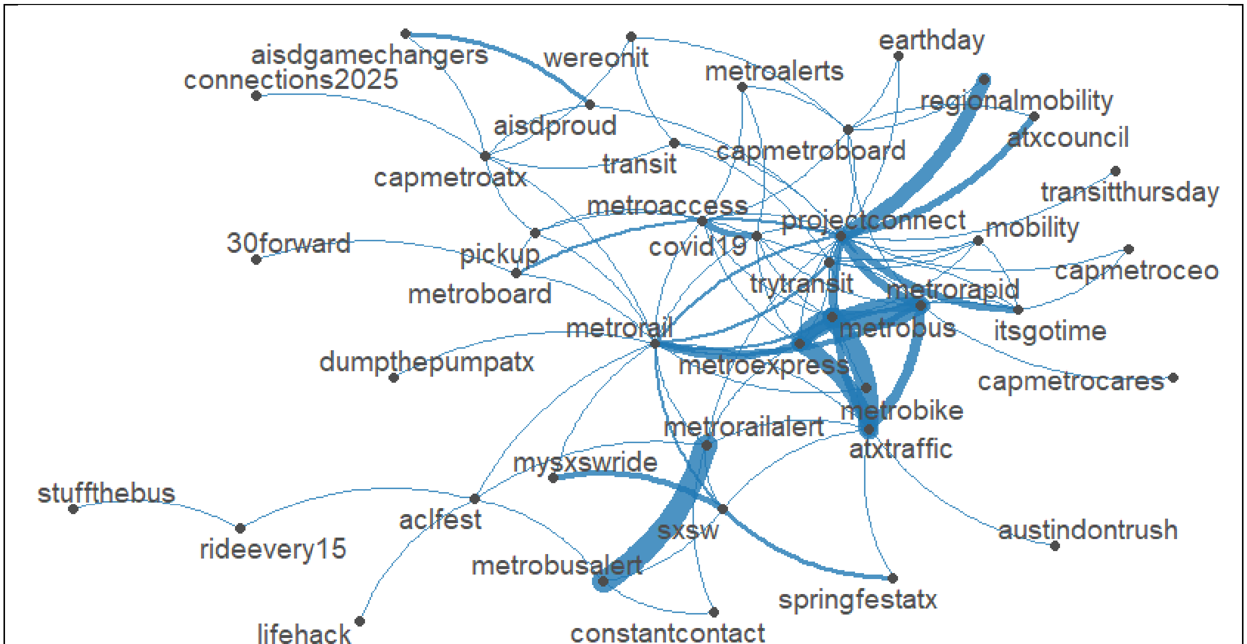
Figure 1. Common social media metrics measured by the surveyed agencies

Results from Text Mining

We collected around 118,000 tweets generated by the seven case study transit agencies. By executing these preprocessing steps, the data is transformed into a 'clean text' format, which is ready for further analysis and mining of valuable insights from the Twitter dataset.

Text network of hashtags

Figure 2 shows the next network of hashtags in the case study of transit agencies' official tweets. The top ten most frequently used hashtags in the case study transit agencies' official tweets include '#metroexpress,' '#metrorapid,' '#metrorailalert,' '#metrobus,' '#regionalmobility,' '#trytransit,' '#mysxswride,' '#atxcouncil,' '#itsgotime,' and 'atxtraffic.' These hashtags are highly relevant and frequently utilized in the transit agencies' social media communication. Visual analysis of the hashtag network shows that certain hashtags like '#trytransit,' '#metrorapid,' '#covid19,' '#metrorail,' '#metroaccess,' and '#projectconnect' appear to be closely interconnected and central to the network. In contrast, hashtags like '#stuffthebus,' '#rideevery15,' '#lifehack,' and '#austindontrush' appear to be further away from the center and less connected to the rest of the hashtags. Several wide edges are observed between certain hashtags, indicating stronger associations or frequent co-occurrences. For example, there are wide edges between 'metrorailalert' and 'metrobusalert,' 'metrorapid' and 'metrobike,' and 'projectconnect' and 'regionalmobility,' among others. The hashtag 'metrobus' shows multiple wide edges with other hashtags such as 'metrorail,' 'metroexpress,' and 'metrorapid,' suggesting frequent usage and connections between these transit-related terms. The analysis highlights the importance of using specific agency or locality-related hashtags (e.g., #atxtraffic, #mysxswride, #austindontrush) to provide more specific and targeted information for a particular transit agency or city, as opposed to generic hashtags like '#metrorail' that do not offer specific agency context.

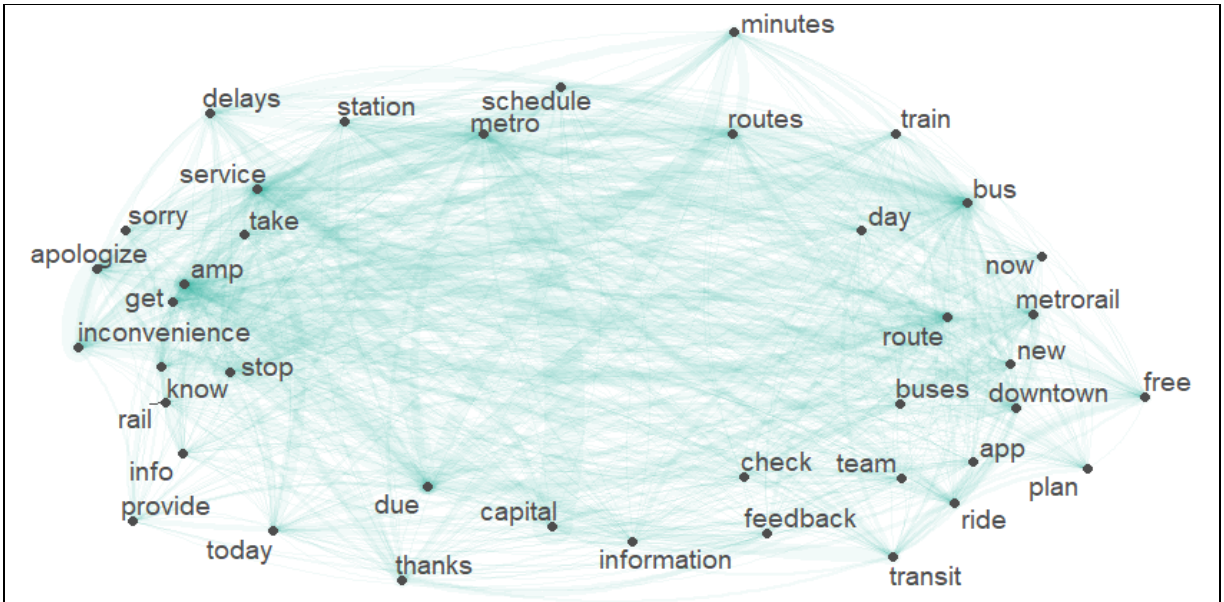


#metroexpress	#metrorapid	#metrorailalert	#metrobus	#regionalmobility
198	160	90	89	51
#trytransit	#mysxswride	#atxcouncil	#itsgottime	#atxtraffic
31	29	28	28	27

Figure 2. Hashtags in case study transit agencies' official tweets

Text network of top keywords

The text network in Figure 3 provides a comprehensive overview of the keywords transit agencies frequently use in their official tweets, highlighting both common themes and specific topics of interest. The top ten most frequently used words include 'route,' 'inconvenience,' 'stop,' 'service,' 'metrorail,' 'get,' 'minutes,' 'due,' 'delays,' and 'new.' These words reflect the major themes and topics that transit agencies frequently communicate with their audience. Notably, there are no words located near the center of the graph, indicating that there is no single dominant keyword or central theme that consistently appears in the tweets. Instead, the most frequent words are distributed across the graph, suggesting a diverse range of topics covered in the tweets. Some words, such as 'minutes' and 'free,' appear visibly further outside the network compared to others. This suggests that these words are less frequently used, but when they are used, they stand out as distinct and important keywords. A comparison with Figure 2, which depicts the hashtag network, shows that the hashtag '#metrorail' also appears as a top feature in the word network. However, there are content differences between the two networks. Figure 2 focuses more on specific types of transit, such as '#metroexpress,' '#metrorapid,' '#metrorailalert,' and '#metrobus,' while Figure 3 focuses more on general details about transit, such as 'route,' 'inconvenience,' 'stop,' and 'service.' The diverse distribution of words indicates the wide range of information and updates shared with the audience, ensuring a comprehensive communication strategy for transit agencies.



Route	Inconvenience	Stop	Service	Metrorail
6165	5313	4991	4868	3903
Get	Minutes	Due	Delays	New
3447	3175	3114	3067	3015

Figure 3. Top 40 most frequent words in case study transit agencies' official tweets

Text clusters of top keywords

The analysis of text clusters developed using the official tweets of transit agencies is presented in Figure 4. Notably, Cluster 4 constitutes the largest proportion, accounting for 37.9% of the tweets. Cluster 1 seems to center around tweets thanking and being grateful for those using the services of the transit agencies, including keywords such as 'thanks', 'please', 'service', and 'feedback'. Cluster 2, however, seems to center around the transit agencies apologizing to consumers for delays, including keywords such as 'delay', 'inconvenience', 'apologize', 'experiencing', and 'minutes'. Cluster 3 seems to be more community and service-focused, with keywords such as 'transit', 'community', 'service', 'project', 'connect', and 'public'. Finally, Cluster 4 seems to be focused on different services offered by these agencies, including keywords such as 'service', 'bus', 'ride', 'metro', 'routes', 'apps', and 'transit'. Overall, the analysis of tweet clusters from transit agencies' official accounts reveals a diverse social media communication strategy.

Figure 4. Four text clusters from the transit agencies' official tweets

CONCLUSIONS

The global reach of popular social networking sites is astounding. It is said that social media marketing is the biggest shift since the industrial revolution. Almost every business, organization, and agency have an official identity in social media. Transit agencies have been using social media as a regular tool to share information and understand public sentiments and attitudes toward their services. There is a need for synthesizing the amount of work conducted on this issue. This study has three unique contributions: 1) it performed a thorough review of the social media usage by the agencies, 2) it completed and analyzed a survey on the representative agencies to understand their social media usage, and 3) it performed text mining on the archived tweets of selected agencies.

However, the study has certain limitations. Social media data can suffer from sampling biases and under-representation of specific groups, which might affect the survey's interpretation. The lack of defining target groups, such as minorities or young adults, could have potentially skewed responses. Additionally, the study's focus on certain considerations or goals might limit a broader understanding of the impact factors involved. While acknowledging the study's limitations, this study design was deliberately broad to encompass a global perspective. By conducting a thorough review of social media usage, analyzing representative agency surveys, and employing text mining techniques, this study has generated multifaceted insights. This study's strength lies in its ability to capture diverse strategies and challenges faced by transit agencies worldwide. These insights, even within the study's defined scope, offer substantial knowledge about the evolving landscape of social media within transit contexts. Furthermore, the current study's limitations serve as valuable signposts for future, more targeted research endeavors, making our analysis a foundational step towards more nuanced investigations in this field.

Furthermore, the ever-evolving nature of social media platforms necessitates careful interpretation of the study's findings within a specific timeline. Future studies should consider the dynamic nature of social media and how it influences transit-related issues, such as pandemic responses, handling misinformation, promoting environmental benefits, ensuring equity, fare reduction initiatives, and safety and livability improvements. Future studies can focus more on social media to convey transit-related issues, such as pandemic responses, misinformation handling, environmental benefits, equity, fare reductions, safety, and livability improvements, as social media platforms grow.

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Carving up the Curb: Evaluating Curb Management Strategies for Ride-Hailing and Ride-Sharing Activity through Simulation

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ABSTRACT

As ride-sharing services increasingly redefine how people move within urban areas, the curb environment (the public space between roadway and sidewalk) will have to be able to accommodate new uses and new users. This study seeks to understand how formalizing a space for curbside pick-up and drop-off (PUDO) activity typical of new transportation modes such as ride-sharing will impact traffic flow and curb use. Microscopic simulation models calibrated using data collected in Atlanta, GA, were devised, and performance metrics such as delay and occupancy rate were collected. By varying traffic flow conditions and changing the percentage of PUDO parking events, an analysis of different curb configurations was conducted, and results were compared with those from a traditional curb design. The introduction of dedicated PUDO zones created significant reductions in delay. With high utilization, these zones have the potential to reduce double-parking, increase curb utilization, and positively affect through traffic.

INTRODUCTION

The curbside is becoming an increasingly important component of the urban environment, with rapidly expanding use cases. For example, the employment of shared mobility services creates additional curb management challenges by changing how curb space is utilized. To manage the evolving curb environment, cities will need to model and test potential curb management schemes that account for shifting drop-off, pick-up, and waiting activities.

The goal of this study is to investigate the potential impacts of pick-up and drop-off (PUDO) activities on the curb and adjacent traffic flow by using microscopic simulation to model potential curb environment scenarios, calibrated to existing behaviors in Atlanta, GA. Scenarios establishing priority access to the curb for shared mobility and ride-hailing activities through the designation of PUDO zones are investigated. Several curb configurations are devised and tested under varying flow and parking-demand characteristics (from low flow and traditional long-term parking demand, to high flow and high PUDO share demand). By studying different curb layouts under a wide array of conditions and examining a diverse set of indicators, the effects of specific curb management strategies on curb performance are explored.

BACKGROUND

The rise of ride-hailing and delivery services has placed increasing demands on the curb, which must often serve a variety of right-of-way functions including mobility, access for people and commercial activities, greening, and vehicle storage (Roe and Toocheck 2017). However, ride-hailing vehicles can be a very productive use of curb space as they serve more passengers per minute of occupied curb space than traditional personal vehicles (Lu 2018). Further, travel demand forecasts with a mixture of autonomous and traditional vehicle types show a reduction in off-street parking demand and a significant increase in curbside loading and unloading demand (Zhang and Guhathakurta 2017), further increasing future pressure on the curb.

A potential solution for increasing curb demand pressure is curbside management, which seeks to improve mobility and safety by prioritizing and optimizing curb space (Marcus and Montgomery 2018). One potential curbside management solution for areas with high passenger PUDO activity is to convert existing parking into PUDO-specific zones. Optimizing the curb's function for passenger loading/unloading can be critical because in-lane PUDO may have significant impacts on traffic flow. For short-duration parking events, such as PUDO, drivers are less willing to spend time searching for curb parking and more likely to double-park (Lu 2018, Kadkhodaei et al. 2022). As vehicles block the flow of traffic, in-lane or double-parking events result in a severe decrease in average speed and an increase in delay and stopped time (Kladeftiras and Antoniou 2013).

Multiple cities have launched pilot programs to measure and test curbside management strategies to optimize PUDO activity. A study in Seattle found that the implementation of a passenger loading zone and geofencing strategy reduced the number of PUDO in the travel lanes and increased curb use compliance (Ranjbari et al. 2013). A case study in Gainesville, FL illustrated the importance of regulating the number, location, and dwell time of PUDO zones (Wang et al. 2022). In California, a study found that increasing the supply of passenger loading space can reduce the incidence of ride-sourcing vehicles double-parking (Lu 2018). Beyond empirical studies based on field surveys, simulation has been used to examine future impacts on the curb. For instance, a study that utilized PTV-VISSIM® to model parking maneuvers found that the number of parking spaces can be optimized to limit road capacity reductions (Madushanka et al. 2020). Simulations of increasing adoption of ride-share services in Lisbon concluded that as ride-sharing adoption increases, the introduction of curb (non-active lane) drop-off zones will result in a reduced impact on traffic fluidity (Philippe Christ and Martinez 2018). Despite advancement in the literature of modeling curbside and the increasing number of empirical curb studies, no study was found that examines the potential traffic and curb impacts from the shift of long-term parking to ride-hailing vehicles while allowing for double-parking and on-street parking. This study seeks to fill this gap by examining actual curb and double-parking behavior for passenger loading/unloading events at an existing on-street parking environment in Atlanta, GA. This data is then used as a base to inform the simulation of multiple curb configurations designed to test different levels of curb management through the deployment of dedicated PUDO zones.

CURBSIDE DATA COLLECTION METHODOLOGY

To calibrate the models, curb activity video footage was manually processed by coding the recordings into qualitative and quantitative measures. Video footage for Spring St. between 8th

St. and Peachtree Pl. in Midtown Atlanta, GA, was obtained. Spring St. is a three-lane, one-way, street running through a vibrant, urban mixed-use district filled with retail and residential uses. This street segment contains paid on-street parking spaces on the east (left) side of the street (Figure 1a) and a one-way cycle track on the west (right) side of the street (Figure 1b.)

(a) (b)

Figure 1. View of Spring St.: (a) on-street parking on the east (left) side of the street, and (b) bike lane and illegal parking on the west (right) side of the street. Image Credit: R. Kiriazes.

There are two on-street parking zones separated by a curb extension; a 90-minute parking zone with four spaces and a 160-minute parking zone with seven spaces (for a total of 11 spaces). Some parking spaces were not clearly striped, so inefficient parking may have occasionally resulted in a ten-space capacity. Double-parking (stopping, standing, or parking on the street side of any vehicle that is stopped or parked at a curb (Georgia Code 2010)) occurred on the east (left) side of the street.

The analyzed video feed of Spring St. was recorded on Thursday March 3rd, Friday March 4th, and Saturday March 12th, 2022, from 8AM to 7PM. Video footage was coded by the research team to capture any parking activity during the observed periods. For each activity, attributes recorded included the start time, end time, event type (parking, PUDO, or delivery), location zone, door access, trunk access, driver leaving vehicle, number of passengers, vehicle type, parking maneuver (pull-in or parallel park), number of vehicles blocked due to activity, number of weaving vehicles due to activity, and parking availability. If an attribute could not be distinguished due to video quality or angle, it was recorded as NA.

CURBSIDE DATA ANALYSIS AND RESULTS

A total of 581 parking events were recorded, distributed across all three days. The majority (76%) of the activities that occurred on each day were coded as a general parking event, where the driver and/or passengers get out of the vehicle, leave for an extended period, and return. Less than a quarter (14%) of curb activities were coded as a PUDO event, where a passenger gets in or out of the vehicle and then the driver continues onwards. Of the 83 PUDO events recorded on Spring St., approximately 40% (n=33) double-parked instead of stopping on the dedicated curb. Double-parking events had a shorter dwell time than on-street events at all curb locations. The data collection process only identified a limited number (3%) of delivery events, where a driver or passenger leaves or returns with a package or bag. Not all curb activity was coded with an event type due to footage visibility issues. This introduces a potential bias in collected curb activity as events occurring at the north end of the block, farthest from the camera, were not consistently visible. Lastly, this analysis did not record traffic volume throughout the day which may impact the willingness of vehicles to stop in-lane. Figure 2 shows the cumulative distribution of all observed parking events.

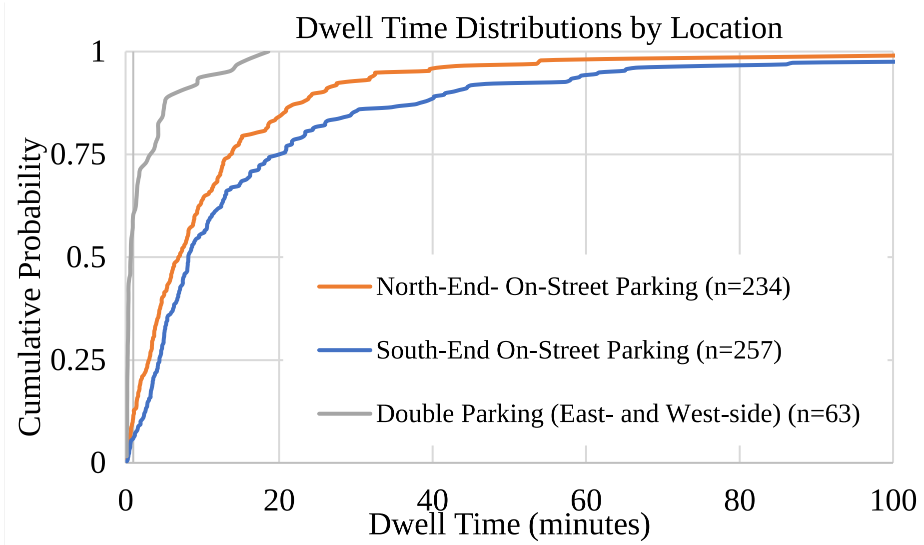


Figure 2. Dwell time CPF by curb location

The dwell time was further examined for PUDO passenger loading and unloading activities. The average dwell time for a PUDO double-parking event was under a minute, while PUDO events in the dedicated curb space averaged under three minutes; this is consistent with other studies (Overtoom et al. 2020). Most events that occurred in the double-parking zone were PUDO events. While all unloading events were under three minutes, approximately 20% of loading activities lasted longer than three minutes, with the longest loading dwell time of 8.03 minutes. Passenger unloading events (average 0.69 minutes) had a lower average dwell time than passenger loading events did (average 1.84 minutes).

PTV-VISSIM® MODELING METHODOLOGY

Video data collection and analysis allowed for the calibration of a simulated curb environment which was modeled using PTV-VISSIM® software. This modeling software was chosen because it allows the study of curb performance at the level of individual vehicles, and can output a variety of performance measures of interest. In this regard several studies have used PTV-VISSIM® to analyze curb activity (Madushanka et al. 2020). The Spring St. field data was used to calibrate the dwell times of vehicles parking at the curb. Two vehicle classes that utilized the curb were defined: (1) General passenger vehicles (GPV), with a parking use of the curb from as little as 30 seconds to 8 hours; and (2) PUDO vehicles, with a parking use of the curb of generally less than 3 minutes. A third vehicle class ("through vehicles") was defined to measure the effects of changing parking behaviors on non-stopping traffic and congestion.

Three alternative curb layouts are considered. All modeled curb configurations contained three one-way, two-lane roadway segments, for a total roadway length of 1350 ft. The central segment contained on-street parking (modified for each alternative design) adjacent to the right lane (Figure 3). Three vehicle inputs, corresponding to the three vehicle classes, were located at the upstream end of the modeled road segment. Upon approaching the parking spaces (approximately 200 ft upstream of the first parking space) vehicles designated to park were assigned a vehicle parking behavior (i.e., if a vehicle would attempt to park or not, the length of time parked, and assigned parking space). PUDO vehicles also had the option of double-parking in the right-hand through lane, while GPV parking only occurred in spaces located directly adjacent to the curb. To model double-parking, a second series of parking spaces was introduced in the right-most lane, directly adjacent to curb parking spaces. Based on field observations, these double-parking spaces were slightly larger (25 ft) than the standard (22 ft) curbside parking space. In all simulations, GPVs were set to drive on if a parking space was not available when assignment of parking occurred, while PUDO vehicles were set to wait for a space to open up when parking was currently full, whether assigned to curb or double-parking.

By varying traffic flow and PUDO ratios (Table 1), 13 total demand scenarios were created. Ten replicate runs were completed for each scenario. The average across replicates is reported within this paper. Among all scenarios, the overall parking event rate was kept constant at 5% of the traffic flow, except for the base scenario (scenario 1), which reflected current conditions as observed in the field. Each simulation run lasted 4500 seconds, and data was collected only during the last 3600 seconds to allow for a 900 second warm up period. For this study, vehicles were loaded into the network stochastically according to a uniform distribution: no upstream controls (e.g., signal heads) were used.

Table 1. Scenario Characteristics

Flow level	*Flow (veh/h)*	*Parking Rate (%)*	*PUDO Share (%)*	*Scenario no.*
Base	1000 veh/h	3.2%	10%	1
Low Flow	1000 veh/h	5%	10%	2
			30%	3
			60%	4
			90%	5
Mid Flow	1500 veh/h	5%	10%	6
			30%	7
			60%	8
			90%	9
High Flow	2000 veh/h	5%	10%	10
			30%	11
			60%	12
			90%	13

Initial Curb Configuration

The initial curb configuration (Figure 3a) was designed to reflect the current typical curb environment in US cities, where parking spaces are open to all vehicle types and (allowed) curb uses. Along the entirety of the parking lot segment, 14 parking spaces were created. The attractiveness of the parking spaces (i.e., likelihood of selecting a specific parking space) was assumed to be uniform. In the right-most lane, a double-parking zone was introduced, with space for 12 vehicles to double-park. A PUDO vehicle would double-park with a likelihood of 40%, based on the Spring St. observations. A simple average likelihood (i.e. 40%) is utilized as the field data set is limited to 83 observed PUDO events. Additional PUDO data collection is necessary to determine if a more complex relationship exists with curb parking space availability, flow rate, time-of-day, etc., and if a more robust double-parking model is needed.

Alternative 1

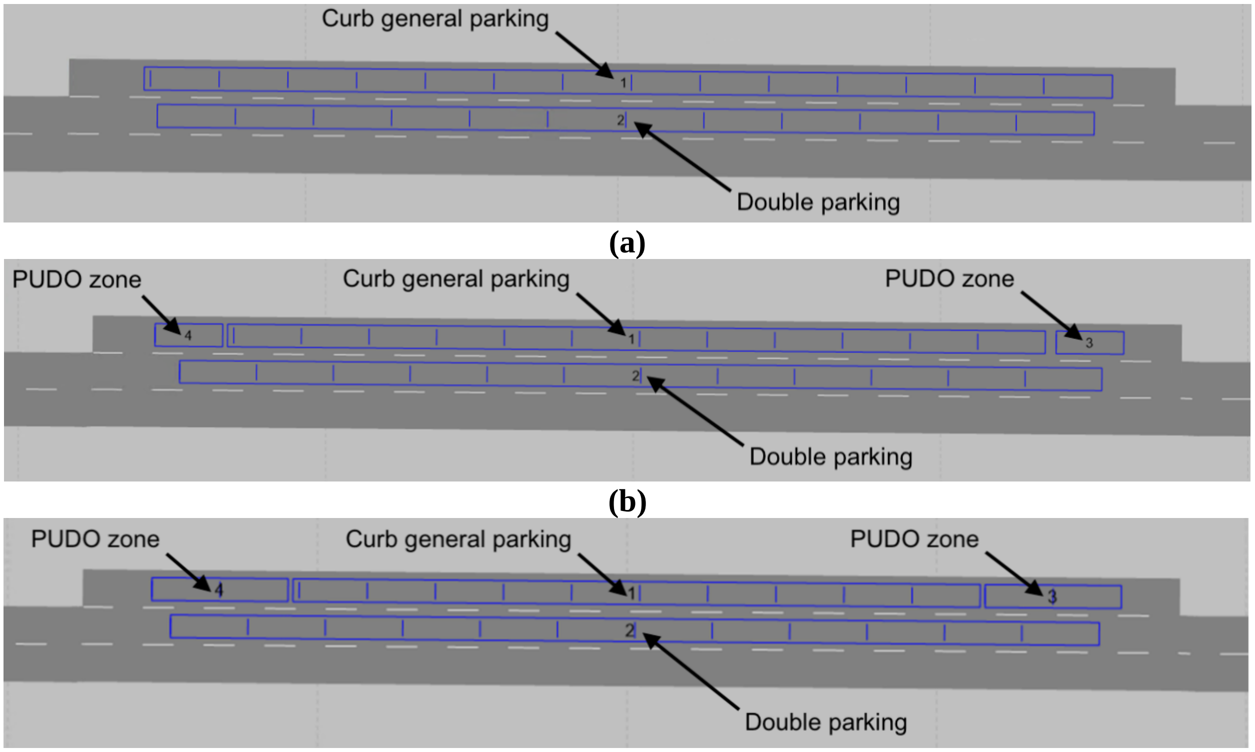
Alternative 1 (Figure 3b) was created to examine the impact of dedicating a limited number of parking spaces for PUDO events by converting two on-street parking spaces from general parking to PUDO only. These parking spaces were placed at the ends of the general parking. It was assumed that if a PUDO space was available, a PUDO vehicle would use it rather than a general space or double-parking. Thus, a PUDO vehicle approaching the curb parking was first assigned to a dedicated PUDO space if available; only if one was unavailable was it assigned to the general or double-parking spaces at respective rates of 60% and 40%. Thus, the effective rate of double-parking decreased as the number of dedicated PUDO spaces increased. The implementation of this logic was accomplished utilizing the PTV-VISSIM® Attribute Modification feature, additional detail may be found in Kiriazes et al. (2022). Operationally, adopting this modeling approach implies that vehicles follow a policy requiring PUDO vehicles to use designated zones when available. The current simulation assumes a 100% compliance with this policy. Future research should confirm driver’s reaction to the presence of dedicated PUDO zones and determine how compliance is affected by the location of the spaces, the presence of active or passive enforcement, and the use of incentives.

Alternative 2

To evaluate the impact of additional PUDO zones on performance metrics, Alternative 2 was established (Figure 3c). For this alternative, a total of four parking spaces were reserved for PUDO parking events, further reducing the number of parking spaces available for long-term parking events. By varying the amount of curb space reserved for PUDO events, changes in curb performance at varying levels of flow and PUDO share can be evaluated among the alternatives and configurations.

Additional Model Assumptions

Given the constant double-parking share of 40%, some PUDO vehicles were directed to the curbside parking spaces even when those spaces were full. In those situations, a PUDO was allowed to block the right lane for 30 seconds, even though a double-parking space was unavailable, reflecting a brief PUDO event. At the end of 30 seconds, the simulation removed the vehicle from the network (i.e., the diffusion setting in PTV-VISSIM). Thus, in congested parking situations, the actual rate of double-parking may be higher than that reported. However, in the majority of scenario simulations, diffusion did not occur or only impacted one or two vehicles. Only at the highest flow and PUDO rates did the number of vehicles diffused increase, in all cases remaining below 10 per hour.



(a) (b) (c)

Figure 3. Curb configurations: (a) Initial configuration, (b) Alternative 1 with 2 curb spaces dedicated to PUDO parking, and (c) Alternative 2 with 4 curb spaces dedicated to PUDO parking.

VISSIM MODELING RESULTS

Three main metrics were used to evaluate the performance of each curb configuration: vehicle delay, occupancy rate, and the share of parking requests declined. Vehicle delay "is obtained by subtracting the theoretical (ideal) travel time from the actual travel time…" (PTV Group 2022). The occupancy rate is the percentage of time that the parking spaces were occupied by parked vehicles during the data collection period. The share of parking requests declined is the number of vehicles that, while approaching the curb with the intention of parking, were not able to find an open space, saw their parking request declined and had to drive on. Only long-term parking vehicles (GPV) were allowed this behavior, so the share of parking requests declined is a direct measure of how the curb is serving long-term parking vehicles. PUDO vehicles unable to park were diffused, as discussed previously. PTV-VISSIM® outputs are presented as boxplots, with each representing the distribution of the 10 replicate trials for each scenario, for the Initial configuration and Alternatives 1 and 2.

Delay

Figure 4 shows both how delay evolved among scenarios (from the base scenario to the high-flow scenario with 90% PUDO share) and among different curb configurations. Minimal to no delay was observed across the low-traffic flow scenario regardless of PUDO percentage or curb layout. In the mid- and high-traffic flow scenarios, higher delays were observed. The average vehicle delay was greatly influenced by the amount of time the right-most lane was occupied by a double-parking vehicle. As the flow rate and PUDO share increased, the likelihood of double-parking increased. In most instances, the majority of the queue formed behind the double-parked vehicle (or the first of the double-parking vehicles, when more than one was present), and the queue increased more rapidly the higher the flow of through traffic.

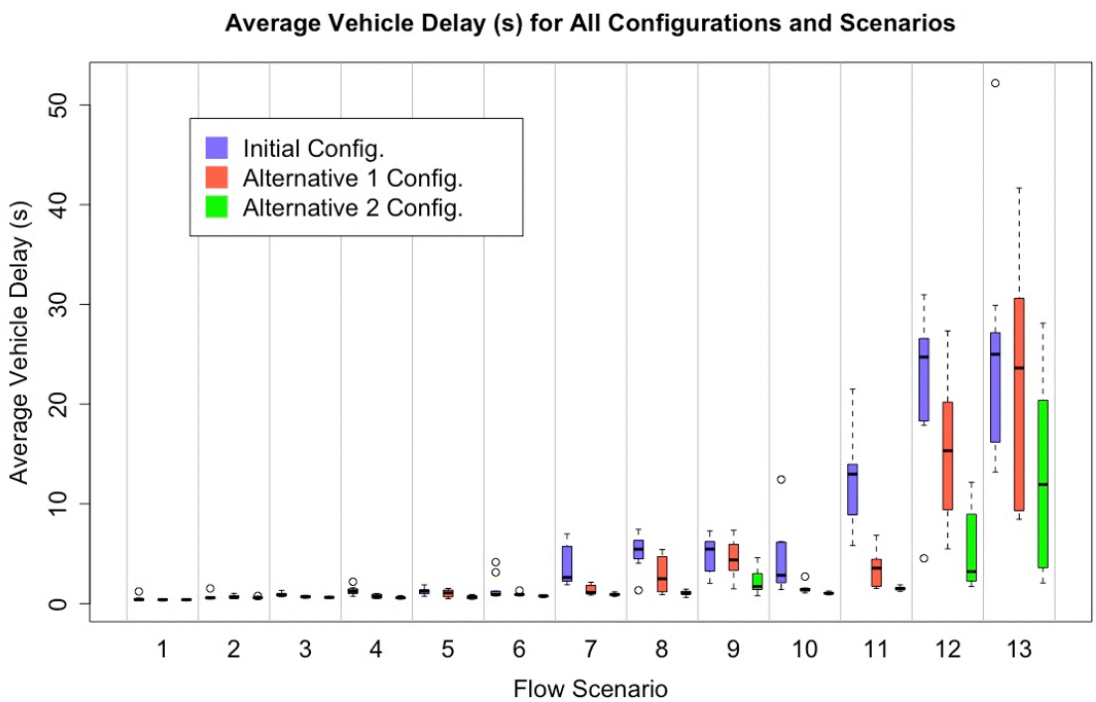


Figure 4. Average vehicle delay for all scenarios and all configurations

Though a significant increase in delay was observed among scenarios (from a negligible average delay to an average of 24 seconds), the deployment of curb management strategies was effective in reducing average vehicle delay, as can be seen in the decreasing delay between the Initial configuration (no dedicated PUDO space) and the alternatives, within any given scenario. Additionally, as the number of available PUDO spaces increased (i.e., from Alternative 1 to Alternative 2), the reduction in delay increased. However, at the highest PUDO rates (90%), the benefits of the dedicated spaces are more muted since the number of spaces proved to be insufficient and significant double-parking still occurred. At the highest flow rate, a limited number of simulation replicate runs ended with unprocessed vehicles (i.e., vehicles were unable to enter the network during the run), which in no single run exceeded 0.5% of the demand. However, the presence of unprocessed vehicles likely indicates that the reported delays at the highest flow rate are slightly lower than actual, since unprocessed vehicles are not included in performance metrics.

Table 2 synthesizes these changes, showing how even the introduction of just a few dedicated PUDO spaces, with a high compliance/utilization rate, can have a significant impact on curb performance in almost all flow and PUDO percentage situations. Welch's Two Sample t-tests were conducted to determine the effect of a change in curb configuration on vehicle delay, where it is seen in nearly all scenarios that the differences are significant.

Table 2. Percent Change in Average Vehicle Delay - All Scenarios and All Configurations.

	Percent change in average vehicle delay												
Scen.	Base	Low Flow				Mid Flow				High Flow			
PUDO %	10%	10%	30%	60%	90%	10%	30%	60%	90%	10%	30%	60%	90%
Init. to Alt 1	-47%	-22%	-61% (**)	-67% (**)	-38%	-57%	-75% (**)	-48% (*)	-10%	-74% (*)	-75% (***)	-29% (-)	-10%
Init. to Alt 2	-50%	-36%	-68% (**)	-83% (***)	-76% (***)	-68% (-)	-87% (**)	-88% (***)	-64% (***)	-83% (*)	-92% (***)	-79% (***)	-51% (*)
Alt 1 to Alt 2	-6%	-18%	-19%	-48% (-)	-62% (*)	-27% (**)	-47% (*)	-78% (**)	-60% (**)	-35% (*)	-69% (**)	-71% (***)	-45% (-)

Welch Two Sample t-test, 95% Confidence Level: (-) = p-value < 0.1; (*) = p-value < 0.05; (**) = p-value < 0.01; (***) = p-value <0.001

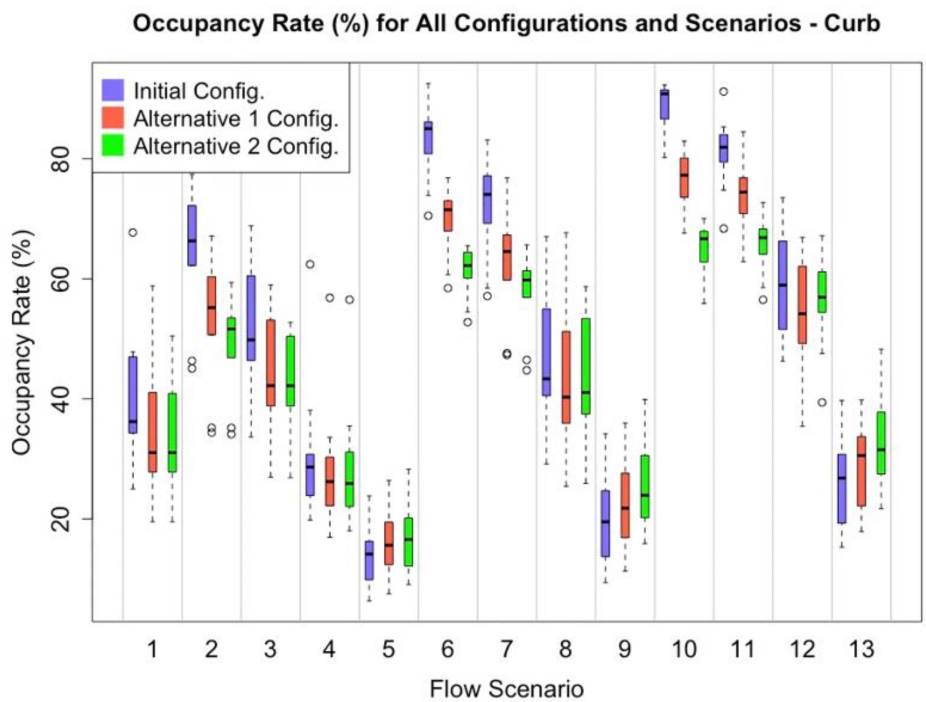
Occupancy Rate

For each curb configuration, the average occupancy rate was examined by subdividing the available parking spaces (which remained unchanged throughout the simulations) into curbside parking spaces and double-parking spaces. The curbside occupancy rate included the general spaces and dedicated PUDO spaces (where applicable). Figure 5 shows a comprehensive comparison of both curb and double-parking across all scenarios and curb configurations. Generally, as the share (and number) of PUDO vehicles increased, the occupancy at the curb decreased and the proportion of double-parking vehicles increased. This is not surprising given that PUDO vehicles tended to stop for a shorter amount of time (thus physically occupying curb parking spaces for less time) and as PUDO share increased, a higher number of parking events occurred in the right-most lane (double-parking).

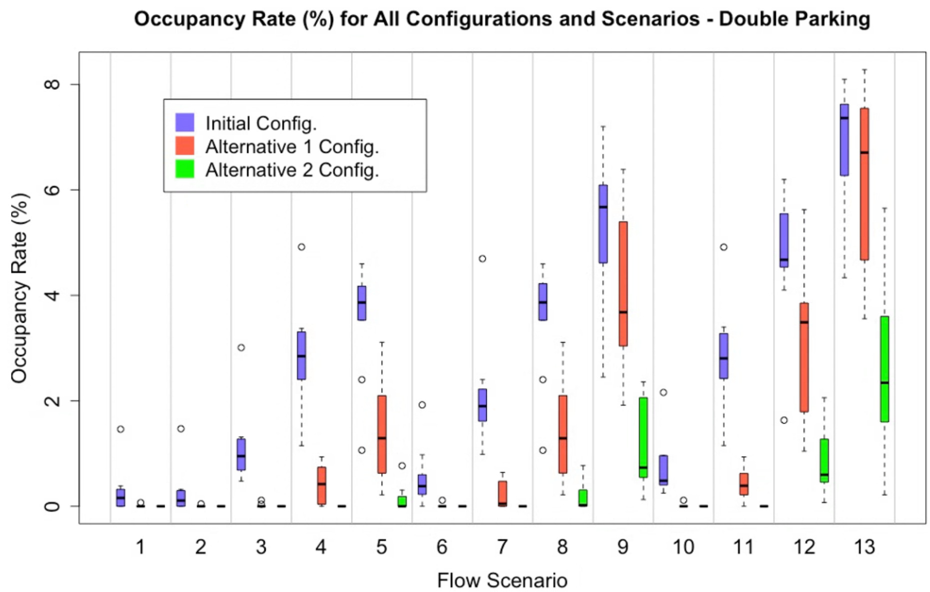
However, it is also seen that the presence of the dedicated PUDO spaces results in a significant decline in double-parking, relative to the base condition, as the PUDO rate increases. This is driven by a significant proportion of PUDO vehicles being redirected to the designated PUDO zones instead of either parking in the general curb parking spaces or double-parking. Additionally (Figure 5a), a slight increase in curbside parking is seen at higher PUDO rates as the number of dedicated PUDO spaces increases, as the curbside occupancy includes the dedicated PUDO spaces.

Share of Parking Requests Declined

While not discussed here in detail, the share of parking requests declined was also considered. Requests declined were a function of the specific demand characteristics (high share of long-term parking requests) and the number of general parking spaces available. The inclusion of dedicated PUDO spaces could result in a high decline rate, however, this trend is not consistent, as increasing rates of PUDO vehicles doubling parking could result in the blocking of general-purpose spaces. For given demand and volume combinations, the reduction in double-parking provided by PUDO spaces outweighed the loss in general purpose spaces. Thus, for any given location, localities will need to determine the optimal ratio of general parking to designated parking for each given site based on the demand characteristics and PUDO share.



(a) Curb Parking



(b) Double-parking

Figure 5. Occupancy rates: (a) Curb parking and (b) Double-parking

CONCLUSIONS

Through data collection and calibrated microscopic simulation modeling, this study investigates the potential impacts of increased PUDO activities in different flow and curb configurations. The data collection phase showed that double-parking behavior is complex, and that a wider study will be required to model it in detail. Through the collection of curbside data, different parking behaviors were identified, and a quantitative distinction between PUDO and long-term parking was observed. Analysis of the simulation results indicates potential benefits from introducing curb management strategies. Should future transportation trends lead to an increase in the share of PUDO activity at the curb, strategies which involve the separation of curb uses appear to be effective in reducing delay for vehicles and optimizing curb utilization. Throughout the simulations, a progressive shift away from traditional, long-term parking towards PUDO activity led to an observed higher curb productivity and lower occupancy, although higher rates of double-parking were recorded. The use of dedicated PUDO zones helps to reduce the likelihood of double-parking and associated delays. Additional field data collection, simulation, and analysis will be required to develop specific guidance for the number of PUDO-dedicated spaces relative to overall traffic and parking demand. This would constitute a targeted management practice with significant potential to improve overall curb utilization and performance.

The current study has several limitations, including a fixed rate for PUDO double-parking, assumed 100% PUDO zone compliance, vehicle diffusion, and unprocessed vehicles. The use of a predefined diffusion time for vehicles waiting for a parking space is a necessary and imperfect modeling solution. With a better system in place, situations with high-parking volume, in which many vehicles wait for parking to become available, can be explored. Nevertheless, despite these limitations, the use of microscopic simulation software proved to be a good tool to explore and examine the impacts of different curb configurations on traffic flow and curb performance. Further data collection including more varied locations and conditions (e.g., the presence of PUDO zones) will allow for improved model calibration, resulting in even more robust simulations. Future researchers should work to gather additional curb and double-parking data under varying conditions (e.g., demand levels, inclement weather, etc.) and for different days of the week or times of the year, to examine more fully the potential impact on double-parking behavior of curbside parking availability and parking purpose (PUDOs, deliveries, etc.). In addition, the effect of PUDO zone placement (e.g., at the end of general parking, mixed within general parking, etc.) should be considered. Additionally, future research efforts should explore modeling scenarios in which an increase in PUDO demand is not linked to a proportional decrease in long-term parking, but represents additional curb parking demand generated by users switching from other forms of transportation (transit, biking, walking, etc.) to ride-hailing services. Finally, as other curb-space allocation strategies are proposed, comprehensive modeling studies should be devised to compare them.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: K. Watkins, M. Hunter, R. Kiriazes, M. Saracco; data collection: A. Foulkes, A. Hatch; analysis and interpretation of results: R. Kiriazes, M. Saracco, M. Hunter; draft manuscript preparation: K. Watkins, M. Hunter, R. Kiriazes, M. Saracco. All authors reviewed the results and approved the final version of the manuscript.

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Is a Detour a Good Choice to Reduce the Commute Delay Caused by a Crash? A Case Study of I-24 Smart Corridor in Tennessee

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ABSTRACT

Traffic congestion, caused by incidents such as vehicle crashes and lane closures, has been annoying to commuters. To reduce the delay caused by unexpected incidents, a detour might be a good option even at the cost of a longer travel distance. We used the smart corridors under the integrated corridor management program: Interstate 24 (I-24) and State Route 1 (SR-1) as a case study and examined the conditions under which detour decisions should be made. We collected 460 crashes and computed the travel time of the direct route (i.e., staying on I-24) and the detour route (i.e., using a stretch of SR-1). Three different detour scenarios were identified at a departure time: strongly recommended, alternative, and not recommended. Additionally, we classified the three detour scenarios into two groups: detour and non-detour by estimating the probability of detour scenarios following 1 h after the incident occurred. A bootstrap logit regression was conducted to determine the impact of various factors on the decision to take a detour. Several important findings are: (1) One-unit increase in injuries leads to a 59.1% increase in the likelihood of taking a detour. (2) When a crash occurs in peak hours, staying on I-24 smart corridor seems to be a better choice. (3) If a crash occurs in HELP patrol area, detour is highly discouraged. This research could provide insights into incident management and give commuters suggestions about the circumstances in which detour is a good choice.

Keywords: travel time, detour, crash, integrated corridor management, commuter

INTRODUCTION

Freeways provide free-flowing, high-speed traffic over long distances, which is the primary option for commuters in terms of saving travel time. However, due to a large amount of traffic and high-speed traffic flow, vehicle crashes occur on freeways from time to time, leading to traffic congestion and extra travel time (Blincoe, Miller, Zaloshnja, & Lawrence, 2015; Gu, Liu, Arvin, Khattak, & Han, 2023). To minimize the impact of crashes on travel time, taking a detour, even if it results in a longer trip, can be a viable solution. The decision of whether to take a detour or not should at least be grounded in the comparison of the travel time for both original and detour route.

Many factors influence the commuter's route choice. Travel time is the most important factor in terms of travel costs (Shiftan, Bekhor, & Albert, 2011). Travel time is primarily affected by traffic congestion resultant from crashes, high travel demand (such as peak hours), lane closures, adverse weather, and other incidents (Hoseinzadeh, Gu, Han, Brakewood, & Freeze, 2021; Lin, Zito, & Taylor, 2005; Yang & Qian, 2019; Zhang & Chen, 2019). Due to the uncertainty and volatility of travel time, transportation agencies usually quantify the reliability of travel time for traffic operation and planning. For instance, the Congestion Mitigation and Air Quality Improvement (CMAQ) program carried out by Federal Highway Administration (FHWA) requires the state department of transportation to report annual peak hour excessive delay per capita (PHED) and level of travel time reliability (LOTTR) on National highway system (NHS) (FHWA, 2018). Along with many other evaluation metrics like the buffer time index (BTI) and planning time index (PTI), the essence of travel time reliability is to measure the consistency or dependability of travel times from day to day or across different times of the day (FHWA, 2017). The abnormal travel time, for instance, measured by the 80^{th} travel time in LOTTR, is usually compared to normal conditions represented by the 50^{th} travel time. However, these metrics are composed by a large amount of historical travel time observations under different traffic conditions. Travel time reliability in the event of a crash is barely available, making it inadequate for use in real-time routing.

To investigate different detour scenarios and their associated factors, this study chooses the I-24 smart corridor as an example. Since 2018, Tennessee Department of Transportation (hereinafter TDOT) has been deploying a smart corridor along I-24 (see blue route in Figure 1) to improve the travel time reliability, mobility, and travel safety between Davidson and Rutherford counties (Tennessee Department of Transportation, 2018). To coordinate with the smart corridor, State Route 1 (hereinafter SR-1) highlighted in red in Figure 1, upgraded signal infrastructure systems contemporaneously. These two parallel routes, along with many connector routes between them, offer multiple route choices for long(short)-distance commuters. The I-24 smart corridor and SR-1each span approximately 30 miles in length. This study aims to investigate whether using a stretch of SR-1 as a detour is a good choice when encountering a downstream crash on the I-24 smart corridor. It should also be noted that the criteria of the detour in this study focus only on travel time irrespective of the extra fuel consumption, emission, and discomfort driving experience resultant from the detour route. The main initiatives of this study are to gain a better understanding of how to effectively manage variable message signs and to assist commuters in making more informed decisions about their routes during crashes downstream.

DATA

To help answer the research question, this study makes use of crash data from E-TRIMS and travel time data from Waze. E-TRIMS, namely, Enhanced Tennessee Roadway Information Management System, is the main portal for transportation-related data managed by TDOT (Scopatz et al., 2014). This study mainly gathered the crash location (e.g., route, latitude, and longitude), timestamps, and crash characteristics (e.g., injuries and lane closure) from the E-TRIMS. With the partnership between TDOT and Waze company, we can add specific route segments to the watchlist (Gu, Zhang, Brakewood, & Han, 2022). Waze provides speed and travel time data collected from Waze application users' location (Liu et al., 2023). We can obtain the data through the special API (Application Programming Interface) provided by Waze (Waze, 2016). Since travelers can only make turning movements at highway interchanges or arterial intersections, this study intentionally split the I-24 and SR-1 at those knots. This results in a total of 66 directional links. Finally, this study employed the six months of Waze and Crash data collected from May 1 to November 31 in 2022 for research analysis.

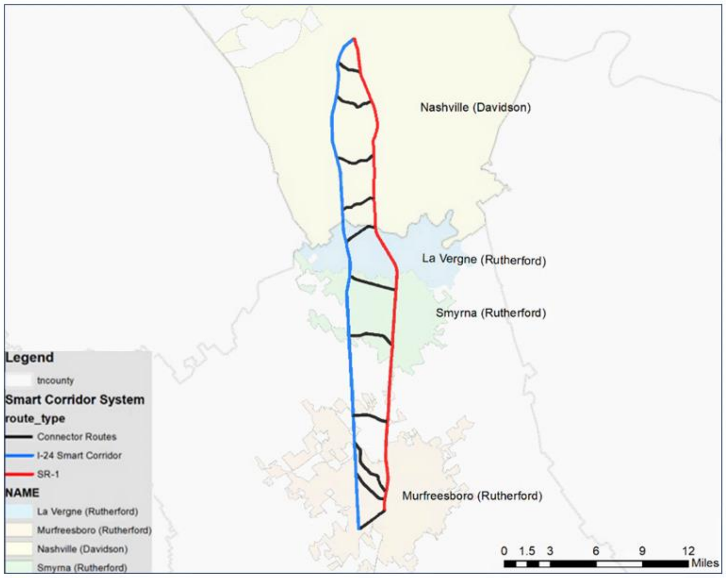

Figure 1. I-24 smart corridor

Crash Frequency

Figure 2 shows the density of crash frequencies per mile on the I-24 smart corridor, with redder color indicating more crashes. By comparison, the stretch of I-24 in Davidson County, especially the highway section between Briley Pkwy and Bell Rd has more crashes than highway sections in Rutherford County. One possible explanation could be that Nashville city experiences more traffic than rural areas in Rutherford County.

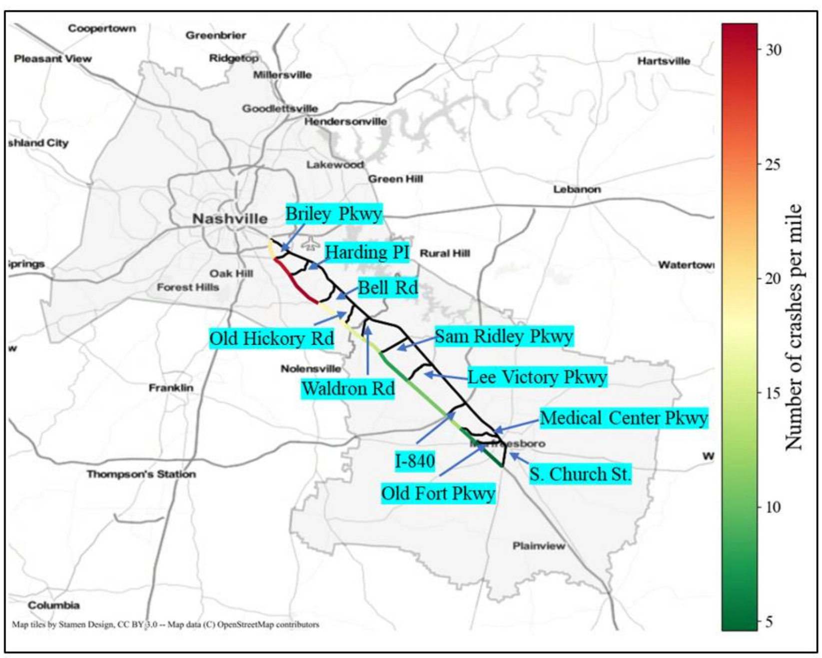

Figure 2. Crash frequency of I-24 smart corridor.

Travel Time Comparison

Figure 3 illustrates the travel time of the I-24 smart corridor and SR-1 between Nashville and Murfreesboro, based on six months of data from Waze. The solid green line and red line represent the average travel time of outbound traffic of I-24 and SR-1, respectively. The corresponding inbound traffic is highlighted by a dashed green line and a dashed red line. Every single dot on the background represents the observed travel time every five minutes. As Figure 3 shows, both routes have only a single traffic peak. The peak of inbound traffic (i.e., entering Nashville) appears in the morning while the outbound traffic peak appears in the afternoon. This is because many residents of Rutherford County commute to Nashville for work in the morning. When they come back from Nashville, they exacerbate the afternoon traffic toward Murfreesboro. Not surprisingly, traveling on I-24 smart corridor generally is much faster than on SR-1. I-24 runs uninterrupted flow while SR-1 is the primary route interrupted by multiple signal intersections. The impact of inbound rush hour on travel time seems to be a bit smaller than the outbound rush. When comparing the rush hour travel time, it can be found that the travel time of the smart corridor is about 20 minutes faster than SR-1 in the morning rush hour, while this difference is even more evident during the afternoon rush hour. While comparing the individual travel time (signified by dots) with average travel time, it is observable that a quite fraction of travel times of the I-24 smart corridor is larger than the average travel time of SR-1, indicating that using SR-1 sometimes can reach the destination faster than I-24 smart corridor. It is also worth noting that travel time on I-24 smart corridor tends to fluctuate significantly after 9 PM and taking SR-1 has been shown to save travel time many times. This is because the study period was within Phase 2 of the I-24 smart corridor project. Many constructions work such as installing overhead gantry and dynamic message signs were conducted at night to mitigate the impact of the road closure on traffic (Tennessee Department of Transportation, 2022). Nonetheless, the average travel time diagram suggests that commuters should use I-24 smart corridor as much as possible except for incidents.

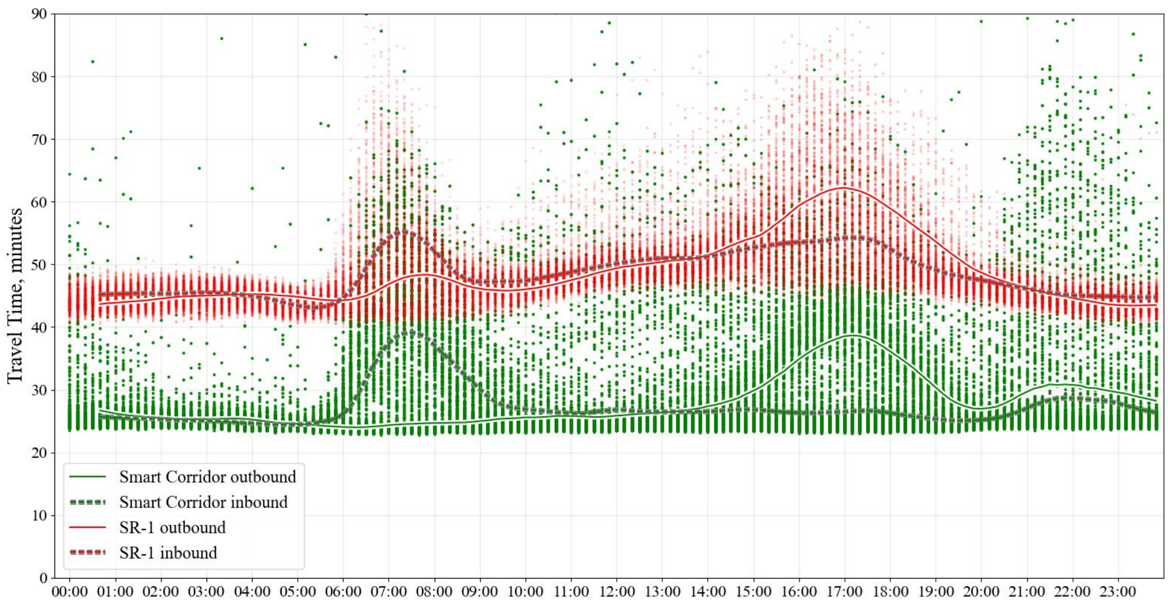

Figure 3. Travel time of I-24 smart corridor and SR-1

METHODOLOGY

Dynamic Travel Time Estimation

When calculating travel time for a route with multiple links, it is important to consider varying traffic conditions on different links, as commuters cannot traverse the entire route instantaneously. Figure 4 illustrates the difference in how instantaneous and dynamic travel time are calculated. Route instantaneous travel time is calculated as the sum of the instantaneous travel time on each link. On the other hand, route dynamic travel time considers variations in speed caused by varying traffic conditions, updating the travel speed based on the distance traveled every minute. In this example, the instantaneous travel time for the detour route departing at 6:15 is 14.32 minutes, while the corresponding dynamic travel time is 12.47 minutes, which is faster and more realistic.

	Detour Route	SR-171	SR-1	SR-254
	Length (mi)	2.24	2.65	2.47
Departure time	6:15	33	32	28
	6:16	35	30	28
	6:17	35	30	27
	6:18	33	30	27
	6:19	34	29	27
	6:20	33	29	27
	6:21	33	29	26
	6:22	32	30	26
	6:23	36	32	25
	6:24	37	33	27
	6:25	36	31	29
	6:26	35	30	26
	6:27	34	30	26
	6:28	34	31	30
	6:29	33	29	30

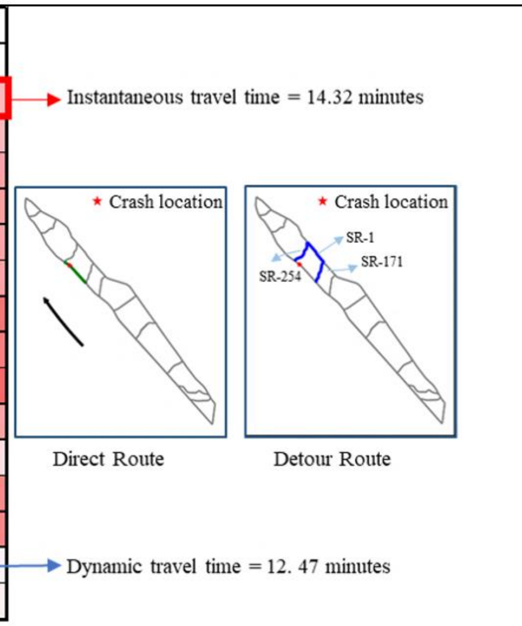

Figure 4. Graphical visualization of dynamic travel time estimation

Detour Identification

As shown in Figure 4, there are multiple options for routing to destination when a crash happens on downstream link. However, as indicated in Figure 3, it is recommended to use I-24 as much as possible because it is generally faster than SR-1 in the I-24 smart corridor. Therefore, this study only examines a specific detour plan, which involves exiting the smart corridor, traveling on a section of SR-1, and then re-entering the smart corridor for the remainder of the journey. Commuters are only advised to steer clear of the link where the crash occurred.

After nailing down the detour plan, the next step is to evaluate the criteria for making detour decision, in other words, determining when a detour should be taken. By examining the direct travel time and detour travel time, four patterns can be identified. As shown in Figure 5, the first case is that detour is substantially faster than staying on I-24 smart corridor thereby detour is strongly suggested. The second case suggests that the benefits of taking a detour only become apparent after a certain period following the incident. The late benefit could be attributed to the long distance between crash locations and upstream interchange where commuters make a detour. The third case shows that detour travel time is close to using I-24 smart corridor and the benefit of taking a detour is intermittent. The fourth case indicates that the effect of a crash on I-24 travel speed is slight, and taking a detour is not necessary at all.

To measure the benefits of taking a detour, the detour efficiency is calculated by determining the percentage of travel time saved compared to remaining on the direct route (i.e., I-24 smart corridor), which can be written as Equation (1):

$$DE_t = 1 - \frac{T_{sr,t}}{T_{sm,t}} \tag{1}$$

where DE_t is detour efficiency at departure time t. $T_{sr,t}$ refers to the travel time of using SR-1 at time t. Likewise, $T_{sm,t}$ represents the travel time of using I-24 smart corridor at time t.

Further, we categorized the above four cases into three groups based on value of DE. We considers 5% as a threshold to empathize the evident advantage of detour. This is because taking a detour may involve additional time spent waiting at traffic signals, which cannot be accurately captured by average travel speed. As shown in Table 1, detour is strongly suggested only when DE is greater than 5%. If DE is less than 5% while larger than 0%, detour's benefit is subtle, and detour is alternative. If DE is less than 0, detour is not suggested at all.

Table 1. Detour scenarios determined by detour efficiency.

	Criterion	Comments	Possible Cases
Scenario 1	DE>5%	Detour is strongly suggested	Case 1
Scenario 2	0%<DE<5%	Detour is alternative	Case 2 and 3
Scenario 3	DE<0%	Detour is not suggested	Case 2, 3, and 4

In the real world, traffic arriving at interchanges is random, and the detour choices made by commuters are also random. Therefore, this study determines the percentage of times when taking a detour is a good choice in the hour following the crash occurrence. Mathematically, it can be formulated as:

$$DR_i = \frac{minutes\ of\ existence\ of\ Scenrio\ i}{60\ minutes\ following\ crash\ occurence} \times 100\% \tag{2}$$

For example, during the 60 minutes following the crash occurrence, taking a detour is strongly recommended for 15 minutes, is an alternative for 10 minutes, and not suggested for the remaining 35 minutes. The corresponding detour scenarios are: 0.25, 0.17 and 0.58, respectively. In other words, it is more likely to be suggested to stay on I-24 smart corridor when a crash happens downstream as this scenario has highest percentage (i.e., probability).

K-means Clustering

By conducting the calculations outlined above, we can determine a set of combinations for detour rates for all crashes. A general rule of thumb is to use 50% as the threshold for deciding whether to take a detour. For example, if sum of detour scenarios (i.e., scenario 1 and 2) is over 50%, then a detour would be recommended. However, the detour rates calculated for each crash are specific to the crash context. A higher detour probability (>50%) may not always mean a better choice. Instead of using a fixed 50% threshold, we attempt to use a more data-driven approach to split detour and not detour cases, using unsupervised K-means clustering. The Pseudocode can be found in Table 2. The number of clusters is two, that is, either detour or not detour.

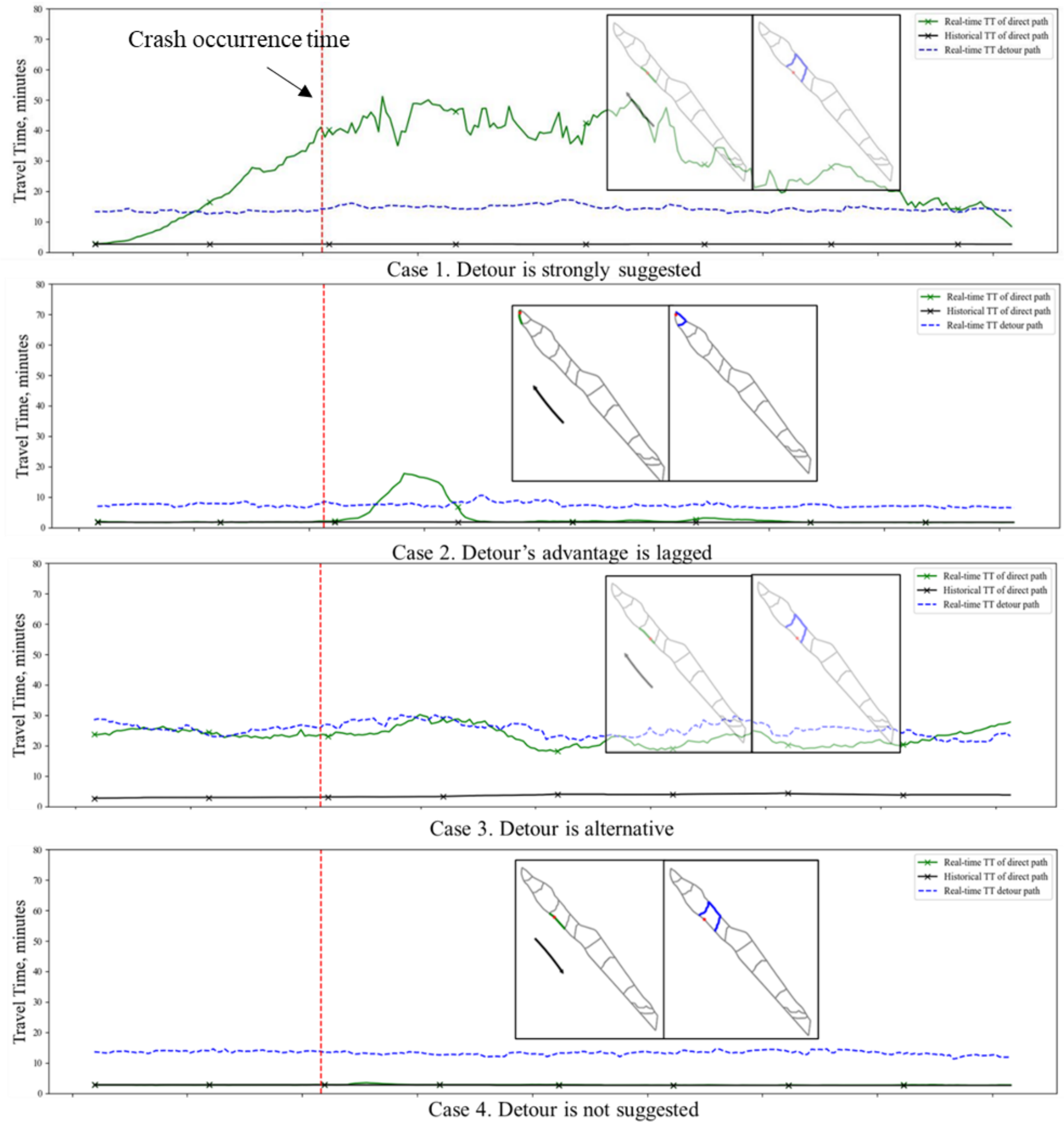

Figure 5. Travel time patterns

Table 2. K-means Pseudocode for clustering detour scenarios

Algorithm: K-means pseudocode		
Steps	**Procedure**	**Comments**
1	Randomly partition the data into two groups and compute the average value (i.e., centroid) of attributes of each group.	Number of groups is determined by domain knowledge in this study
2	Reassign the point in each group to the nearest centroid.	Each point consists of detour rate of (>5%, 0%~5%)
3	Recalculate the centroid of each group.	
4	Repeat Step 2 and 3 until group centroids does not change.	New centroids stay stable.

Logit Regression

Further, we applied a logit regression model to understand how different factors contribute to the decision to take a detour. The logit regression formulates the logarithm of odds ratio with respect to its associated factors, such as weather and lane closure. A logit regression can be written by Equation (3):

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_i x_i \quad (3)$$

In this study, p_i denotes the probability that suggested detour due to the crash. β_0 is a regression constant, and β_i is the regression coefficient for factor x_i.

RESULTS

Descriptive Statistics

Table 3 displays the descriptive statistics of variables used in logit regression. The number of observations is 460. The detour choice is the outcome variable, specifically whether to take a detour. The cases in which a detour is suggested make up only one ninth of the total cases. Additionally, the detour ratio in distance is calculated to determine the level of additional distance associated with taking a detour. As we can see in Table 3, the minimum detour route is 1.51 times of direct I-24 link. By contrast, in the worst situation, commuters must travel 5.97 times of direct I-24 link to avoid the crash impact. Number of injuries data is collected from E-TRIMS to indicate the severity of crash. On average, there are 0.79 persons who got injured due to crashes. Besides, some built-environment variables such as crash frequency during (non)peak hours, (out)inside of HELP patrol area, crash on roadway are summarized in Table 3, respectively. HELP patrol area is the place where there are many floating road rangers. They can respond to freeway incidents quickly and minimize traffic congestion (Zhang, Gu, Huang, & Han, 2022). It's noteworthy that there were more crashes during peak hours than during non-peak hours. More crashes were seen in the area patrolled by HELP rangers and on roadways, compared to areas without HELP patrols and off-road areas.

Table 3. Descriptive statistics of variables

Continuous variable	Min	Mean	Max	Std.
Detour ratio in distance	1.51	2.66	5.97	0.98
Number of Injuries	0	0.79	8	1.04
Discrete variable	Frequency (GonzÃ¡lez-Gurrola, MartÃ-nez-Reyes, & Carlos-Loya)			Frequency (No)
Detour choice (outcome)	51			409
Crash occurs in peak hours	324			136
Crash occurs in HELP patrol area	279			181
Crash on roadway	371			89

1. The total number of observations is 460.
2. Detour ratio is the ratio of detour distance to direct distance.
3. Peak hours refer to 6-10 and 15-19 on weekdays, rest are non-peak hours.

Detour Identification

Table 4 shows the results of K-means clustering. Cluster 1 has an average detour probability of 0.0133 for scenario 1 and 0.0029 for scenario 2. In contrast, cluster 2 has significantly higher detour probabilities for both scenario 1 (i.e., 0.6303) and 2 (i.e., 0.0228), indicating a greater tendency to take a detour.

Table 4. K-means clustering results.

Cluster	**Centroids of cluster**	**Explanation**
Cluster 1	(Detour probability = 0.0133, alternative detour probability = 0.0029)	Detour is **NOT** suggested in next one hour.
Cluster 2	(Detour probability = 0.6303, alternative detour probability = 0.0228)	Detour is **suggested** in next one hour.

Analysis of contributing factors

As shown in Table 3, the number of detour cases is unbalanced. Directly using unbalanced data for logit regression might generate misleading results (Fernandez-Felix, GarcÃ-a-Esquinas, Muriel, Royuela, & Zamora, 2021). Hence, logit regression is performed in a manner of bootstrapping to overcome potential bias caused by data unbalance. The program conducts 1000 logit regression. The data used for each logit regression is obtained through stratified sampling, with one ninth of the data coming from cases in which a detour is suggested and the remaining eight ninths coming from cases in which a detour is not suggested. The estimated coefficients are fitted by normal distribution, as Figure 6 shows. This is because the coefficient asymptotically approaches normal distribution when the number of regression times is large (Rosenblatt, 1956).

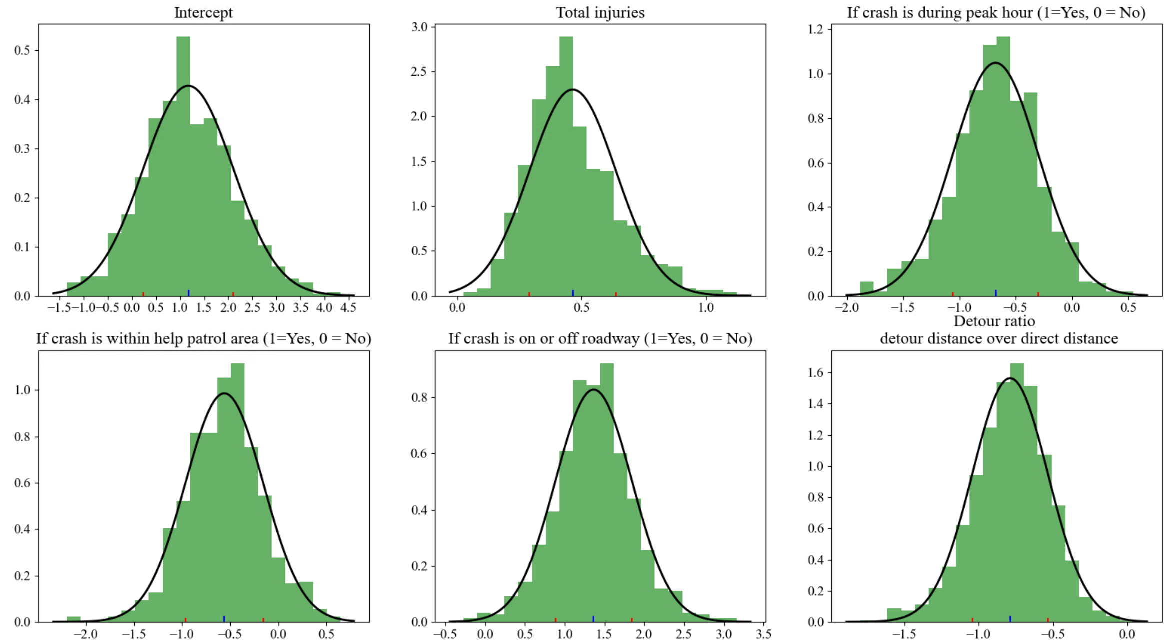

Figure 6. Coefficients of Logit regression under bootstrap framework

Table 5 shows the estimated parameters at 95% confidence level (i.e., lower bound and upper bound), estimated average value, and corresponding marginal effect. It can be found that the higher number of injuries found in the crash, the more likelihood of making a detour. On average, a one-unit increase in injuries leads to a 59.1% increase in the likelihood of taking a detour. When a crash occurs in peak hours, the results suggest that staying on I-24 smart corridor seems to be a better choice. It can be observed that the likelihood of a detour in this case is 49.3% less compared to not taking a detour. Likewise, if a crash occurs in HELP patrol area, or alternatively, in Nashville area, detour is highly not suggested because detour is 42.9% less likely compared with not taking a detour. If a crash occurs on the roadway which might block travel lanes, it is strongly recommended to take a detour to SR-1, as the likelihood of doing so is 2.91 times higher than not taking a detour. Lastly, detour ratio in distance, not surprisingly, has a negative impact on making a detour. The larger the detour ratio in distance, the less likely it is to make a detour.

Table 5. Coefficient Estimation

Parameters	Lower bound	Average	Upper bound	Average Marginal Effect
Intercept	1.1705	1.1722	1.1739	222.9%
Number of Injuries	0.4640	0.4643	0.4547	59.1%
Crash occurs in peak hours	-0.6801	-0.6794	-0.6787	-49.3%
Crash occurs in HELP patrol area	-0.5609	-0.5601	-0.5594	-42.9%
Crash on roadway	1.3640	1.3649	1.3658	291.5%
Detour ratio in distance	-0.7895	-0.7891	-0.7886	-54.6%

*Note the marginal effect shows the probability of detour compared to not detour. The negative sign suggests staying on smart corridor whereas positive sign indicates detour is a good choice.

CONCLUSION

Commuters' travel time can be delayed by unexpected vehicle crashes. Under such circumstances, making a detour may be a good option to prevent or reduce the impact of crashes. This study examines the circumstances in which detour decision should be made. The case study shown in this study is I-24 smart corridor and its parallel route SR-1. The detour is made to only circumvent the link where the crash happened. We extracted 460 crashes that occurred on I-24 smart corridor between May and November 2022. The travel time of direct route and detour route are calculated based on Waze speed data. Based on patterns of travel time, we identified three scenarios for making a detour: strongly suggested, alternative, and not suggested. Further, we estimated the probability of detours for three scenarios by monitoring the situation for one hour after the incident occurred. As the decision made near the upstream interchange would only either be making a detour or staying on I-24 smart corridor, three scenarios are categorized into two groups by unsupervised K-means clustering. The first group, which had an average detour rate of 0.0133 for scenario 1, was designated as the group with no detours. In contrast, the second group had a detour rate of 0.6303 for scenario 1, indicating that detours were recommended. A bootstrap logit regression was conducted to determine the impact of various factors on the decision to take a detour, using the results of the clustering analysis as a basis. Several important findings are summarized as follows.

1. On average, a one-unit increase in injuries leads to a 59.1% increase in the likelihood of taking a detour.
2. When a crash occurs in peak hours, the results suggest that staying on I-24 smart corridor seems to be a better choice.
3. If a crash occurs in HELP patrol area, or alternatively, in Nashville area, detour is highly not suggested because detour is 42.9% less likely compared with not taking a detour.
4. If a crash occurs on the roadway which might cause travel lane blockages, it is strongly recommended to take a detour to SR-1.

However, there are some limitations of this study. Firstly, the proposed study does not consider the potential traffic congestion of SR-1 caused by detour traffic pouring from I-24. However, not all commuters are willing to make a detour, as they may encounter increased fuel consumption and stop-and-go traffic conditions on SR-1. Secondly, the detour plan examined in this study only circumvents the crash link, which is shortsighted to some extent if the destination is far from the crash location. This claim is still doubtful and needs further research using Waze data. Lastly, the detour plan focuses only on the shortest travel time regardless of the additional cost incurred from taking the detour.

Nonetheless, this study has some real-world applications. Firstly, this study provides insights into incident management, specifically in terms of how to effectively use public broadcasts such as dynamic message signs and portable message signs to convey information about crashes or detour suggestions to road users. For instance, should traffic operation center use some "startling" message such as "number of injuries" and "multivehicle crash on roadways". From the perspective of system benefits, diverting partial traffic of main road to other roads is necessary in some cases to decrease the main road congestion caused and prevent secondary crashes. Secondly, this study gives commuters suggestions about the circumstances in which detour is a good choice. Although some existing navigation apps like Google and Waze can estimate and update the delay dynamically, the end of incident clearance is largely unknown to road users. The road users should also weigh their commute experience based on the crash characteristics that can be obtained through the public broadcasts.

ACKNOWLEDGEMENTS

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Developing a Vehicle Dynamic Model for Analyzing the Impact of Roadway and Vehicle Characteristics on Speed Profiles

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ABSTRACT

This study delves into the dynamic model of heavy vehicle motion on steep road gradients, employing a semi-empirical method to unravel the intricate interplay of various factors on vehicle performance. Guided by the principles of Newton's second law, the model takes into account forces acting along the longitudinal, lateral, and vertical axes, incorporating critical elements such as road geometry, surface friction, and vehicle characteristics. The propulsive force, rolling resistance, aerodynamic drag, and grade resistance are examined as pivotal forces. The developed MATLAB program serves as a tool to assess the impact of key variables, including weight-to-power ratio, engine power, road conditions, truck type, and tire type, on heavy vehicle performance. Weight-to-power ratio emerges as a primary influencer, while road conditions and tire type exhibit minimal effects. This study provides valuable insights into the analysis of heavy vehicle behavior on steep upgrade sections of highways, contributing to a broader understanding of truck performance dynamics.

Keywords: Vehicle dynamic model, truck performance, speed curve, road upgrades.

INTRODUCTION

The speed profile of vehicles is used in simulation programs, road evaluation packages, and roadway design assessments (Traffic engineering handbook). Regarding heavy vehicles, especially trucks, this profile is utilized to determine the critical slope length and the location for constructing climbing lanes. There are various methods for extracting the speed profile of vehicles, ranging from simpler ones where the speed is read from the graph along the path to complex computer algorithms in simulation programs. The main challenge of current methods is that they extract the speed profile for individual or composite vehicles based on the weight-to-power ratio, while the average and distribution of the weight-to-power ratio depend on the type of vehicles and the type of transported loads, which vary for different routes

In mountainous terrains and regions marked by steep slopes, the management of truck and heavy vehicle traffic presents a unique set of challenges. Understanding the performance of heavy vehicles on steep upgrades is so important from the perspective of highway performance and safety. Climbing lanes emerge as a crucial tool for optimizing road capacity, enhancing safety, and ensuring efficient traffic performance in such areas. The effectiveness of these ramps, however, is often hindered by economic considerations, limiting their construction unless a critical need arises (AASHTO). In contemporary times, the surge in truck traffic, coupled with the utilization of heavier, more modern, and powerful trucks, has underscored the significance of designing and constructing climbing lanes. These ramps have evolved into essential components for bolstering the quality of road services, addressing the growing demands of the transportation landscape. Concerns over road safety further underscore the importance of efficient speed control mechanisms. Statistically, undesirable and abrupt speed reductions, particularly those exceeding 10 miles per hour, have been shown to significantly correlate with increased accident rates on roads (Highway Safety Manual).

To extract the critical slope length, the AASHTO standard has provided speed profile tables for trucks using a specific weight-to-power ratio. The fundamental problem with these speed profiles is that they are extracted only for a specific weight-to-power ratio and are not applicable for other ratios. Additionally, the initial speed presented in these profiles is limited to 55 miles per hour, whereas modern trucks, especially on highways and freeways, often operate at higher speeds. Furthermore, for locations with heavier trucks, AASHTO has suggested that a more representative speed profile should be extracted based on the weight-to-power ratio, but no computational method has been provided for this purpose. Moreover, AASHTO's curves do not consider the impact of different pavement types and various path conditions. One of the main drawbacks of AASHTO's speed profile is the speed discrepancy at equilibrium depending on the acceleration or deceleration state on slopes of 1 to 3 percent, contradicting the fundamental principles of vehicle dynamics.

Therefore, there is a crucial need to find a specific formulation for extracting truck speed profiles based on nominal dynamics, kinematics, and operational characteristics of trucks on slopes. Additionally, for a quick estimation of critical slope length, it is preferable to provide a simplified and approximate formula and model as an alternative solution to complex calculations, ensuring reasonable and acceptable accuracy.

In this study, our primary goal was to conduct a comprehensive review of existing research studies within the domain of vehicle performance evaluation on upgrade sections of roads. Through this review, we aimed to discern and systematically document the key factors that exert influence on road design, particularly on steep slopes. Additionally, our objectives encompass a detailed examination of mathematical and semi-empirical models associated with estimating vehicle speed on upgrade sections. By scrutinizing these models, our aim was to pinpoint the most effective method for extracting precise vehicle speed profiles. Building on this foundation, we sought to propose a methodical and robust approach for estimating vehicle speed, considering specific characteristics, and extend an algorithm that facilitates the calculation of speed profiles across roads with varying slopes. Furthermore, our research endeavored to contribute to practical road design by developing a computerized computational program. This program, coded in MATLAB, was designed to extract vehicle speed profiles, incorporating diverse vehicle characteristics and accommodating the specifications of the desired road layout. Ultimately, our study aspired to provide valuable insights and practical tools for the optimal design of upgrade sections, particularly in mountainous regions.

LITERATURE REVIEW

One notable contribution to the field of vehicle dynamic models, comes from Walton et al. (1975), who undertook the task of developing speed profiles for various models of trucks and recreational vehicles in the United States. Their primary objective was to refine highway design guidelines, with a specific focus on the creation of climbing lanes that take into account both highway capacity and safety considerations. To achieve this goal, Walton et al. collected field data on selected roads in the state of Texas. The outcome of their research was the establishment of distance-speed curves, providing valuable insights for designing climbing lanes that align with the capacity of the highway and enhance overall safety.

In another study, Stanley (1978) devised a computer program aimed at identifying the optimal locations for runaway truck ramps along specific highway downgrades. Additionally, the program determined the suitable length and slope for each ramp. This innovative approach involved predicting the truck's speed by leveraging the vehicle's kinematic energy theory. Subsequently, utilizing a vehicle dynamic model, the program calculated the necessary slope and length of the runaway truck ramp.

In a study conducted by Gillepse (1985), the focus was on predicting truck speed loss on grades. Gillepse strategically chose 20 sites in Michigan for comprehensive data collection, employing empirical methods to measure truck speeds at these selected locations. Following this fieldwork, Gillepse developed a computer program designed to extract speed-distance curves for various vehicles. Utilizing this model and program, Gillepse generated performance curves for the four primary classes of trucks in the United States, across different highway grade sections. This meticulous analysis provided valuable insights into the speed dynamics of trucks on varying grades.

Archilla and Fernandez (1996) highlighted significant changes in truck characteristics in Argentina in recent years, suggesting that previously developed models may no longer be suitable for the evolving truck fleet. Notably, the weight-to-power ratio of Argentine trucks differs from those in North America, rendering guidelines based on the latter inappropriate. Recognizing this, the researchers emphasized the necessity of developing new models to predict truck performance on steep uphill sections of highways. To address this need, Archilla and Fernandez formulated a speed prediction model grounded in simple force balance equations, which were carefully fitted to field data. Their models extended beyond speed prediction, encompassing the capability to foresee acceleration and deceleration performance curves. To validate the reliability of their model, the researchers compared predicted and observed speed profiles of a specific truck, with a known weight-to-power ratio, along selected uphill sections. This rigorous validation process ensured the accuracy and applicability of their developed models.

In another study, Abdelwahab et al. (1997) aimed to establish a systematic approach for determining the necessity and optimal locations of truck escape ramps, along with defining the essential characteristics of these ramps in the Canadian context. Their model incorporated a comprehensive set of variables, including the type of vehicle, gross weight of the truck, brake type, as well as the features of horizontal and vertical curves on the highway. Additionally, considerations such as the availability of a brake-check area at the top of the grade, information about driver actions at the brake-check area, brake checking, gear selection, crash history data, and the presence of obstacles in the path of a runaway vehicle were taken into account. To implement their approach, Abdelwahab et al. drew upon findings from previous research on vehicle performance models. This allowed them to generate necessary data, encompassing aspects such as the descent speed of the truck, cornering stability, and brake temperature.

Bester (2000) critiqued the prevailing methods for determining vehicle speed profiles, deeming them unsuitable for certain applications. In response to this limitation, he introduced a straightforward computational method for extracting speed profiles. This approach operated under the assumption of a linear relationship between acceleration and vehicle speed. Bester specifically tailored his method for application to combination tractors. The key involved measuring their speed distribution at three or four specific points along the trajectory of their movement.

Donnell et al. (2001) initiated a research project in the United States aimed at enhancing predictive models for truck speeds on two-lane rural highways. Analyzing 13 specific sites and employing simulation tools for vehicle performance analysis, they expanded regression models to predict truck speeds on both uphill and downhill slopes. Additionally, their investigation delved into the impacts of road length, gradient, and horizontal curve radius.

Rakha et al. (2001) broadened the dynamic vehicle model, incorporating factors such as tractive force, aerodynamic characteristics, rolling resistance, and slope to predict the maximum acceleration of vehicles. Their comprehensive approach considered a range of variables, encompassing vehicle specifications, road and pavement conditions, as well as tire characteristics. Maoromatis et al. (2003) formulated an analytical dynamic model to investigate the influence of highway horizontal profiles on the performance of heavy vehicles, particularly on steep upgrade sections. Their analysis revealed that sharp horizontal curves have a notable impact on the performance of heavy vehicles, particularly when encountered on gentle slopes.

Lan and Mendez (2003) also addressed the issue that the AASHTO regulations only provided speed profile designs for a specific type of truck and did not offer a specific calculation method for heavier and larger vehicles. They proposed a method and formulation to obtain speed profiles for various types of trucks based on their functional characteristics and dynamic and kinematic equilibrium on slopes. In addition to the weight-to-power ratio, they also considered engine power in constructing speed profiles and presented an approximate calculation method with acceptable accuracy for manual calculations.

Yu (2005) conducted a comprehensive study in Virginia, USA, with the objective of modeling the intricate dynamics of heavy vehicles navigating steep road sections. His analysis incorporated a myriad of factors, including engine power, weight-to-power ratio, road type and conditions, aerodynamic characteristics, engine efficiency, tire type, and axle load percentage. To simulate the performance of trucks on slopes, Yu employed sophisticated TruckSIM simulation software, which facilitated the development of dynamic models featuring variable power. This simulation-based approach not only provided insights into the intricate interplay of these multifaceted factors but also proved invaluable for practical applications. Yu's dynamic models contributed significantly to the design of climbing lanes, offering a nuanced understanding of how various parameters influence truck performance on steep gradients. Furthermore, these models played a pivotal role in calculating the equivalent vehicle factor, a crucial component in traffic calculations. In a different study, Arkatkar and Arasan (2010) examined how steep grades and their lengths affect vehicle performance in varied traffic conditions. They found that the equivalent vehicle factors for different types of trucks changed significantly based on factors such as traffic volume, as well as the length and steepness of the slope.

METHODOLOGY

Model Development

The dynamic model of vehicle motion associates forces acting along the longitudinal, lateral, and vertical axes of the vehicle with factors such as road geometry, road surface friction, and technical characteristics of the vehicle such as speed, weight, center of gravity, slope, lateral slope rate, tire adherence, and other relevant influencing factors. Most common dynamic models typically determine the speed difference of vehicles on inclines based on a function of initial speed, slope magnitude, and the weight-to-power ratio of the vehicle. Researchers have significantly broadened models of truck performance to gain a deeper understanding of how trucks behave on steep road sections. A multitude of methods has been devised to explore vehicle performance, encompassing simulation techniques (Gilpsee, 1985), effective weight-to-power ratio methods, semi-empirical approaches (Mannering et al., 1998; Fitch, 1994; Archilla et al., 1996), inverse acceleration methods, and weight-to-engine-power methods. These diverse methodologies contribute to a comprehensive analysis of truck behavior, allowing researchers to capture nuances in performance and make informed assessments related to steep road conditions. Through the evolution and application of these models, the transportation industry has gained valuable insights into optimizing vehicle behavior on challenging road gradients.

Computer simulation models have the capability to investigate the performance of trucks with detailed accuracy. The development of these models requires an understanding of vehicle dynamics, road dynamics, and their interaction. Typically, two models are developed in this approach, one for the road and one for the vehicle. Due to the complex nature of these models, their value is more scientific than practical. For transportation science, we often simplify these models. Multiple performance models have been developed by researchers using the semi-empirical method. In these types of vehicle performance models, the forces affecting the vehicle are typically divided into tractive or engine force, aerodynamic resistance forces, rolling resistance forces, and grade resistance forces. In this study, we also focused on utilizing semi-empirical method to develop our vehicle dynamic model.

The principles of vehicle performance are based on fundamental physics, especially Newton's Second Law of Motion. This law states that the acceleration of an object is directly proportional to the net force acting on it. In the case of a moving vehicle, multiple forces come into play, influencing its motion. The propulsive component of the vehicle receives the necessary force to move forward, and this force helps overcome resistance forces caused by gravity, air, and tire movement on the ground. The acceleration of the vehicle depends on various factors, including: The force received by the propulsive component of the vehicle; Road and pavement conditions (material and surface quality); The structure, covering, and aerodynamics of the vehicle; The total weight of different components of the vehicle and parts connected to it. The motion of the vehicle can be fully understood and studied by analyzing the forces acting on it in the direction of motion.

The propulsive force (F_t) at the tire-road contact surface of a vehicle moves it forward. This propulsive force is provided by a power source or engine and is transmitted to the moving wheels through the power transmission system. The magnitude of this force, which propels the vehicle, is a function of the vehicle's speed and the engine power. There are two main factors contributing to the reduction of this propulsive force. The first factor involves engine accessories such as the fan, water pump, fuel pump, and compressor, which absorb a portion of this force and create friction due to processes such as air passage through the fan against the vehicle's motion. The second factor is power losses in the power transmission system, leading to the wastage of another portion of the force supplied by the engine. Rakha et al. (2001) presented the following relationships for calculating the truck's propulsive force, which we have also used in our model.

$$F_{max} = 9.8066 * M_{ta} * \mu$$

$$F_t = 3600*\beta*\eta*(P/V)$$

$$\beta=1 \text{ if } V>V_0;\ \beta=(1/V_0)(V+1-(V/V_0)) \text{ , if } V<V_0$$

$$V_0=1164w^{-0.7499}$$

$$F = \min(F_t , F_{max})$$

The maximum force, denoted as F_{max}, is equal to the maximum traction capability in generating rolling resistance and is a function of the weight on the driving axle of the vehicle and the coefficient of surface friction. The coefficient of surface friction depends on the material of the road surface and its condition. In these equations, M_{ta} is equal to the weight on the driving axle of the vehicle. The percentage of weight on the driving axle for common passenger vehicles is typically 60 percent (Fitch, 1994). In the equation, the coefficient β is introduced to account for the effect of gear ratio at low speeds. Although this coefficient does not explicitly and directly represent the impact of the gear ratio, it encapsulates the main and fundamental behavioral characteristics arising from power reduction associated with gear changes, and its validity has been established (Rakha et al., 2001). V_0, which is the optimal speed in these equations, is the speed at which the vehicle achieves maximum power from the engine. Additionally, w in these equations represents the ratio of weight to power of the vehicle.

There are resistance forces that attempt to create resistance against the motion of the vehicle. These forces include rolling resistance, aerodynamic drag, and grade resistance. In the following paragraphs, we briefly examined each of these forces.

Rolling resistance of tires on the road surface is due to the hysteresis or energy losses created in the tire materials. When the tire rolls, the front half of the contact area becomes loaded, and the rear half becomes unloaded, creating higher pressure in the front half compared to the rear half. This phenomenon causes a change in the direction of the ground reaction force towards the front. This forward movement against the ground reaction force creates a resisting force against tire rolling. In conditions such as sandy or heavy snowy paths where the surface is soft in contact with the tire, the deformation of the ground causes significant rolling resistance. The equation commonly used to calculate rolling resistance force is the one presented by Fitch (1994):

$$R_r=9.8066*C_r*(C_2V+C_3)(M/1000)$$

The coefficient of rolling resistance (Cr) is a function of various factors, including tire material, tire structure, tire temperature, tire inflation pressure, road geometry, surface material hardness, road surface material, and the presence of liquid on the road surface. Coefficients C_2 and C_3 are also introduced to account for the influence of the tire type on rolling resistance in the provided equation.

A moving vehicle experiences a force opposing its motion, known as drag or aerodynamic drag resistance. The formation of this force is primarily due to the shape of the vehicle and the effect of the material covering the vehicle. The forward motion of the vehicle pushes the air in front of it, creating increased air pressure in front, where the air cannot simultaneously escape from the vehicle's path. This results in a high-pressure air zone in front of the vehicle. Simultaneously, the air behind the vehicle cannot fill the space left by the forward motion of the vehicle, creating a low-pressure zone that extends behind the vehicle. Consequently, the forward movement of the vehicle creates two pressure zones. The high-pressure area in front of the vehicle resists the vehicle's motion by pressing against it, while the low-pressure area in the rear, expanding as the vehicle moves backward, resists the vehicle's motion by pulling against it. The air close to the vehicle's surface moves at approximately the same speed as the vehicle, while the air farther from the surface remains stationary. Between these two air layers (the moving layer and the stationary layer), molecules are in motion over a wide range of speeds. The speed difference between air molecules creates friction, and this friction is the cause of the second part of aerodynamic drag, known as the covering effect. Various researchers have proposed different equations for calculating aerodynamic drag force, all of which relate the magnitude of this force to the square of the vehicle's speed. Therefore, its role becomes critical at high speeds. Rakha et al. (2001) proposed the following equation for calculating aerodynamic resistance, which is used in this study.

$$R_a = C_1 C_d C_h A V^2$$

The drag coefficient, represented as C_d in the formula, is a common metric in the design of vehicles such as cars, airplanes, and ships, reflecting their aerodynamics. The drag coefficient of a vehicle depends on how it allows air to pass around its body. In this equation, C_1 is the constant value for air density at 59 degrees Fahrenheit and sea level pressure, and C_h is calculated for the variation in air density due to altitude (in meters) as follows:

$$C_h=1-8.5*10^{-5}*H$$

When a vehicle moves on an inclined path, either uphill or downhill, its weight creates a component of force that always acts downward. This force component resists the motion of the vehicle, especially when moving uphill, or assists the vehicle's motion when moving downhill. The magnitude of this force component, known as the grade resistance force, is equal to the product of the vehicle's weight and the sine of the incline angle. Since the incline angle is typically small, the tangent of the angle is approximated as the percentage grade for simplifying calculations. Therefore, the equation for grade resistance simplifies to $R_g=W*G$, where R_g is the grade resistance force, W is the weight of the vehicle, and G is the percentage grade.

In accordance with Newton's law, the resultant of forces acting on an object is equal to the product of its weight and the acceleration imposed on it. Therefore, by calculating the driving and resisting forces acting on the vehicle at each moment using the following equation, which is the fundamental equation of Newton's law, the instantaneous acceleration of the vehicle can be determined:

$$\mathrm{a} = \frac{\mathrm{F}}{\mathrm{M}} = \frac{\mathrm{F_t} - \mathrm{R_a} - \mathrm{R_r} - \mathrm{R_g}}{\mathrm{M}}$$

The speed of the vehicle at each moment can be calculated by having its acceleration and the velocity at the previous moment. Additionally, the distance traveled at each moment relative to the origin time can be calculated by having the instantaneous velocity compared to the previous moment. Therefore, a dynamic model capable of calculating the vehicle's acceleration at each moment and estimating its displacement and velocity based on that is suitable for creating a speed-distance graph, or the performance curve of the vehicle.

Now, the current problem-solving process in our developed program will be examined. The test environment consists of a specific vehicle and a road with fixed characteristics but variable slope. The test vehicle enters a road segment with a specified initial speed (V_0) for evaluation. The goal of the program is to achieve the speed in the next moment, for example, one second after entering this inclined road segment. According to the principles of physics of motion, having the instantaneous acceleration, the velocity in the next moment can be estimated. To calculate the vehicle's acceleration at each moment, the values of forces acting on the vehicle at that moment need to be calculated. The applied forces on the vehicle include the motor's driving force and resistance forces, which are functions of the vehicle's characteristics, road characteristics, and the vehicle's speed. The road and vehicle characteristics are included in the model's inputs, and the initial speed is known at the start of motion. Assuming that $V(t+\Delta t) = V(t) + \bar{a}(t) * \Delta t$, where $\bar{a}(t)$ is the average instantaneous acceleration from time t to t+Δt, with the simplifying assumption that the instantaneous acceleration is equal to the acceleration at the initial moment, the model can be expanded with acceptable accuracy, simplifying its behavior.

With the initial velocity, the acceleration at the beginning of the motion (a_0) can be obtained. By calculating the acceleration at the initial moment and having its velocity, the vehicle's speed in the next moment, for example, one second later, can be estimated. Now that one of the desired values, the speed, has been specified, the variable of the traversed distance must also be calculated. According to the basic laws of motion, $X(t+\Delta t) = X(t) + \tilde{v}(t) * \Delta t$, where $\tilde{v}(t)$ is the average velocity between time t to t+Δt. Again, with the simplifying assumption that noticeable changes in velocity do not occur in the short time interval of one second, the average instantaneous velocity is considered equal to the velocity at the beginning of that time interval, making it easy to calculate the traversed distance in this time interval. Now, both speed and distance variables at the first moment after the start of motion are obtained, and by repeating this process until the traveled distance reaches the upper limit set by the user, a performance curve for a specific vehicle can be created on a slope. Now this process must be repeated for different slopes under consideration, and ultimately by aggregating the created graphs for each slope in an overall graph, the speed-distance graph or the performance curve of the vehicle can be obtained. We developed the program, using MATLAB, and a sample of program's output is presented in Figure 1.

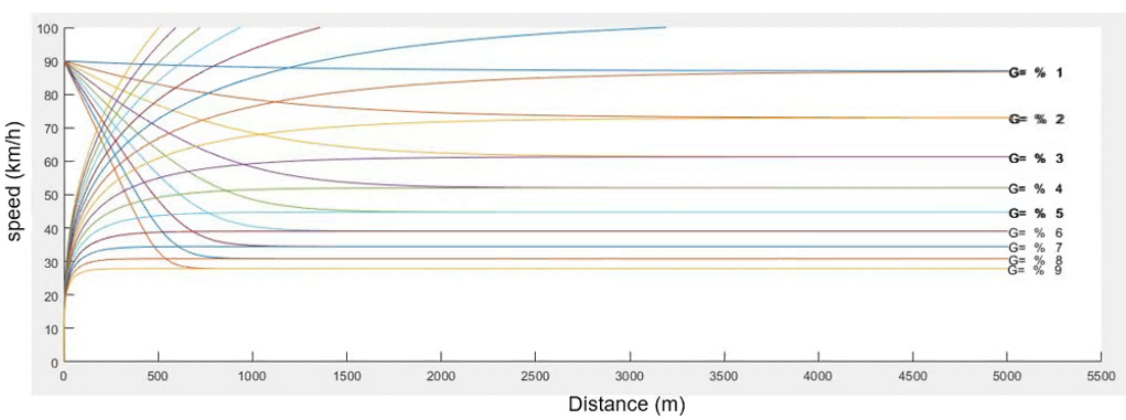

Figure 1. Sample output of the program (speed profile of a truck with w/p=73hp/lb.)

Model Validation

To validate and assess the accuracy of the model developed in this research, a comparative analysis is conducted by applying the extended model to solve problems examined in similar articles and studies. One notable reference in the study of truck motion dynamics on upgrades is the research by Archila and Fernandez (1996) conducted in Argentina. In their study, three specific sites on kilometers 1120 to 1170 of National Highway No. 7 in Argentina were selected, each spanning 1200 meters and featuring slopes of 0.4, 4.2, and 6.2 percent, respectively. Key variables in Archila and Fernandez's model include the weight-to-power ratio, engine power, vehicle speed, and slope value. The researchers presented the performance curve or speed profile of the truck for two weight-to-power ratios (136 and 190 kilograms per kilowatt) across slope values ranging from -3 to +8 percent. To compare the output of the model developed in this research with the extended model by Archila and Fernandez, speed profiles with values matching those in the Archila and Fernandez model within the same slope range were generated. Figure 2a illustrates the comparison of the output of this research model with the Archila and Fernandez model for the weight-to-power ratio of 136 kilograms per kilowatt, while Figure 2b presents the comparison for the weight-to-power ratio of 190 kilograms per kilowatt.

Within the slope range of -3 to +8 percent, the results generated by the extended model in this research closely align with those of the Archila and Fernandez model, exhibiting minimal differences. Notably, for slopes below 2 percent, the Archila and Fernandez model indicates marginally lower speeds when compared to the model developed in this research. However, this difference remains below 5 percent, falling within an entirely acceptable range. The discrepancy can be traced to the absence of the coefficient β, accounting for the effect of gear change at low speeds in the Archila and Fernandez model, as well as slight variations in the equations and coefficients employed to construct the vehicle performance model. Also, the model developed by Archila and Fernandez lacks consideration for tire type and its consequential impact. Additionally, there is no clear specification regarding the combination of the truck and the percentage of weight on the drive axle in their model.

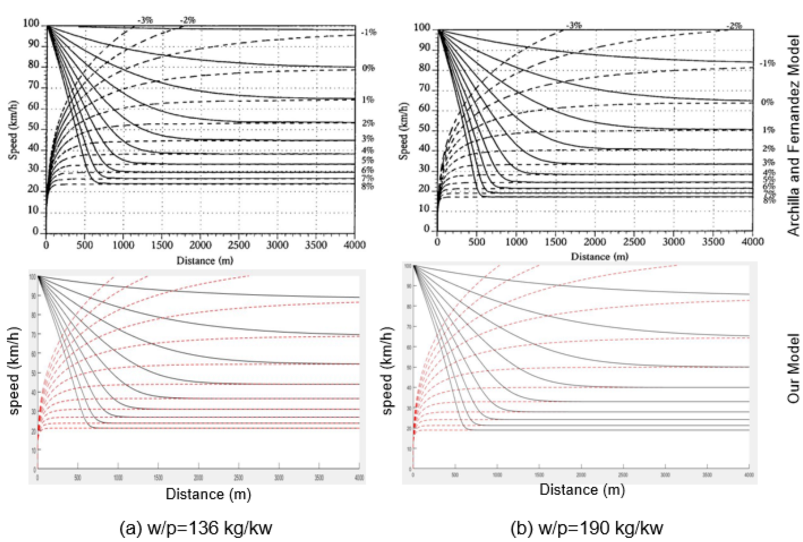

Figure 2. Comparison of our model's results with the model of Archila and Fernandez

Another study used for validating our model is the research by Rakha et al. (2001), which aimed to find a suitable dynamic model for assessing the behavior of trucks on steep grades. One of the outputs of the model developed by Rakha et al. is the performance curve of a truck with a 261 kW engine power, 33 percent weight on the drive axle, 94 percent power transmission coefficient, drag coefficient of 0.78, no aerodynamic aid, and a frontal cross-sectional area of 10.7 square meters. The test truck was equipped with radial tires and operated on a road with good asphalt pavement conditions in slope ranges between 0 to 6 percent for acceleration and deceleration cases with initial speeds of 0 and 120 kilometers per hour, respectively. In this research, we solved the same problem, and the model's output was compared with the results of the Rakha et al. model, as presented in Figure 3. As evident from the comparison of the presented graphs, the difference between the results of our model and the model developed by Rakha et al. is less than 5 percent under all conditions. The calculated speeds by the Rakha et al. model is slightly higher than the values computed by our model. This minor difference is attributed to variations in the modeling approach and the unspecified details of their work in the TruckSIM dynamic simulation software environment.

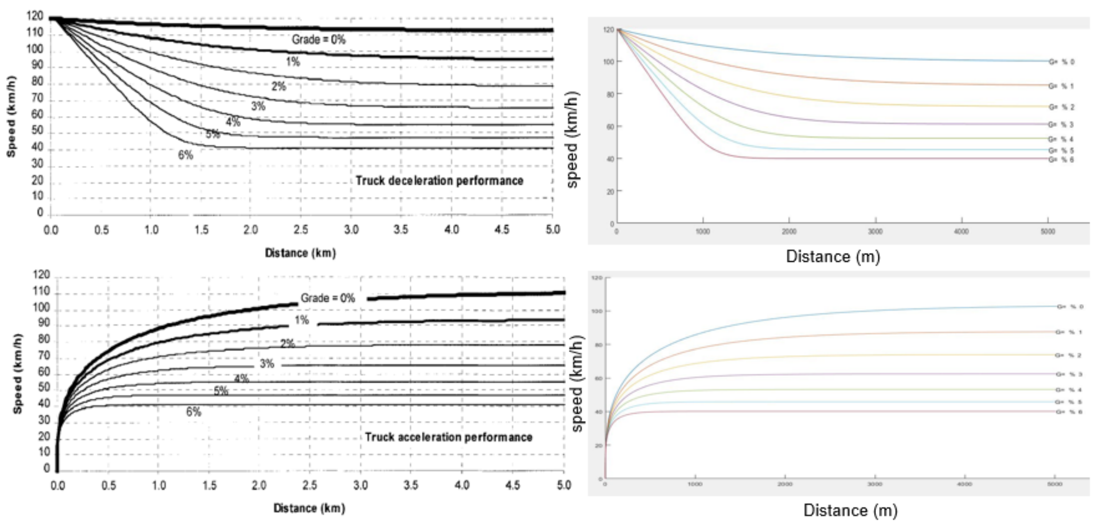

Figure 3. Comparison of our model's results with the model of Rakha et al.

By examining the issues addressed in reputable research works in the field of heavy vehicle performance on steep grades, and comparing the outputs, we have demonstrated that the results generated by the model developed in this research exhibit acceptable accuracy and reliability.

RESULTS AND DISCUSSION

This section aims to assess the role of various factors in the performance of heavy vehicles. Critical variables in the dynamic model of heavy vehicle performance on steep grades include weight-to-power ratio, engine power, road type and conditions, truck type, and tire type. By constructing different scenarios and comparing the model outputs, the role of each of these factors in the performance of trucks and heavy vehicles on uphill routes will be scrutinized.

The weight-to-power ratio in trucks emerges as the most pivotal factor influencing their performance on steep inclines. Across various weight-to-power ratios, the truck's performance on a given route exhibits significant variations, making this factor a focal point in truck performance studies. The standalone engine power of a truck holds substantial significance in assessing the vehicle's performance. However, when the weight-to-power ratio remains constant, alterations in engine power yield negligible variations in the vehicle's speed profile. With an increasing road gradient, the role of engine power becomes increasingly critical. The type and conditions of road paving are additional factors intertwined with vehicle performance. These factors contribute to the calculation of forces generated by the engine and rolling resistance. The developed model underscores that, under stable conditions, altering this factor has minimal impact, with its role significantly less than that of the weight-to-power ratio. In steep slopes, this factor assumes a less prominent role, and it is essential to note that road conditions and material do not affect the equilibrium speed of trucks on inclines. The type and structure of tires, crucial elements in vehicle dynamics, exert minimal influence on the performance of heavy vehicles on steep grades. They also do not play a role in determining the equilibrium speed of trucks on inclines. The structure and type of the truck similarly have a limited impact on its performance on inclines when considering constant weight-to-power ratios, engine power, and road conditions. The equilibrium speed of trucks on inclines remains unrelated to this factor.

Among the forces acting on a moving vehicle on inclines, rolling resistance and the driving force of the engine take center stage, with air resistance only becoming significant at high speeds. For exceptionally steep slopes, the laws of force equilibrium differ, necessitating a comprehensive investigation into factors such as the surface friction coefficient, road structure, and material in a comprehensive study.

CONCLUSION

In conclusion, the dynamic model presented in this study offers a comprehensive understanding of heavy vehicle performance on steep road gradients. By integrating fundamental physics, Newton's Second Law, and semi-empirical methods, the model captures the intricate interplay of forces affecting vehicle motion. The significance of weight-to-power ratio in influencing truck performance on inclines is underscored, highlighting its pivotal role. Engine power becomes increasingly critical with steeper gradients, while road conditions and tire types exhibit minimal impact under stable scenarios. The developed MATLAB program facilitates the analysis of various factors, contributing to a nuanced comprehension of heavy vehicle behavior. Rolling resistance and engine driving force emerge as central forces, with aerodynamic drag gaining significance at higher speeds. The study provides valuable insights for the transportation industry, aiding in the optimization of heavy vehicle performance on challenging road conditions. As technology advances and vehicle dynamics evolve, continued research in this domain remains crucial for enhancing safety, efficiency, and sustainability in the transportation sector.

Based on the findings of this research, the following recommendations are proposed for future studies to further explore the landscape in the examined domain and gain a deeper insight into the factors influencing the performance of heavy vehicles:

- Conduct a comprehensive study for calibrating models based on specific conditions and categorizing heavy vehicles based on their features.
- Collaborate with mechanical engineering experts to delve into specific dynamic characteristics of vehicles, assessing the impact of mechanical features. This approach will contribute to a more detailed understanding of the studied area.

- Explore the critical factors that significantly influence the performance of heavy vehicles, especially in steep downhill sections and areas with extremely high gradients.
- Develop and refine dynamic models by incorporating additional variables. Foster collaboration between transportation and mechanical engineers to enhance the accuracy and reliability of these models.
- Focus on improving computational programs to ensure a more precise representation of a broader range of objectives.

These proposed directions for future research aim to contribute to a more comprehensive and nuanced understanding of the dynamics of heavy vehicles in diverse road conditions. By addressing these areas, researchers can advance the field and contribute valuable insights to transportation engineering and vehicle performance studies.

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Addressing Urban Traffic Congestion: A Hybrid DQN-Autoencoder Model with HyperOPT Tuning

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ABSTRACT

In this study, we propose a novel method for managing traffic lights by integrating deep Q-networks (DQN) with auto-encoders. The aim is to enhance traffic fluidity and mitigate congestion in simulated environments. To achieve this, we incorporate the average vehicle velocity as a key metric within the system's observation space. Additionally, we employ optimization techniques such as HyperOPT and leverage the data compression features of auto-encoders to improve decision-making quality. Our approach was evaluated on a two-way, single-intersection network, subjecting to a vehicle flow rate varying between 100 and 600 vehicles per hour. We compared our hybrid DQN-auto-encoder method against a DQN-only baseline, using average waiting time as the evaluation metric. The results indicate that our model markedly outperformed the baseline, reducing the average waiting time to 212 s (standard deviation 12 s), as opposed to 340 s observed in the baseline, while a traditional non-algorithmic approach yielded an average waiting time of about 1,100 s.

INTRODUCTION

Urban traffic congestion has been a critical issue for cities around the globe. It greatly affects the economy, environment, health, quality of life, urban planning, etc. In the past decades, many researchers have delved into various methodologies and techniques to address this challenge. The approaches include but are not limited to traffic adaptive control (TRAC) (Spall, 1997), genetic algorithms (Teklu, 2007; Park, 1999), max pressure strategies (Varaiya, 2013), and adaptive traffic-responsive strategy (Baldi, 2015).

While conventional methods have been employed to tackle urban traffic congestion, their effectiveness remains inadequate in addressing the complexity and unpredictability of traffic flows. Traffic systems, characterized by a myriad of vehicles with varied and unforeseeable trajectories, present challenges that exceed the capabilities of existing traffic control and management frameworks. This shortfall underscores the urgency for more sophisticated, flexible, and intelligent solutions to manage urban traffic congestion effectively (Kim, 2019). Moreover, the ongoing urban expansion and intensification of cityscapes (Djahel, 2014) further amplify the necessity for innovative traffic control systems. These systems need not only to be capable of adapting to evolving traffic patterns but also possess the ability to learn and evolve in response to these changes, thereby ensuring sustainable and efficient urban mobility.

To address the limitations of conventional traffic control methods, there has been a significant shift towards the adoption of reinforcement learning (RL). The use of RL algorithms in traffic management dates back two decades, with pioneering work that utilized RL to minimize overall waiting times by adapting dynamically to fluctuating traffic scenarios (Wiering, 2000). A major leap forward occurred in 2017 when deep learning was integrated with RL algorithms in traffic control, enhancing the capabilities of traffic data processing and signal management (Gao, 2017). This integration, especially with advanced technologies like graph convolutional neural networks, has facilitated a more in-depth understanding of traffic dynamics across various intersections. A graph convolutional neural network approach was developed to automatically extract features of multi-intersection road networks instead of manually obtaining these features (Nishi, 2018). An RL algorithm that is capable of tackling complex traffic problems at multiple intersections was introduced, which makes substantial progress towards practical traffic management problems (Lin 2018). A method combining speed guidance systems with RL-based traffic signal control, tailored for future traffic conditions, was introduced to minimize the total queue length and reduce traffic congestion (Maadi, 2022). A novel approach by blending fuzzy logic with deep Q-learning, merging the adaptability of RL with the robustness of fuzzy logic, was introduced to address the challenges of complexity and uncertainty in traffic networks (Tunc, 2023). A cooperative multi-objective architecture was recently proposed to address the challenges (e.g., suboptimal, unstable) in RL, as well as link carbon emissions and global traffic throughput (Tang, 2023).

Despite the advancements brought by RL in traffic signal control, there is still space for substantial improvement, particularly in comprehensively understanding traffic dynamics. This led to the progression towards integrating additional key metrics into the RL framework, such as the average speed in the observation space, as pursued in our research approach. It enhances the RL model’s ability to not only react to current traffic scenarios but also anticipate and adapt to emerging patterns, making the system more responsive and efficient. Our research proposes a novel solution to address existing challenges by incorporating reinforcement learning into traffic management by combining an auto-encoder with a Deep Q-network (DQN). By integrating average speed into the observation space of the deep learning algorithm, we provide the RL model with a more comprehensive understanding of traffic flow. This allows for effective control of traffic signals, addressing the complexities of urban traffic congestion with greater precision. The goal is to create a proactive traffic control system that can actively learn from changing traffic circumstances and adapt to them, all while being optimized for real-world urban intersections.

The contributions of this work are as follows.

1. Inclusion of average speed and enhanced RL model: The paper introduces the incorporation of average speed into the observation space, taking a different approach from the existing methods. The inclusion of average speed enhances the reinforcement learning model’s capabilities as the parameters and dimensionality increase upon its inclusion, thus helping the model to learn more about the observation space.
2. Integration of DQN with Auto-encoder: The integration of Deep Q-Learning (DQN) with auto-encoder enhances the RL as the auto-encoders can be used to extract important features and minimize dimensionality in the state space. The encoded representation leads to better exploration-exploitation balance and thus offers an effective hybrid model for reinforcement learning tasks.

METHOD

This paper primarily focuses on using reinforcement learning algorithms to optimize traffic signal control. This work aims to dynamically determine the optimal duration for each phase of the traffic light (green, yellow, red) based on real-time observations, improving vehicular flow and throughput in urban areas. Incorporating average speed into the observation space marks a distinct strategy compared to previous studies. This addition provides the reinforcement learning model with an expanded set of data to learn from and observe. Consequently, this enhancement empowers the model to make more informed and effective decisions relevant to the specific environment it is tasked with in the context of reinforcement learning. To find the optimal solution, HyperOPT was utilized to navigate the hyperparameter space effectively. This approach is effective in identifying the best settings for our reinforcement learning algorithm, thereby significantly enhancing our capability to refine and advance the traffic signal control system.

Reinforcement Learning

Reinforcement learning is a type of machine learning where an agent learns decision-making by interacting with its environment, executing actions, and receiving feedback in the form of rewards (Sutton, 2018). The central goal of RL is to derive an optimal strategy, termed a policy, instructing the agent on actions to maximize cumulative rewards over time. This process involves crucial components such as the agent (decision-maker), the environment (external influence), states (representations of the environment), actions (agent decisions impacting the environment), rewards (scalar feedback for agent actions), and the policy (strategic guide for decision-making). The interplay between these elements characterizes the dynamics of reinforcement learning.

Q-Learning

Q-learning aims to learn the optimal action-value function $Q^*(s,a)$, which represents the expected return of taking an action a in the state s and following the optimal policy thereafter. The update rule for Q-learning is: $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma\, max_{a'} Q(s',a') - Q(s,a)]$, where α is the learning rate, r is the immediate reward after taking action, γ is the discount factor, s' is the subsequent state after the current state s.

Deep Q-Network (DQN)

We employed the Deep Q-Network (DQN) (Mnih, 2015), an adaptation of the traditional Q-learning algorithm, for our study's objective. DQN seamlessly integrates deep neural networks to approximate Q-values, offering enhanced capabilities in handling large-scale and intricate challenges like optimizing traffic light control in urban settings. Noteworthy features of DQN include its utilization of a neural network as a function approximator, adeptly generating Q-values for diverse actions in each state. Experience replay is employed, allowing the algorithm to break correlations between consecutive experiences by randomly sampling batches from a replay buffer. DQN further enhances stability by incorporating a target network, periodically updated with the primary network's weights. The training process involves minimizing the squared difference between predicted and target Q-values, encapsulated in the concise loss function $L(\theta) = \mathrm{E}_{(s,ar,s') \sim U(D)}[(r + \gamma\, max_{a'}\, Q(s', a'; \theta^-) - Q(s, a; \theta))^2]$. These features collectively make DQN a robust choice for addressing complex problems in reinforcement learning.

Auto-Encoder

Autoencoders (Rumelhart, 1986), a neural network variant, specialize in unsupervised learning tasks, notably excelling in data compression and de-noising. Their primary objective is to learn efficient encodings of input data, often employed for dimensionality reduction. The autoencoder comprises key components: the Encoder, responsible for compressing input into a reduced-dimensional latent-space representation; the Decoder, which reconstructs the input from this representation; and the Bottleneck, representing the minimum dimensionality. The network's performance is evaluated by the Reconstruction Loss, typically measured using Mean Squared Error (MSE), assessing the disparity between the original and reconstructed data. The Latent Space Representation encapsulates the compressed data produced by the encoder. Activation Functions, such as ReLU or Sigmoid, introduce non-linearity crucial for handling complex data structures in encoding and decoding processes.

Our Approach

The foundation of our RL system was formed by combining the capabilities of the Deep Q-Network (DQN) architecture with auto-encoders. This integration allows the auto-encoder to effectively represent and compress the state space, ensuring that the DQN operates optimally with the environment's high-dimensional data. With this framework established, our focus shifts to adjustments (tunings) to adapt the DQN and Auto-encoder model to the specific challenges of our traffic signal control problem.

Observation Space

Each traffic signal agent's observation is stacked as a vector:

$$obs = [p_o, m_g, m_v, \rho_n, Q_n]$$

where:

- p_o is a one-hot encoded vector highlighting the currently active green phase.
- m_g is a binary variable that indicates if the minimum green time duration has been surpassed for the ongoing phase.
- m_v is the average speed of all the vehicles at the intersection.
- ρ_n represents the density of vehicles in an incoming lane n, it is calculated as the ratio of the total number of vehicles in the lane to its maximum capacity.
- Q_n indicates the queue density in an incoming lane n, determined by the proportion of vehicles with a speed below 0.1 m/s to the lane's total capacity.

Action Space

The action space for this reinforcement learning task is discrete and corresponds to selecting the next green phase that will be open for a specified duration. The action space is represented as an integer, where each value from 0 to the number of green phases minus 1 corresponds to a specific green phase. This is used as an index to keep track of the current green phase of the traffic signal. In traffic signal systems, different phases represent different sets of lights being green to control traffic flow. For example, $A = \{1, 2, 3\}$ indicates the set of all traffic signal phases (i.e., 1, 2, and 3 indicating green, yellow, and red, respectively). Taking an action "$a \in A$" means selecting an appropriate traffic signal phase for the next time step, which will be "Keep" or "Switch," such that if the agent chooses a set of non-conflicting phases to be assigned the green light, then it will be "Keep"; otherwise, a mandatory yellow phase will be enforced before the "Switch." This discrete action space allows the agent to control the traffic signal's behavior by determining which direction of traffic should have the right of way at any given moment.

Reward Function

The agent's learning and decision-making are molded by the reward functions:

1. Diff-Waiting-Time Reward: A function evaluating the disparities in waiting times across traffic phases. The aim is to ensure uniform waiting times, thus facilitating smooth traffic flow. The reward is given by

$$\Delta t(s, a, s') = \sum w_{v_i}^{t-1} - \sum w_{v_i}^{t}$$

   Here, $w_{v_i}^{t}$ denotes the waiting time of a vehicle, which is the number of seconds the vehicle has a speed less than 0.1 m/s at an intersection. As the delay increases over time, the reward is always a negative value as we are looking to decrease Δt.

2. Average-Speed Reward: This reward emphasizes the average speed of vehicles, giving preference to scenarios where vehicles maintain a decent pace. This reward is expressed as

$$m(s, a, s') = \frac{\sum_i v_i}{N}$$

   Here, v_i refers to the speed of the vehicles, and N represents the number of lanes.

3. Queue Reward: This reward focuses on curtailing the number of halted vehicles, signaling that traffic is flowing without extended stops, which is given by

$$Q(s, a, s') = -Q$$

   Here, Q represents the number of vehicles that are waiting at the intersection.

4. Pressure Reward: This reward quantifies the difference between outgoing and incoming vehicles, advocating for a balanced distribution of vehicles across lanes. It is expressed in the following form.

$$p(s, a, s') = \sum_{out} v_{out} - \sum_{in} v_{in}$$

Here, v_{in} represents the number of vehicles coming into an intersection, and v_{out} represents the number of vehicles going out of the intersection.

5. Average-Speed-Maximization Reward: It is intricately tied to the vehicles' average speed, which is given by

$$\text{max\_}v = \frac{\sum_i v_i}{L}$$

A higher mean speed leads to a better reward, symbolizing efficient traffic movement.

Epsilon-Greedy Strategy with DQN + Auto-Encoder

The intricate combination of our DQN and auto-encoders, augmented by an epsilon-greedy strategy, forms the core of our learning mechanism. Central to this framework is the auto-encoder, which is pivotal in efficiently compressing and representing the state space effectively, equipping the DQN to process high-dimensional data. Upon observing the current state, s, the agent either opts for a random action a with a likelihood ε, or, drawing from its learned experiences, selects the action that maximizes its Q-value: $a^* = argmax_a Q(s, a; \theta)$.

Following the action and transitioning to the new state, s, the agent logs the reward r and refines the DQN parameters: $Q(s, a; \theta) \leftarrow r + \gamma \, max_{a'} Q(s', a'; \theta)$.

The tuning of reward functions, integration of the epsilon-greedy strategy (Wang, 2021), and the DQN-auto-encoder architecture all together to form a robust, and adaptable reinforcement learning framework. In the illustrated framework (as shown in Figure 1), we show the architecture of the RL-based Traffic Signal Control (TSC) system. The model integrates a Deep Q-Network (DQN) with an autoencoder, a neural network structured to encode and reconstruct high-dimensional input data into a lower-dimensional encoded format. Situated in a standard urban traffic intersection, the agent leverages the autoencoder to transform complex traffic parameters such as lane density, queue length, and average speed into simplified representations. The DQN then processes this condensed representation, guiding the agent to make informed decisions about adjusting traffic light timings for optimized traffic flow. Upon executing a decision, the agent receives feedback from a reward system that quantifies the effectiveness of its actions based on metrics like waiting times and vehicle speeds. An auxiliary HyperOPT module fine-tunes the system's hyperparameters, ensuring its precision and adaptability.

SIMULATION SETUP

The simulations for our paper were conducted on a MacBook Pro featuring an M1 chip with an 8-core CPU, 14-core GPU, and a 16-core Neural Engine, coupled with 16GB of memory. In the simulation, we employed the Simulation of Urban MObility (SUMO) to model a 2-way single intersection scenario as shown in Figure 2. With the road network, the flow of vehicles is set as follows:

- From north to south and from north to west, 300 vehicles per hour were generated.
- From north to east, the flow is slightly lower as 250 vehicles per hour were generated.

For the deep learning aspect, we utilized the capabilities of PyTorch and implemented the DQN (Deep Q-Network) algorithm, an established RL algorithm.

To capture an extended temporal perspective, we set the simulation time to 40,000 seconds, allowing us to observe and evaluate traffic dynamics effectively over a prolonged period. In terms of training hyperparameters, we adjusted the learning rate to 0.01, optimizing the learning process for our DQN model.

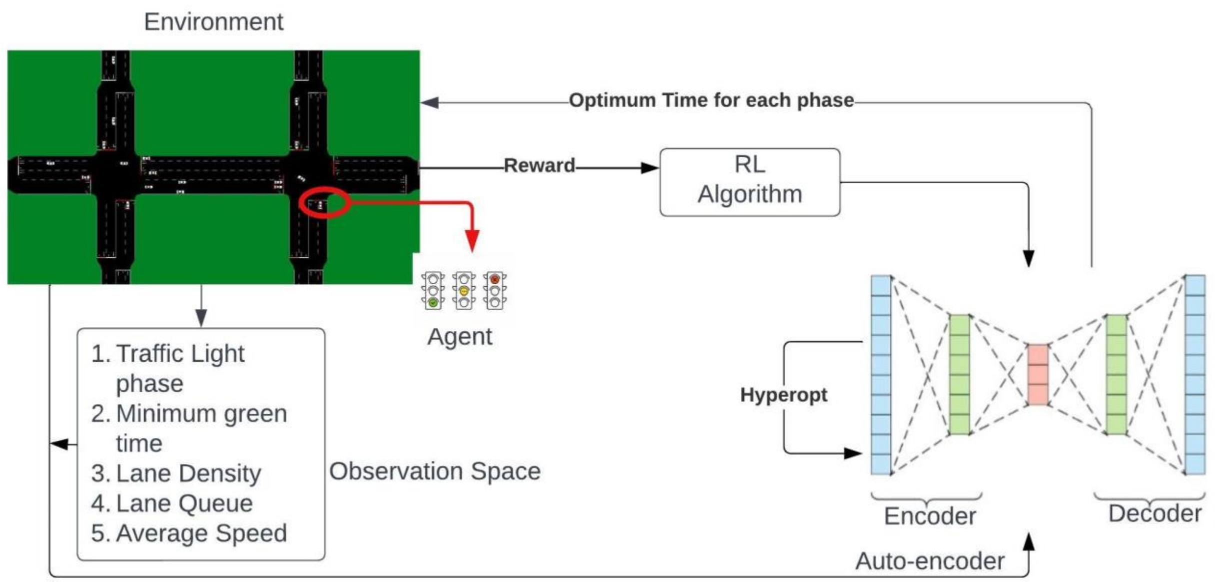

Figure 1: Workflow of the proposed method.

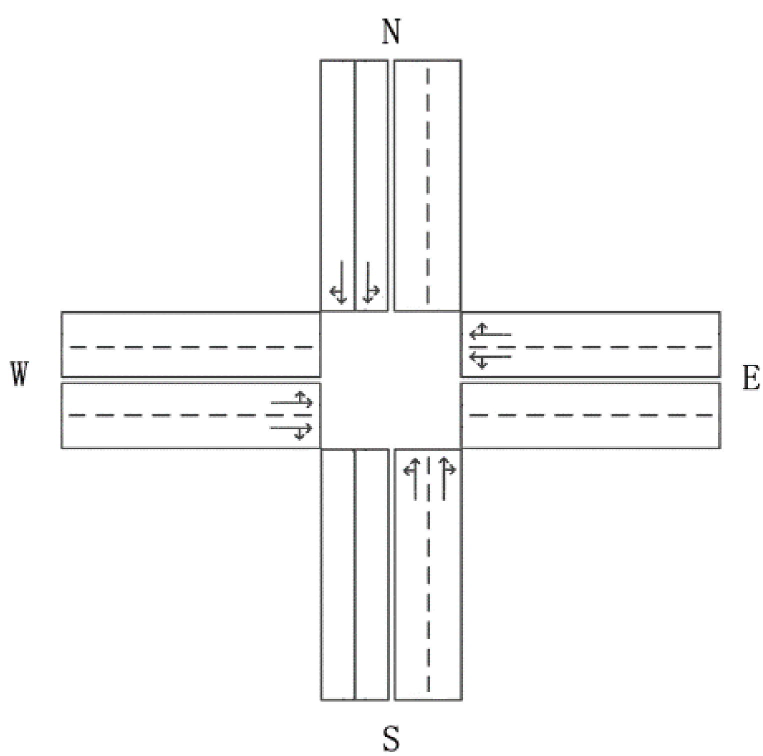

Figure 2: 2-way single-intersection road network.

RESULTS AND COMPARATIVE ANALYSIS

Our extensive analysis, conducted over 400 episodes using the SUMO traffic simulation, focused on evaluating the effectiveness of three distinct methodologies in managing traffic congestion, as measured by the average waiting time of vehicles. These methodologies included a pre-existing implementation of traffic management (DQN - Deep Q-Networks) (Xu, 2022), our innovative approach that employs the DQN with an Auto-Encoder, and a naïve method devoid of deep learning techniques, wherein the traffic signals have been programmed with a fixed time interval for each of the phases. The timings have been set based on real-world traffic signals, where the signals change every 30 seconds.

In our research, we carried out two types of simulation tests using SUMO. The first type of test looked at how well two different traffic control methods improved as they were trained over time. The second type of test checked how reliable these methods were. We ran each method five times in simulations that lasted 40,000 seconds each. This was done in a virtual environment that mimics a two-way road with a single intersection. By doing this, we wanted to make sure that the results we obtained were not just a one-time thing but could be repeated reliably.

Convergence Test

As shown in Figure 3, the baseline method shows a gradual decrease in mean waiting time as the number of episodes increases, suggesting that the method is learning and improving over time. However, the improvement is slow, and the waiting times remain relatively high, averaging above 300 seconds even after 400 episodes. This indicates that while the baseline method is making progress, it’s not very efficient. The decision to stop the baseline method training due to slow progress and limitations of the device makes sense, given these observations.

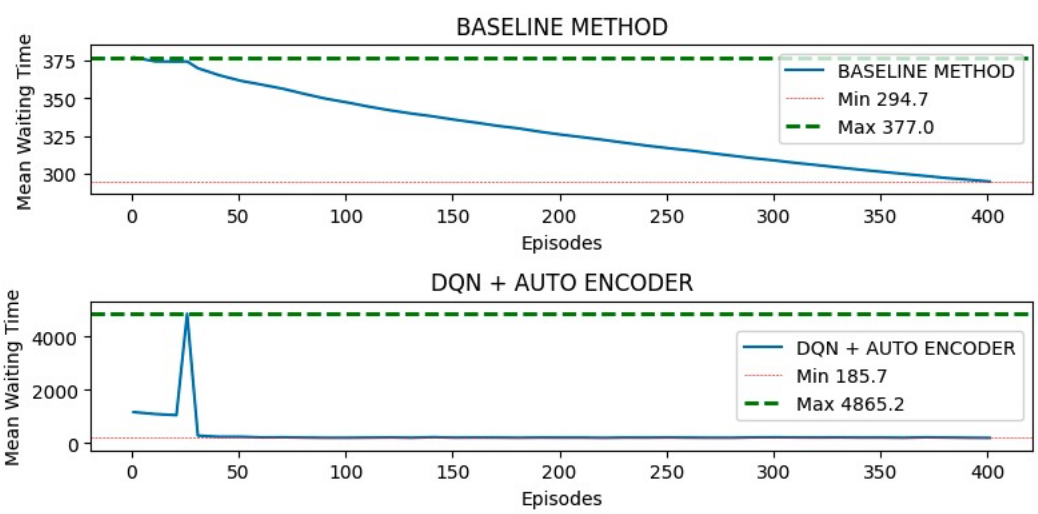

Figure 3: Comparative Analysis between the baseline method and our DQN + Auto-encoder approach.

On the other hand, the DQN + Auto Encoder method shows a very different pattern. Initially, there's a significant spike in mean waiting time, but this quickly drops and begins to stabilize.

After this initial fluctuation, the waiting times reduce dramatically, suggesting that the method starts to converge to a more effective strategy much faster than the baseline method. Despite some variability, the general trend for the DQN + Auto Encoder method is towards lower waiting times, with episodes leveling out at a much lower mean waiting time compared to the baseline method. This indicates a more efficient learning process and a quicker convergence towards an optimized solution for traffic management.

The sharp peak in the beginning for the DQN + Auto Encoder method could be due to the initial exploration phase, which is common in reinforcement learning algorithms where the system tries out different strategies to learn which one works best. After this phase, the algorithm starts to exploit the best-known strategies, leading to the observed improvement and stabilization in performance.

Repeatability Test

In the evaluation of different traffic management methodologies within a SUMO framework, three distinct approaches were taken into consideration: a naïve approach, a baseline method, and an integration of Deep Q-Networks (DQN) with Auto-Encoders. This assessment was carried out through a repeatability test, each conducted 5 times and lasting 40,000 seconds based on the policy of the 400th episode, in a 2-way single intersection scenario. The result is shown in Table 1.

Table 1: Average waiting time at a 2-way single intersection for different methods

Method	Mean (seconds)	Standard Deviation (seconds)
Naïve	1132	135
Baseline	340	37
DQN + Auto-Encoder	212	12

The naïve approach registered the highest mean duration at 1132 seconds, accompanied by a substantial standard deviation of 135 seconds. This significant deviation underscores a variability in performance and shows potential inconsistencies in the application of this method.

The baseline method exhibited a notable enhancement in efficiency, providing a mean duration of 340 seconds, noticeably lower than the naïve approach. Its standard deviation, positioned at 37 seconds, also indicated improved consistency in performance compared to the naïve method.

Our method, the integration of DQN with Auto-Encoders, outperformed both preceding methods. This approach achieved an impressive mean duration of 212 seconds, significantly reducing the waiting time. Furthermore, it maintained a standard deviation of 12 seconds, the lowest among the evaluated methods. This minimal deviation is indicative of a high level of consistent performance, reinforcing the method's reliability.

The efficacy of the DQN + Auto-Encoder approach in this context is attributed to the synergistic combination of Deep Q-Networks with Auto-Encoder mechanisms. This integration not only accelerates the processing time but also ensures a consistent performance, proving to be an optimal solution for traffic management in a 2-way single intersection environment within SUMO.

CONCLUSION AND DISCUSSION

The inclusion of average speed into the observation space gives a different approach as compared to previous approaches. This integration of a DQN with an Auto-Encoder represents a considerable advancement in the reinforcement learning models' ability to react, anticipate, and adapt to emerging patterns in traffic congestion management. The model resulted in reduced average waiting times and improved consistency. This method surpassed traditional DQN implementations and significantly outperformed the naïve method. Our results strongly advocate for the implementation of effective data-driven solutions to address the complexities of modern urban traffic management.

For future research, the focus could shift to include vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. This approach aims to create a more connected and efficient traffic management system. By enabling vehicles to share important information like their location, speed, and planned routes in real-time, a more cooperative traffic network can be developed. Upcoming studies could also work on creating new algorithms that use V2V and V2I communications to improve how vehicles change lanes and merge on ramps. These improvements are crucial for helping vehicles work together better when merging, which can help keep traffic flowing smoothly and reduce road congestion. Research in this area has the potential to greatly improve the safety and effectiveness of our highway systems. It could lead to better coordination between vehicles, making overall traffic movement smoother and reducing delays.

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Impact of Free Flow Speed Estimation Method on Project Prioritization

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ABSTRACT

Transportation project prioritization relies heavily on assessments of performance and outcome; however, inconsistencies in analytical techniques of performance measures can significantly skew the results. This study conducts a comprehensive examination of free-flow speed (FFS) estimation methods and the impact of delay threshold selection, demonstrating their pivotal roles in result interpretation and project prioritization. A comparative analysis of several FFS estimation methodologies reveals that methods based on the 85th percentile of observed speeds yield highly correlated FFS estimates, while the 95th percentile methods or simple arithmetic operations of posted speed limits produce divergent results. Moreover, the study underscores the substantial influence of congestion threshold selection on the calculated delay, exhibiting significant variation at statewide, district, and corridor levels. These thresholds not only affect the magnitude of calculated delays but also alter the perceived severity of congestion. The research results underscore the vital need for transportation agencies to adopt standardized methodologies for FFS estimation and congestion delay threshold selection in order to enable consistent, unbiased project evaluation and data-driven prioritization.

INTRODUCTION

Free flow speed (FFS) is a fundamental metric widely used in numerous transportation applications. These applications extend from capacity analysis such as estimating the level of service, performance measurements like congestion delay (Lan et al., 2019; Zhao and Ventakanarayana, 2019) and travel time reliability, to simulation analysis (Hou et al., 2013). The role of FFS is especially crucial to cost-benefit evaluation and project prioritization (Xu and Lambert, 2015; Wolniak and Mahapatra, 2014; Williges and Mahdavi, 2008; Peer et al., 2012). Statewide project prioritization or funding allocation programs, typically employed by state departments of transportation (DOTs) and metropolitan transportation agencies, are common applications in this context. The SmartScale initiative in Virginia is one example of these programs (Virginia DOT, 2023). The concept of SmartScale is to score and prioritize projects to be funded by the Commonwealth Transportation Board based on established selection criteria.

Reduction in traffic delay is often employed as a key performance measure for evaluating project benefits (Xu and Lambert, 2015; Wolniak and Mahapatra, 2014; Williges and Mahdavi, 2008; Peer et al., 2012). However, the lack of a unified delay definition across projects can lead to potential bias in estimating benefits. Within delay estimation, a key parameter is invariably the FFS. Given its essential role in performance measures, this paper explored FFS estimation methods, with a specific focus on congestion delay analysis.

Free flow refers to traffic flow unaffected by upstream or downstream conditions (HCM, Transportation Research Board, 2022). The speed at which free-flow prevails is named free-flow speed (FFS). FFS is usually calculated from field observations or pre-defined algorithms. Measuring FFS in the field under light traffic condition is the most accurate method to estimate segment FFS (Dowling et al., 2016). Due to high costs of field data collection, researchers developed various algorithms to calculate FFS, ranging from arithmetic equations (e.g., posted speed limit plus 5 mph) to complicated statistical or machine learning models. The identification of free-flow states usually follows one of the three principal approaches:

- a threshold of flow rate (TRB,2022; Dowling et al., 2016),
- a threshold of headway (Abdurrahman et al., 2014; Leong and Muhammad, 2019), and
- speed-density graphs.

Once the free-flow state is identified, FFS could be calculated as the mean or quantile of the speeds of free-flow traffic. FFS could also be modeled as a random variable with different probability distributions, like in traffic simulation models (Hou et al., 2013). The 85th percentile of off-peak speeds is commonly used in some studies such as the Federal Highway Administration (FHWA) Urban Congestion Report (FHWA, 2020) and the Urban Mobility Report produced by the Texas A&M Transportation Institute (TTI) (Schrank et al., 2021). It should be noted that in some literature, especially those studies on mobility performance measurement, the term reference speed is often used interchangeably with FFS.

In terms of congestion measures for project prioritization, vehicle hour of delay is commonly used at road segment level, it is computed as the product of the additional travel time induced by congestion and the traffic volume of the segment. However, the selection of a congestion threshold has great influence over this measure and is a subject of debate. The definitions of congestion thresholds generally fall into three main categories:

(1) a percentage of free-flow or reference speed, as utilized in the FHWA Urban Congestion Report (90% of FFS) (FHWA, 2020), Urban Mobility Report (80% of FFS) (Schrank et al., 2021), and Texas' Most Congested Roadways (80% of FFS) (TTI, 2023);
(2) a percentage of a road segment's posted speed limit, as utilized in the Washington DOT Corridor Capacity Report (70% or 85% of posted speed limit) (Washington DOT,2018);
(3) a fixed speed threshold, as used by Virginia DOT Operations Performance Report (Virginia DOT, 2021), Caltrans Mobility Performance Reports (60 mph) (California DOT, 2023), and Minnesota DOT Congestion Report (45 mph) (Minnesota DOT, 2021).

This study undertakes a comprehensive exploration of how FFS and delay definitions influence project prioritization. The goal is to critically compare and evaluate FFS estimation methods, particularly in the context of interstates, and to investigate the effect of congestion threshold on the estimated delay outcomes, with attention given to the implications on benefit analysis and project prioritization. First, a comparative analysis of several common FFS estimation methodologies is conducted, including techniques based on the 85th percentile of observed speeds, the reference speed (usually a specific percentile of speeds on a segment) provided in probe data sets, and methods based on simple arithmetic operations of post speed limits (PSL). This analysis, focusing predominantly on interstates due to the greater availability of their speed data, aims to assess the robustness of FFS derived from these methods and gain insights into the real-world applicability of such methods. The study then expands the exploration to understand factors that influence FFS estimates. This exploration focuses on variables of potential interest to traffic agencies, such as the PSL.

Subsequent to the assessment of FFS methods, the study investigates the effects of varying congestion thresholds on the estimated delay metrics. An examination is carried out on congestion thresholds based on different percentages of FFS and PSL, and the resulting delay magnitudes and rankings are compared. By comparing how the resulting delay alter at different spatial aggregation levels, the congestion severity across regions is assessed, along with implications for project prioritization. These explorations aim to improve the understanding of FFS estimation, the impact of congestion threshold on delay estimation, and their critical roles in transportation planning and project prioritization.

METHODOLOGY

Data Collection

The primary dataset for this study is the 15-minute probe speed data from the National Performance Management Research Data Set (NPMRDS). NPMRDS is provided by the FHWA for free to States and MPOs, and is often used in analyses for performance monitoring purposes. The spatial units for this data are defined by directional roadway stretches with varying lengths known as Traffic Message Channel (TMC) segments. Traffic volumes, served to compute vehicle-hours of delay, were also essential to the study. The Annual Average Daily Traffic (AADT) and the average hourly volume profile factors were obtained for each TMC from the Virginia Department of Transportation (VDOT). Posted speed limited (PSL) and the number of through lanes were also obtained from VDOT. All data were aggregated at TMC segment level.

The study network is all interstate highways in Virginia. The network consists of 2,189 directional miles of roads. This network exhibits extensive diversity, characterized by varying traffic volumes, vertical grades, weather patterns, number of lanes, ramp density, and urban-rural traffic patterns. There were 1,787 TMC segments, with lengths ranging from 0.004 to more than 9 miles, and an average length of 1.2 miles. The study period covers 3 years from January 1, 2019 to December 31, 2021.

Calculation and Exploration of Free-Flow Speed

Three methodologies for estimating FFS, each named for their respective authors, were evaluated: FHWA FFS (FHWA, 2020), TTI FFS (Schrank *et al*, 2021), and Jha FFS (Jha, 2017). The FHWA FFS is derived from the 85th percentile of speeds during defined off-peak periods on weekdays (9am-4pm, 7pm-10pm), and weekends (6am-10pm). The TTI FFS is calculated as the 85th percentile speed using overnight weeknight data (10pm-6am), supplemented by weekday mid-day speeds (11am-4pm) if insufficient late-night observations exist (less than 50%). The Jha FFS method utilizes the 85th percentile of weeknight speeds from 9pm-6am. Through comparative analysis, the similarities and differences among the FFS estimates produced by these methods were explored in terms of correlation. In addition, some commonly used FFS estimated were also included in the comparative study: (1) the Florida DOT's method of using PSL plus 5 mph as FFS (Florida DOT, 2023), and (2) the NPMRDS Reference Speed. FFS estimates derived from the "percentile-of-speed" category were compared against those from the NPMRDS Reference Speed and Florida DOT methods.

Delay Calculation and Exploration

The impact of varying congestion thresholds on delay estimation was evaluated through total network delay (as the sum of delay across all roadway segments) and delay ranking of segments within the network. The congestion thresholds considered are commonly applied in the field, and can be categorized as follows:

1. Percentage of free-flow speed: (a) 90%, (b) 85%, (c) 80%, (d)75%, and (e)70% of FFS,
2. Percentage of posted speed limit: (a) 100% and (b) 85% of PSL,
3. Percentage of reference speed: 80% of NPMRDS reference speed, and
4. Fixed threshold: a constant of 45 mph.

RESULTS

Comparison of FFS Estimates from Different Methods

Figure 1 illustrates a comparative analysis of FFS estimates generated by the three methodologies (FHWA FFS, TTI FFS, and Jha FFS) using 2019 data. The FFS estimates for each TMC were compared pairwise. Although only 2019 results are presented here, the findings were consistent across the 3-year study period from 2019 to 2021.

From Figure 1(a), the pairwise comparisons across three methods yielded high correlation coefficients (CC) of 0.98 for each pair, indicating a strong correlation between the methods. This was further supported by a subset analysis for segments with a PSL of 55 mph (Figure 1(b)), with CCs between 0.94 and 0.95, and similar CCs across other PSL groups (55, 60, 65, 70 mph), with CCs ranging from 0.91 and 0.97.

The similarity in FFS estimates extended beyond PSLs and was observed across factors including urban-rural designation, segment length, and number of through lanes. Figures 1(c) and 1(d) illustrate example comparisons for urban-rural designation and segment length. The results indicate robust correlations among the three methods across those factors, with CC values ranging as follows:

- Urban-rural (Figure 1(c)): Urban (CC = 0.97), Rural (CC = 0.95 – 0.97)
- Segment length: 0 to 9 miles by each mile (CC = 0.76 – 0.99)
- Number of lanes per direction: 2 to 6 lanes by each lane count (CC = 0.91 – 0.99)

The lower CC of 0.76 observed from the segment length comparisons may be attributed to the scarcity of TMCs with extended lengths (only 28 TMCs were longer than 7 miles, and 58 TMCs were longer than 6 miles). From these comparisons, FFS estimates produced by all three methods exhibit similar trends, irrespective of factors such as PSL, urban-rural designations, segment lengths, and the number of through lanes.

Table 1 compares the FFS estimates from the three methods to the PSLs for urban and rural designations. Each row presents results for a unique PSL and urban-rural combination, with columns showing the maximum, average, variance, and minimum value of the difference between FFS estimates and PSL. Notably, results for PSL = 60 mph in rural areas are omitted due to its small sample size (n = 2), and caution is advised for the PSL = 55 mph in rural areas category (n = 7). The results in all other columns are based on sample sizes mostly exceeding 100. The data indicates that FFS estimates generally exceed PSL, and the differences between PSL and FFS narrows as PSL increase. The "Var" columns reveal that segments with lower PSL exhibit greater variances. It is also observed the differences between FFS estimates and PSL on rural segments displayed higher average and variance. Among the methods, the TTI method, despite showing similar trends to the other two methods, yielded lower FFS estimates, regardless of PSL or urban-rural designations. The average differences between FFS estimates from the

FHWA, Jha, and TTI methods and PSL are 4.9 mph, 5.1 mph, and 1.4 mph, respectively, reinforcing that the TTI method's lower FFS estimates.

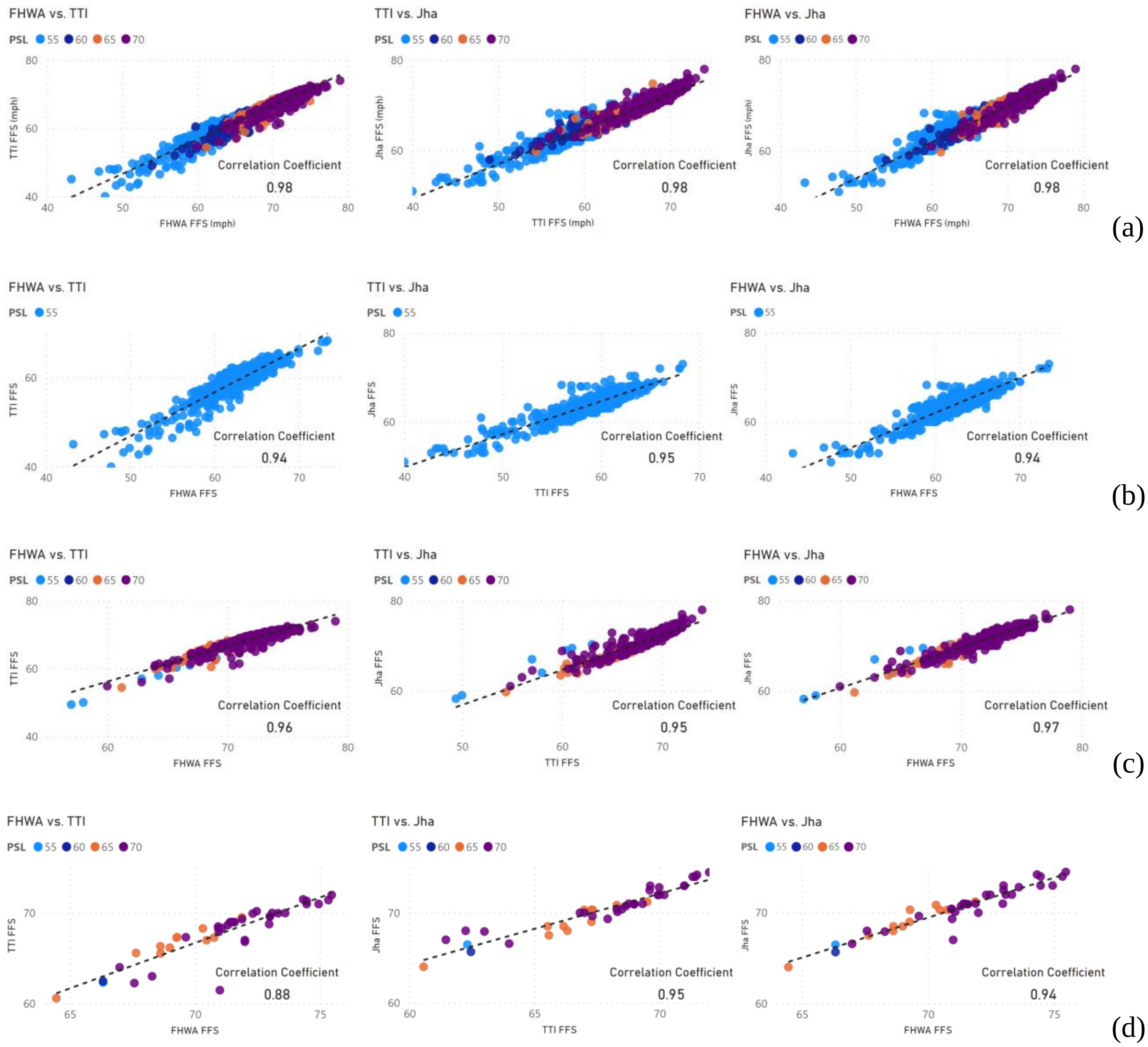

Figure 1. Comparison among FHWA, TTI, and Jha FFS estimates (a) across all roadway segments, (b) on segments with posted speed limits of 55 mph, (c) rural segments, and (d) segment lengths between 4 to 5 miles.

Comparison of FFS Estimates with Commonly Used Reference Speeds

Arithmetic Operations Based on Posted Speed Limit

One commonly used FFS method involves simple arithmetic operations based on the PSL (e.g., PSL plus 5mph) of a segment due to its simplicity, as exemplified by Florida DOT (Florida DOT, 2023). Table 1 shows that FHWA and Jha FFS estimates are often about 5 mph above PSL, suggesting an effective approximation. However, the accuracy of this simple method varies with PSL: lower PSLs often result in FFS more than 5 mph above PSL, while higher PSLs tend to yield smaller increases. Despite its straightforward nature, this arithmetic operation method displays systematic bias, necessitating cautious interpretation of its results.

TABLE 1. Comparison between FFS Estimates and Posted Speed Limit Breakdown by Urban-Rural Designations

PSL	FHWA FFS – PSL (mph)				Jha FFS – PSL (mph)				TTI FFS – PSL (mph)				Urban/ Rural
	Max	Avg	Var	Min	Max	Avg	Var	Min	Max	Avg	Var	Min	
55	14.1	8.4	17.3	2	15.3	10.3	21.5	3.2	8.0	2.0	24.5	-5.6	Rural
55	18.4	7.5	14.5	-11.8	18.0	8.9	10.7	-4.0	13.3	4.2	16.1	-15.0	Urban
60	-	-	-	-	-	-	-	-	-	-	-	-	Rural
60	10.9	6.3	6.7	-6.0	10.5	6.6	4.7	-2.0	8.5	2.6	9.0	-11.0	Urban
65	8.8	4.7	5.6	-3.8	8.0	4.2	6.2	-5.3	5.9	1.6	8.4	-10.6	Rural
65	10.0	4.8	3.8	-0.9	9.8	4.9	2.7	-0.5	6.5	1.4	4.4	-7.7	Urban
70	9.0	2.3	5.8	-10.0	8.0	1.6	5.2	-9.0	4.0	-1.1	6.6	-15.2	Rural
70	6.0	1.8	3.2	-6.3	5.0	1.4	3.0	-7.0	1.7	-1.5	4.0	-11.0	Urban
All	**18.4**	**4.8**	**14.0**	**-11.8**	**18.0**	**5.1**	**17.1**	**-9**	**13.3**	**1.4**	**15.3**	**-15.2**	**All**

NPMRDS Reference Speed

The NPMRDS Reference Speed (hereafter RS), associated with each TMC, is another commonly used FFS estimate. The RS is determined as the 95th percentile of speeds recorded from 10 pm to 5 am over a 6-month period spanning from April 1 to September 30, 2017 (RITIS, 2023). Figure 2 presents a comparative analysis of RS against FFS estimates from TTI, Jha, and FHWA methods, providing several key observations:

1. RS composed entirely of integer values, yielding a discrete appearance on the x-axis.
2. Significantly lower CCs, ranging from 0.64 to 0.74, are observed between RS and each of the three FFS estimates. This contrasts with the high CCs around 0.98 among FFS estimates themselves.
3. RS displayed considerable variability and lacked a consistent trend with PSL in the scatterplots. For example, RS values varied widely from 56 to 88 mph for segments with a PSL of 55 mph and ranged from 62 to 85 mph for segments with a PSL of 70 mph.
4. Some extreme RS values are present in the upper range such as 88 mph, which are likely due to the 95th percentile basis of the metric that emphasizes higher outlier speeds. This indicates that caution should be exercised when directly utilizing the RS value for calculating performance metrics like delay or planning time index.

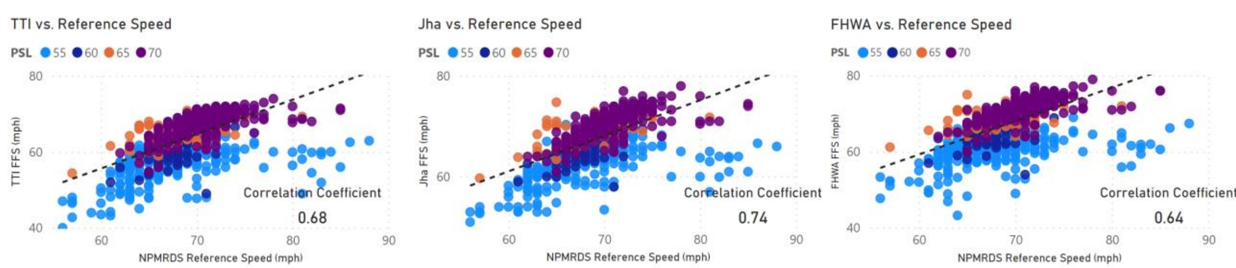

Figure 2. Comparison of FHWA, TTI, and Jha FFS Estimates to NPMRDS Reference Speed

Comparison of Delays from Different Congestion Thresholds

Statewide Congestion Analysis

Figure 3 presents a comparison of statewide delay (measured in vehicle-hours) calculated using varying delay thresholds with FHWA FFS. As expected, strict thresholds (e.g., 90% of FFS), result in higher total delay values when compared to lower thresholds (e.g., 70% of FFS). Notably, the reduction in total delay is greater when transitioning from higher to moderately high thresholds (e.g., 90% to 85% of FFS) versus lower thresholds (e.g., 75% to 70% of FFS). This can be attributed to the fact that stricter thresholds tend to capture all speed reductions on roadways, while lower thresholds only capture the most severe congestion events. Since severe congestion occurs less frequently than moderate congestion, the magnitude of delay change is smaller when transitioning between lower thresholds, however, it should be highlighted that the percentage change in delay may not necessarily be smaller.

Analysis of the statewide delay values reveals that utilizing PSL as the congestion threshold results in the highest delay value, while the fixed threshold of 45 mph yields the lowest delays. Comparing across years, a significant decline in delay in 2020 was observed, due to the COVID-19 pandemic's impact on traffic volume. Despite increased delay in 2021, the total delay remained below the pre-pandemic levels. A noteworthy pattern emerges in the comparison between delays calculated using the PSL threshold and the fixed 45 mph threshold. In 2019 and 2021, delay calculated by the PSL threshold was roughly 1.56 times the delay calculated by the 45 mph threshold; however, this ratio increased to 1.9 in 2020. This discrepancy may arise from the reduction in traffic volume in 2020, which presumably mitigated the occurrence of the most severe congestion scenarios (captured by the 45 mph threshold).

The substantial variation in total delay estimates across different congestion thresholds underscores the significant influence that the chosen delay definition has on the magnitude of calculated delay. Hence, it highlights the critical need for a standardized delay calculation methodology to avoid potential bias in benefit assessment.

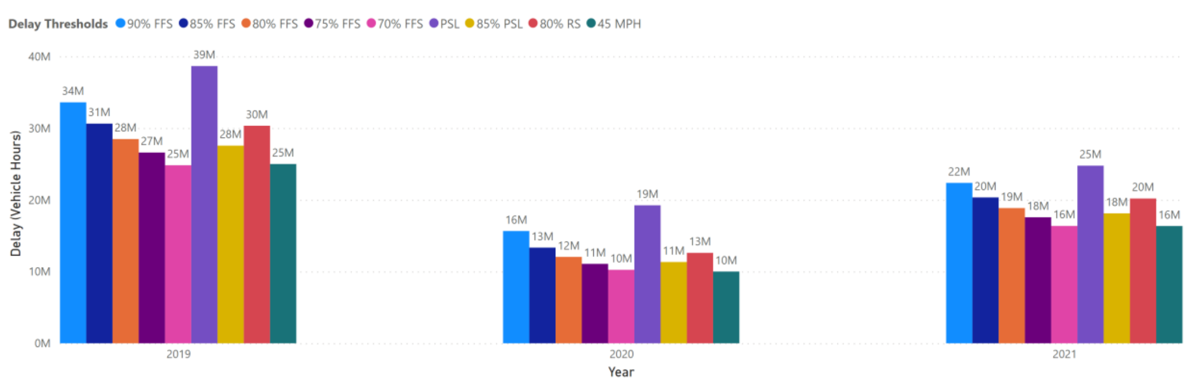

Figure 3. Comparison of Statewide Vehicle-Hours of Delay Calculated using Different Thresholds

Districtwide Congestion Analysis

A comparative analysis of delay across VDOT's nine districts (see Figure 4) was conducted for the year 2019. Table 2 shows that the Northern Virginia District, the most densely populated area, experienced the highest delay at all thresholds, followed by the Hamption Roads District (the 3rd largest mileage of interstate roads); while the Richmond District has the most interstate mileage, it ranked third in total delay, indicating the summation of total delay may not be correlated with the toad mileage in each district.

Figure 5 reveals that the highest total delays per district are estimated either by the 90% FFS threshold or the PSL threshold methods. In districts like Northern Virginia and Fredericksburg, delays derived from the 90% FFS threshold exceed those with PSL threshold, whereas in other districts, PSL threshold methods lead to higher delays. Table 3 shows that the difference between FFS and PSL varies by district, as well as the difference between 90% of FFS and PSL. Generally, when the average value of (90% FFS – PSL) is negative, the delay resulting from the PSL threshold tends to exceed that calculated using the 90% of FFS threshold.

Figure 4. Districts of Virginia Department of Transportation

Table 3 also indicates FFS estimates are generally higher than the PSL and the differences decrease for segments with higher PSL. Given the variation in PSL distributions across different Districts, it is imperative to approach comparative delay analyses with caution to prevent biased outcomes. Incorporating this into a more comprehensive perspective, it is crucial to exercise caution when comparing delay values across segments with different PSLs, ensuring meaningful interpretations of delay magnitudes across various Districts and roadway segments.

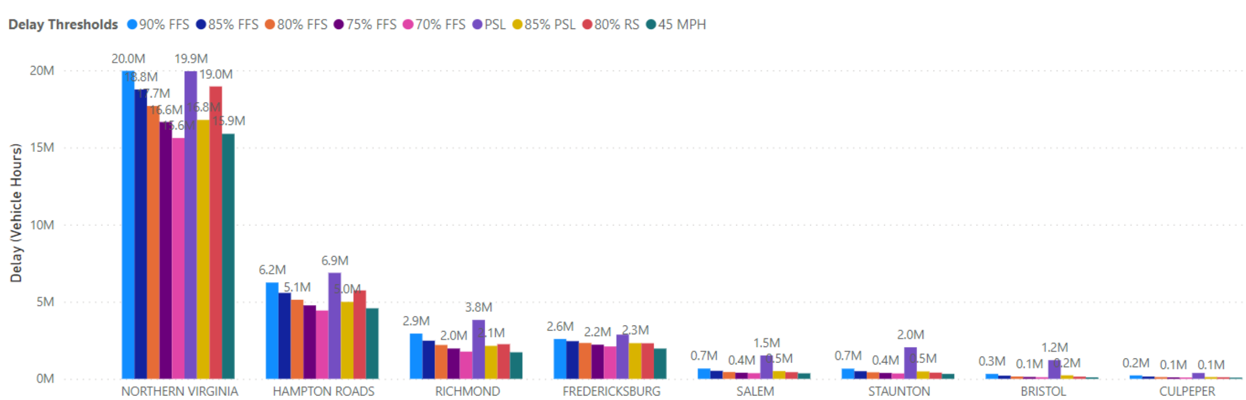

Figure 5. Comparison of Districtwide Vehicle-Hours of Delay Calculated using Different Thresholds

TABLE 2. Mileage of Studied Segments by District.

District	Total Mileage (mile)	Rank of Total Delay
Richmond	514.6	3
Staunton	462.4	6
Hampton Roads	311.2	2
Bristol	241.3	7
Salem	239.0	5
Northern Virginia	222.8	1
Fredericksburg	99.0	4
Culpeper	98.8	8

TABLE 3. Breakdown of PSL, FFS, and Difference Between PSL and FFS, by District.

District	Average of PSL	Average of FFS	Average of (FFS-PSL)	Average of (90%FFS-PSL)
Northern Virginia	56.3	64.1	7.8	1.4
Hampton Roads	59.4	66.0	6.6	-0.0
Richmond	63.2	69.4	6.2	-0.8
Fredericksburg	66.6	71.6	5.0	-2.2
Culpeper	67.8	72.8	5.0	-2.3
Salem	64.5	67.6	3.1	-3.7
Staunton	68.8	71.6	2.7	-4.4
Bristol	69.1	70.4	1.2	-5.8

Corridor-wide Congestion Analysis

Figure 6 highlights two major commuter corridors in Northern Virginia District, I-66E and I-395N, that carry substantial traffic volumes into Washington D.C. Table 4 summarizes the annual vehicle-hours of delay for these corridors during weekdays from 6 am to 8 pm, under varying delay thresholds. For I-395N, the highest delay is observed using the 80% RS threshold, while for I-66E, both the 90% FFS and PSL thresholds result in maximum delay.

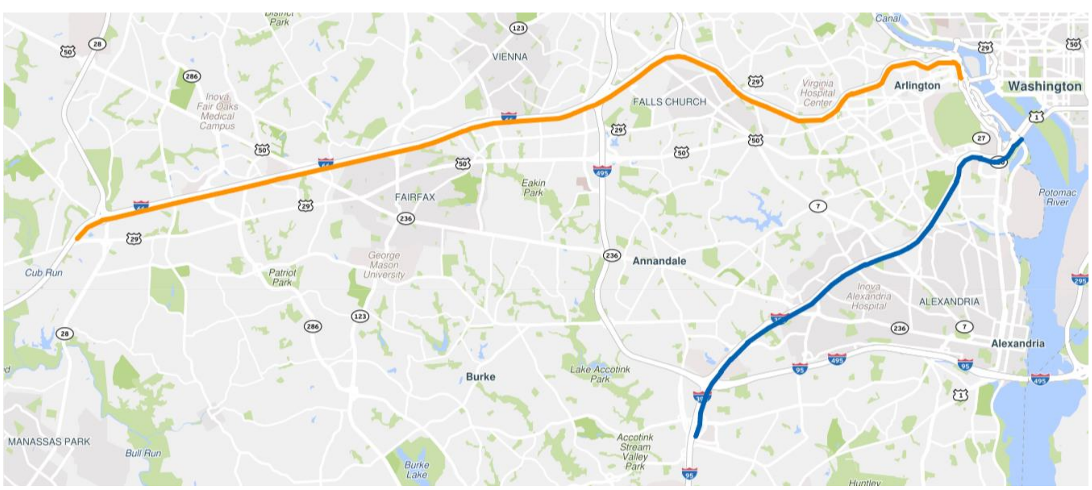

Figure 6. Commuting Corridors of Interstate I-66 Eastbound (orange line) and Interstate I-395 Northbound (blue line)

Under the PSL, 90% FFS, 80% FFS, and 80% RS thresholds, I-66E exhibits greater delay than I-395N. Conversely, when employing lower thresholds of 70% FFS and 45 mph, I-395N registered higher delays. This may suggest that the I-395N corridor experienced more instances of severe congestion, such as segments operating at speeds lower than 45 mph. However, if one defines delay as any reduction in speed below PSL, I-66E could have a higher overall delay. This observation demonstrates how different delay definition can yield conflicting results, emphasizing the necessity for a consistent methodology.

TABLE 4. Estimated Delay for Interstates I-395N and I-66E under Different Congestion Thresholds for the Year 2019.

	Delay (vehicle-hours) Under Different Congestion Thresholds					
	PSL	**90% FFS**	**80% FFS**	**70% FFS**	**80% RS**	**45 MPH**
I-395 N	1,844,682	1,837,350	1,651,944	1,484,327	1,881,445	1,559,865
I-66 E	1,925,097	1,927,980	1,665,607	1,422,298	1,909,922	1,515,820

Observations and Discussions

Free-Flow Speed

FFS estimation methods based on the 85th percentile of observed speeds, specifically FHWA, TTI, and Jha methods, show strong correlations in their results. Conversely, methods using the 95th percentile or arithmetic operations on PSL exhibit weaker correlations with those based on the 85th percentile. While the 85th percentile methods generally produce FFS estimates higher than PSLs, the discrepancy diminishes with increasing PSL. Although the FHWA and Jha methods yield FFS approximately 5 mph above PSL, a uniform addition of 5 mph to PSL does not adequately reflect the variabilities in the PSL-FFS relationship across roadways of different PSLs.

Congestion Threshold

The choice of congestion threshold significantly influences the resulting magnitude of estimated delay, as demonstrated through analyses at different spatial aggregation levels. Comparability of delay patterns and rankings are contingent on the chosen delay threshold. When evaluating delay-based metrics, caution should be exercised for comparisons across regions with varying PSL distributions, as varying threshold inconsistencies can lead to skewed outcomes.

Importance of Consistent FFS Estimation Method and Congestion Threshold

From the aforementioned observations, it can be concluded that adopting consistent FFS methodology and congestion threshold for delay estimation is important for transportation project prioritization for several key reasons:

- Enhanced Consistency: Standardization facilitates equitable comparisons and evaluations of projects from diverse geographical areas or originating from different localities. Without a common benchmark, projects evaluated using different FFS methods or varying congestion thresholds for delay estimation yield incompatible assessments. A unified approach ensures that projects are assessed on an equitable basis.

- Reduced Bias: Different FFS methods and congestion thresholds can produce markedly different outcomes, leading to potential biases in project prioritization. For instance, a method yielding higher FFS estimates or the use of excessively high delay thresholds could overstate a roadway segment's congestion problem, leading to unwarranted project prioritization. Therefore, selecting parameters that align with the agency's objectives is crucial to ensure a balanced and objective project evaluation process.

CONCLUSIONS

This study demonstrates how discrepancies in FFS estimations and congestion delay thresholds substantially influence transportation planning and decision-making. Specifically, this research reveals that the selection of FFS methods and congestion threshold for delay estimation critically alter delay calculations, influencing perceptions of the extent and severity of traffic congestion. These findings underscore the vital need for consistency in FFS and delay methods to ensure credible and consistent project evaluation and prioritization. Without consistent definitions, a project location could appear congested purely due to analytical assumptions rather than actual traffic conditions. Thus, delay reduction benefit estimates are similarly vulnerable to distortion, risking biased project prioritization. In response to the findings, transportation agencies should adopt consistent FFS and delay approaches grounded on their objectives and analytical needs.

Future research should extend beyond interstates to include diverse roadway segments and examine the impact of FFS estimates on other performance measures like travel time reliability. Nonetheless, the importance of establishing consistent analytical approach is evident, though the optimal definitions of FFS and congestion delay may evolve with future research and to align with the agency's goals.

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Assessing the Impacts of Real-Time GPS Navigation Applications on Trip Routing and Diversion Rates

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ABSTRACT

Smartphone navigation applications and in-vehicle navigation technologies provide drivers with real-time traffic conditions and route guidance among other numerous benefits. These technologies promise transformative improvement in daily commutes and prevent the possible increase in traffic delays and congestion. The limits of such benefits are dependent on the frequency of using the navigation applications, diversion rates, and the percentage compliance with the suggested re-routing. Commuters in Broward County, southeastern Florida, were surveyed to understand their preferences and the factors affecting route choice decisions. A multiple linear regression model was used to predict actual traffic diversion rates and to validate the survey results. Major findings of this research included a variety of characteristics associated with navigation applications, drivers' behavior, and roadway facility usage. In general, navigation applications have a significant re-routing potential, and drivers are likely to divert 20% to 39% of the time. It was found that most drivers would consider a re-routing suggestion when the delay per 1-h trip is approximately 15–30 min. Finally, the results were consistent with the regression model and showed that the actual diversion rate ranged from 1% to 20%.

Keywords: Navigation Applications, Real-time Traffic Conditions, Traffic Diversion, Commuters Survey, Advanced Traveler Information Systems.

INTRODUCTION

Transportation authorities and local governments are striving to improve traffic safety and mobility through the continuous design and implementation of intelligent transportation technologies. Nowadays the widespread of routing applications through smartphones and wireless devices have profoundly impacted the transportation system and the mobility habits of drivers. Routing applications that utilize Global Positioning System (GPS) such as Google Maps and Waze have become widely used among travelers all over the world. Navigation applications can natively provide useful real-time information through technologies and communication protocols such as Bluetooth, Wi-Fi, and satellite navigation. Routing applications are intended to bridge the functionality of the Advanced Traveler Information Systems (ATIS) and provide mobility information for drivers about real-time traffic conditions. The current technology in routing applications allows commuters to plan their trips according to traffic conditions and suggest alternate routes with improved mobility.

ATIS and connected vehicle-based technologies provide significant benefits and cost-effective solutions to address the performance issues facing transportation networks (Arafat et al., 2021). Over the last few years, ATIS prototyping and assessment have been a focus of transportation research. These information services record or infer user decisions and other contextual trip data that when suitably processed can improve transportation system management. For example, the provision of transit schedule data to Google Maps to support the Google transit trip planner is another key achievement within the transit traveler information industry (Burgess et al., 2012). The use of navigation technologies has increased significantly in the past years due to the useful real-time information provided by these technologies. The extent of the benefits of these technologies relies on the user's behavior and characteristics. Thus, it is increasingly important to understand the impact of these technologies on traffic routing and the roadway facility selection by drivers, and its implications on traffic congestion management.

The beneficial aspects of traveler information systems have received wide attention in the academic literature. Tools such as microscopic simulation and laboratory experiments bring a range of benefits in modeling intelligent transportation systems and ATIS (Arafat et al., 2020). For instance, researchers investigated the benefits of navigation applications using a laboratory simulation experiment (Wade et al., 1991). The goal of the experiment was to understand the impacts of four different navigation technologies on driver behavior and diversion decisions. The simulation was carried out for freeway trips utilizing real-world freeway scenes and computerized auditory feedback. The researchers included variables such as age group, familiarity with the trip route, and either commercial or noncommercial driving experience. The study results showed that the characteristics of navigation applications have a significant impact on the diversion behavior among drivers and their anticipation of traffic congestion. Adler et al., (1993) developed mathematical equations to model the potential impact of ATIS on driver behavior and diversion rates using laboratory simulation. The results showed that ATIS significantly influences traffic diversion rates.

Shirazi et. Al., (1988) examined the influence of traffic information systems such as electronic Dynamic Message Signs (DMS), radio reporting, and traffic information telephone numbers, on the frequency of diverting from freeways in Los Angeles, California. The findings from 400 surveyed commuters showed that 41% of the commuters are willing to divert to an alternative freeway while 31% of the respondents never divert. In general, 70% of drivers would consider diverting during stop-and-go traffic conditions when the available navigation information is reliable. In an attempt to understand the impact of traffic conditions on route diversion, Mahmassani et al., (1990) surveyed commuters in Austin, Texas, and identified their preferences. The survey collected commuting data from 3,000 randomly selected households in large residential suburban areas with two highly major congested corridors. The survey results showed that traffic congestion is one of the primary reasons that influence diversion rates, particularly in the evening peak period. In addition, geographic and network characteristics appear to be a primary influence on route switching in the morning peak period. It was found that the availability of information through ATIS and in-vehicle navigation had a significant positive impact on route switching frequency.

The rate of diversion is a function of the increased delay per trip as a result of congestion. Drivers are more encouraged to take alternate routes to avoid traffic congestion when the delay per trip exceeds a certain percentage of trip duration. Khattak et. Al., (1996) studied the benefits of ATIS during congested traffic conditions and the impact of trip characteristics on route selection. The researchers developed a multinomial logit model to estimate the changes in travel decisions due to travel time and commute information. The study surveyed 586 commuters from the Bay area in Berkeley, California. The results showed that the majority of commuters would not necessarily consider diversion based on ATIS and 45% of the respondents did not change their travel plans despite having expected congestion information.

Theoretically, the usage of routing applications has the potential to assist road users in solving traffic congestion problems and suggesting alternate routes to provide travel time savings and avoid delays. However, the limits of such benefits are dependent on the frequency of using the route guidance applications, diversion rates, and the percentage compliance with the suggested re-routing. The objective of this research study is to understand the current user preferences related to the likelihood and frequency of using route guidance applications. In addition, the study investigates the influence of these applications on roadway facility usage, drivers' speed, and travel time savings. The outcome of this study will help transportation planners and policymakers to better understand the impact of these technologies on the influx of vehicles toward different roadway facilities and develop effective strategies for traffic congestion management.

LITERATURE REVIEW

The benefits of real-time traffic information provided by navigation technologies and the impacts on diversion rates have been explored in previous research studies. Cohn (2009) explored such benefits by combining four traffic information data sources into a single feed and communicating this information with drivers through connected personal navigation devices. The study reported that navigation technologies offer the ability to choose travel routes based on accurate and real-time information. In addition, these applications allow motorists to plan their routes before departure and to make better choices related to departure times.

Jou and Mahmassani (1996) surveyed the behaviors of commuters in Dallas and Austin, Texas to analyze the day-to-day commuter decisions and the factors affecting route choice decisions. The researchers collected responses from samples of households in both cities. The study compared several factors related to traffic and socioeconomic characteristics and assessed the transferability of the model parameters. The results showed that the survey responses were statistically similar in both cities. More frequent route diversion rates were captured in the evening period than in the morning period. In addition, the study reported that socioeconomic characteristics, traffic conditions, and routine stop variables have a similar impact on the diversion rates during the morning period in both cities.

Traveler Information technologies provide a time-dependent shortest path from origin to destination for travelers (i.e., pre-trip planning) or from the current location to a destination (i.e., rerouting) (Hadi et al., 2019). Previous research efforts suggest that the benefits of ATIS and navigation applications depend on understanding drivers' route-switching behavior. This route behavior is a complex process that relies heavily on variables such as the socioeconomic characteristics of drivers and latent individual characteristics. Pal (1998) incorporated three latent factors including risk acceptance, traffic information trust, and level of expectation in a binary logit model to understand route diversion intentions among drivers. The study results showed that the latent factors and socioeconomic characteristics such as age, gender, and marital status were statistically significant. Hadi et al., (2019) developed a tool that evaluates the impact of advanced technologies that include ATIS on the transportation system performance during existing and future year conditions. The researchers reported that traveler information dissemination technologies provide multi-modal information dissemination and trip planning tools that are useful for users.

According to the review of the literature above, the drivers' route-switching and commuting behavior can be different from one city to another. Researchers conducted commuting surveys in several cities and reported various trip routing and diversion behaviors according to the different socioeconomic characteristics. There is a gap in the literature particularly in quantifying the frequency of using the navigation technologies on different roadway facilities and the travel time savings as a result of such use. This study is designed to understand the current drivers' preferences in southeastern Florida regarding the use of navigation technologies and the influence of traffic diversion on roadway facility usage, drivers' speed, and traffic congestion.

METHODOLOGY

Comprehensive commuter navigation surveys were conducted to quantify the frequency of using navigation technologies and the traffic diversion rates as a result of such use. Commuters in Broward County, southeastern Florida were surveyed through an online survey and in-person survey to identify how various types of navigation applications are currently used. The goal is to understand how often daily commuters would divert between different roadway classifications using suggested routes by navigation applications. The survey collected data related to commuting characteristics, means of in-vehicle navigation, factors influencing diversion rates, and commuters' compliance rates towards the improved suggested routes.

Data Collection

Data were collected for more than 300 responses that represent a sample of the major cities including Hillsboro Pines, Sunrise, Coconut Creek, Davie, Lauderdale Lakes, and Plantation. The study location and selected sites are shown in Figure 1. Regarding the in-person surveys, the interviewers approached individuals and provided a summary of the overall objective of the survey. Participants were further screened as only adults who regularly drive a vehicle and mainly use a navigation method were eligible for participation in the survey.

Data Validation

Regression models have been widely used in previous transportation research studies (Sharafeldin et al., 2022). Tariq et al. (2022) developed a model that predicts the rate of traffic diversion during freeway incidents derived from real-world traffic diversion patterns. This study utilized the results from that work to further validate the quality of the survey results and provide a comparison between diversion rates based on the input from the survey respondents and the prediction model. Using this model, actual diversion rates were predicted for the incidents that occurred within the same study area where the surveys were conducted. Below is a short description of the prediction model and the detailed methodology can be found in Tariq et al., (2022).

The traffic data for the study area was obtained from the Regional Integrated Transportation Information System (RITIS). In addition, the traffic incident data including incident severity and location were retrieved from the incident management database managed by the Florida Department of Transportation. Utilizing the R software package, a Multiple Linear Regression analysis was conducted to estimate the correlation between the traffic diversion rate (Y) as the dependent variable and Xi as the explanatory variables that are expected to influence the diversion rates. The Multiple Linear Regression is expressed as shown in Equation 1:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots\cdots\cdots + \beta_n X_n \tag{1}$$

Where:
Y = dependent variable (i.e., diversion rate),
X_1 to X_n = independent variables,
β_1 to β_n = regression coefficients.

The regression model shown in Equation 1 considered several independent variables that are expected to have a significant contribution to the traffic diversion rates. The variables include the incident location and severity, the number of blocked lanes, and a surrogate measure for the congestion level on the freeway namely "time slice of incident occurrence". Table 1 shows the relationship between the variables used in the model. The adjusted R-squared coefficient of determination for the developed model is 0.6025. The Mean Absolute Error (MAE) of the dependent variable (Y) compared to the actual diversion rate is 3.20%. As shown in Table 1, the four variables considered in the analysis are significant at the 5% confidence level.

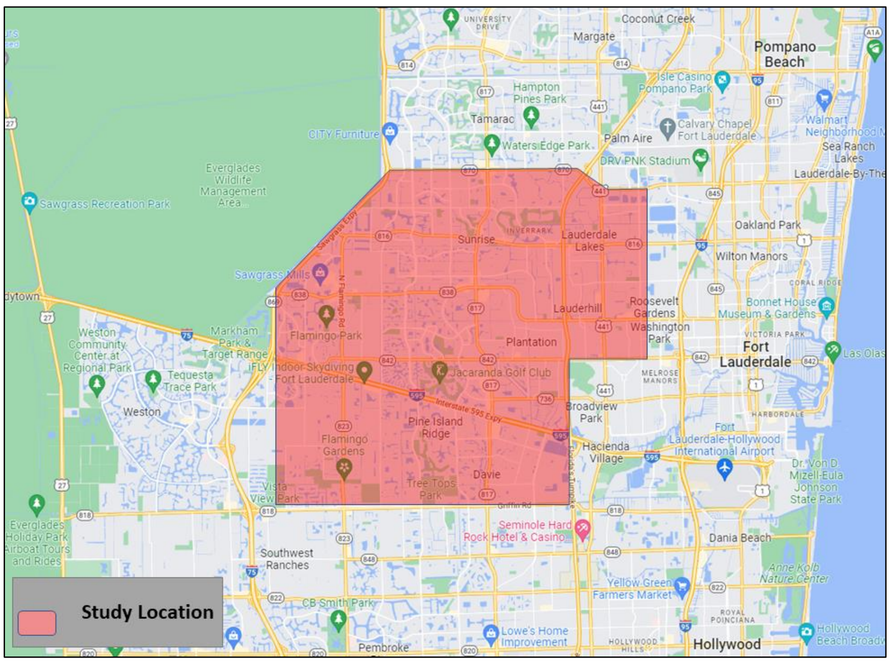

Figure 1: Study Location Map

Table 1. Regression Model Significance

Variables	Coefficient	Pr(>|t|)
Incident Location	0.4242	0.033404
Incident Severity	2.2655	0.006277
Number of Blocked Lanes	1.7089	0.000392
Time slice of Incident Occurrence	-2.6621	0.010086
Multiple R-squared	0.614	
Adjusted R-squared	0.6025	
P-value	2.2e-16	
Mean Absolute Error	3.20%	

To compare the model results with the survey results, the delay for each incident is calculated using queuing theory to estimate the diversion rate as a function of delay as shown in Equation 2:

$$\text{Vehicle Delay} = \frac{60\ t_r\ (\lambda - \mu_r)}{\lambda} \quad (2)$$

Where:
Vehicle Delay = calculated as minutes per vehicle,
t_r= incident duration,
λ = traffic demand (veh/hr),
μ_r= reduced capacity due to blocked lanes (veh/hr),
The incident duration was considered from the start time to the end time of each incident. In addition, the traffic demand was incorporated using traffic volume provided by freeway detectors in a five-minute resolution. Moreover, the reduced capacity due to lane blockage is calculated using Equation 3:

$$\text{Remaining capacity, } \mu_r = f * \text{C (pc/hr)} \quad (3)$$

Where:
C = capacity of the freeway (1900 pc/hr/ln),
f = capacity adjustment factor (obtained from HCM for lane blockage)

Data Analysis and Results

The surveys captured a total of 315 responses for the online survey and 41 responses for the in-person survey. All responses were collected from people who regularly drive within the study area at least twice per week. The majority of the respondents who filled out the in-person survey were 61% males with 83% being between 18 to 44 years old. Regarding the online survey, the majority of respondents were 64% females, among them 69% were 18 to 44 years old.

Vehicle-based Navigation Applications

Different questions were designed to test the public's awareness and experience with Traveler Information Systems and other means of vehicle navigation. The survey listed several navigation techniques such as smartphones, DMS, and websites that are commonly used by drivers for accessing real-time traffic and weather information. In addition, new vehicles nowadays feature stand-alone navigation systems that are used for route guidance.

The results from both surveys were quite similar and show that approximately 44% to 50% of drivers use iPhone applications during navigation. Figure 2 shows the percentage use of different vehicle navigation technologies and the most common methods of navigation used. The majority of the collected responses show that Google Maps was the most common application used compared to Waze, INRIX, and TomTom.

Additional questions were asked to estimate the frequency of using navigation applications. Results from the online survey show that approximately 38% to 40% of drivers use mapping applications almost daily, 18% to 26% use the applications at least once per week, 13% to 16% use the technology at least once per month, and the remaining drivers use the technology several times per year or never use them. In addition, the in-person survey results were quite similar and show that the majority of drivers use mapping applications almost daily. Drivers were asked to classify the use of navigation applications by roadway classification. Results show that 32% percent of drivers use the applications on freeways, while 37% and 25% use the applications on major roads and neighborhood streets, respectively.

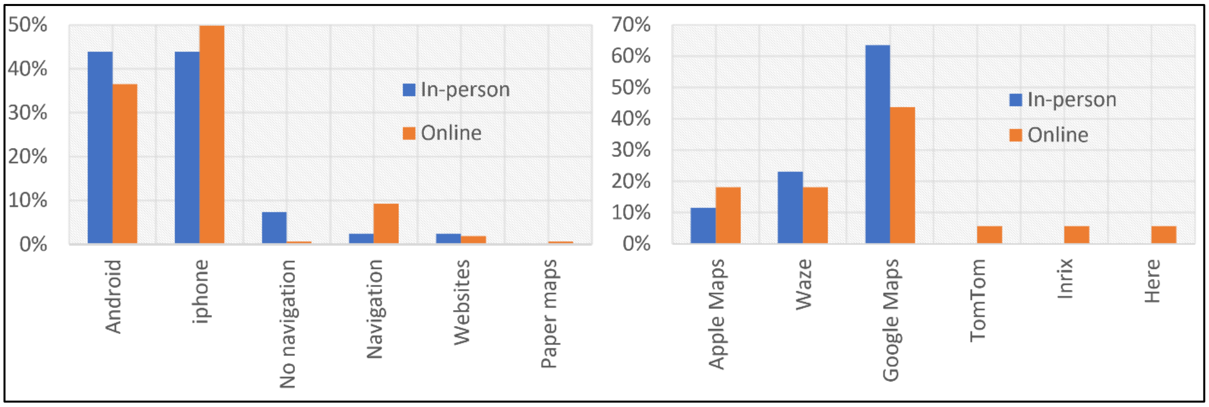

Figure 2. Vehicle Navigation Methods

Trip Type and Diversion Rates

The purpose of commuter trips and trip duration are also additional parameters that trigger the use of navigation technologies. Drivers tend to use mapping applications normally for first-time trips and infrequent trips more than regular-commute and non-commute trips. Commuters were asked to estimate their percentage use of navigation applications by trip type (i.e., regular commute, regular non-commute, infrequent, and first-time trips) and trip duration. For analysis purposes, the application usage is divided into three categories as follows; 1 to 5 minutes per trip (i.e., low use), 5 to 30 minutes per trip (i.e., moderate use), and 30 to 60 minutes per trip (i.e., high use). Results from Table 2 shows that on average drivers use navigation applications moderately for regular commute trips, non-commute trips, infrequent trips, and first-time trips.

Table 2. Percentage of navigation applications usage by trip type and duration.

Online Survey	**No Use**	**Low Use**	**Moderate Use**	**High Use**	**> 1hr**	**N/A**
Regular commute trips	22.0%	11.2%	39.5%	16.3%	10.5%	0.5%
Regular non-commute trips	40.7%	11.9%	35.6%	5.4%	4.6%	1.8%
Infrequent trips	15.5%	12.5%	48.5%	12.8%	8.4%	2.3%
First-time trips	2.9%	11.1%	43.5%	19.4%	20.9%	2.2%
In-person Survey	**No Use**	**Low Use**	**Moderate Use**	**High Use**	**> 1hr**	**N/A**
Regular commute trips	25.6%	13.9%	37.2%	16.3%	6.9%	0.1%
Regular non-commute trips	40.5%	14.3%	19.1%	7.1%	14.3%	4.1%
Infrequent trips	18.2%	22.7%	40.9%	9.1%	2.2%	6.9%
First-time trips	6.4%	6.4%	34.0%	14.9%	36.2%	2.1%

Respondents were asked to estimate the probability of diversion during an incident based on the trip type. The results show that drivers consider diverting if the travel is mostly for regular commute trips (56 %) and infrequent trips (26%). According to the online survey, drivers are less likely to divert during regular non-commute trips and first-time trips. However, the in-person survey shows that approximately 17% of the respondents would consider diverting during regular non-commute trips.

The survey participants were asked to estimate their average diversion rate in the last three months. The results show that the diversion rate follows a normal distribution as shown in Figure 3. It can be inferred from this figure that the majority of the respondents are likely to divert 20% to 39% of the time. The frequency of diversion rate was compared to the gender and age of the commuters. The results show that variables such as gender and age had no statistically significant correlation to the frequency of diversion rates.

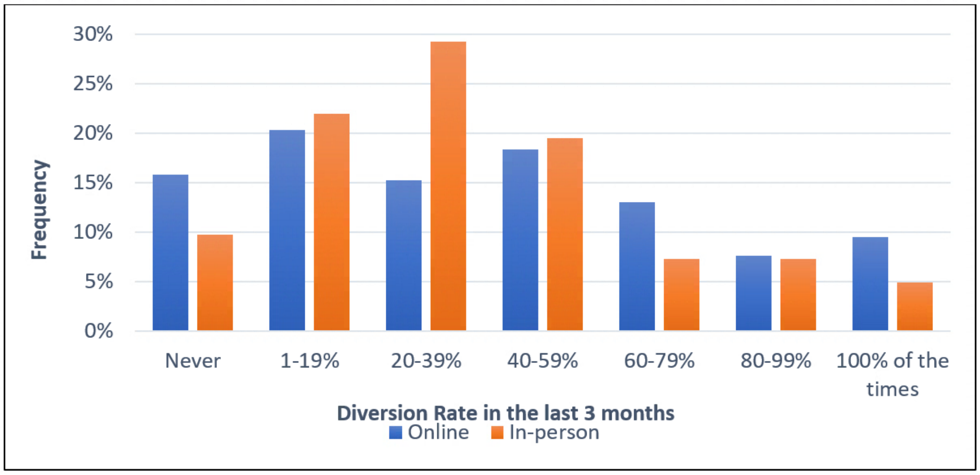

Figure 3. Diversion Rates Based on Routing Applications

The accurate prediction of traffic diversion and the change in diversion rates with the support of available traveler information systems can significantly reduce traffic congestion and delays during incidents. Drivers tend to divert during incidents based on their own experience and the incident history on a specific route. The delay threshold for drivers to switch from their usual route was one of the main questions of the surveys. Commuters were asked how much an increase in delay for a one-hour trip would make them consider diverting. The results from the online survey show that approximately 14% of the respondents would consider diverting when the delay per 1-hour trip is as low as 7 minutes. On the other hand, 9.5% of the respondents would never divert even if the delay per 1-hour trip is as high as 30 minutes. According to Table 3, both the online and the in-person surveys show that the majority of the population would divert when the delay per 1-hour trip is approximately 15 to 30 minutes.

Table 3. Percentage of Diversion Per Delay Time

Answer	Online		In-person	
	%	Count	%	Count
Less than 7 min.	13.7%	43	7.3%	3
7 to 15 min.	23.9%	75	26.8%	11
15 to 30 min.	46.2%	145	58.5%	24
More than 30 min.	6.7%	21	5.0%	2
Never divert	9.5%	30	2.4%	1

Compliance Rate and Impacts on Roadway Classification, Speed, and Driver Alertness

The surveys were programmed to test the compliance rate of drivers with the suggested routes. The results from both surveys were similar and show that the majority of drivers would follow the re-routing 60% to 80% of the time. A notable result from this survey is that 19% to 32% of the respondents do not follow the suggested routes if the travel time savings are not sufficient or require a lot of maneuvering through neighborhoods. Users of the navigation applications were asked whether such use affects the selection between different types of roads (i.e., freeways, major roads, and neighborhood streets). Table 4 shows the impact of roadway classification on the percentage use of navigation applications. The results show a large increase in driving on freeways compared to major roads and local roads.

Table 4. Impact of Roadway Classification on Navigation Applications Use

Online Survey	Large increase	Small increase	Neither increase nor decrease	Small decrease	Large decrease	N/A
Freeways	39.9%	24.6%	24.6%	5.4%	1.7%	3.8%
Major Roads	36.2%	32.7%	20.3%	6.0%	1.6%	3.2%
Neighborhood streets	34.0%	22.6%	30.3%	8.3%	1.6%	3.2%
In-person Survey						
Freeways	43.9%	31.7%	14.6%	4.9%	4.9%	-
Major Roads	32.5%	30.0%	17.5%	17.5%	2.5%	-
Neighborhood streets	34.1%	17.1%	26.8%	12.2%	9.8%	-

Finally, the survey captured the users' perception of speed and alertness while using the navigation applications. Table 5 shows the impact of navigation technology use on speed and driver alertness. The results show that 53% of drivers reported an overall increase in alertness and speed.

Table 5. Impacts on Speed and Driver Alertness

Online Survey	Large increase	Small increase	Neither increase nor decrease	Small decrease	Large decrease	N/A
Speed	27.7%	24.8%	35.9%	6.7%	1.9%	3.0%
Driver Alertness	22.5%	30.8%	24.4%	12.7%	5.7%	3.9%
In-person Survey						
Speed	26.8%	21.9%	31.7%	12.2%	7.4%	-
Driver Alertness	19.5%	19.5%	14.6%	26.8%	19.6%	-

Comparison of Regression Model Results and Survey Results

This section shows a comparison between the diversion rates reported from the surveys and the Multiple Linear Regression model. Diversion rates at different delay levels were calculated for the incidents that occurred within the same study area by incorporating the regression coefficients shown in Table 1 into the model. The results from the regression model show that actual diversion rates ranged from 1% to 20%.

Regarding the survey results, the diversion rates were calculated based on the increased trip delay due to an incident. If the delay increase is more than 20% and the respondent diverts 30% of the time in the last three months, the probability of diversion for that driver is equal to zero when the delay is less than 20%. On the other hand, if the delay is more than 20%, then the driver considers diversion as an option and diverts 30% of the time based on other factors such as the type of trip, time of day, weather, etc. In such a case, the probability of diversion is 30% when the delay is more than 20%. Similarly, if a driver diverts 100% of the time and considers the diversion as an option at a 50% increase in delay, that means the driver always diverts when the delay is more than 50%. Figure 4 shows the average diversion rate versus the delay increase per trip for the survey data and the model prediction data. The results show that there is a consistent increasing trend of the average diversion rates with the increase in delay among the three methods. In addition, the survey results were consistent with the regression model and showed that the actual diversion rate ranged from 1% to 20%.

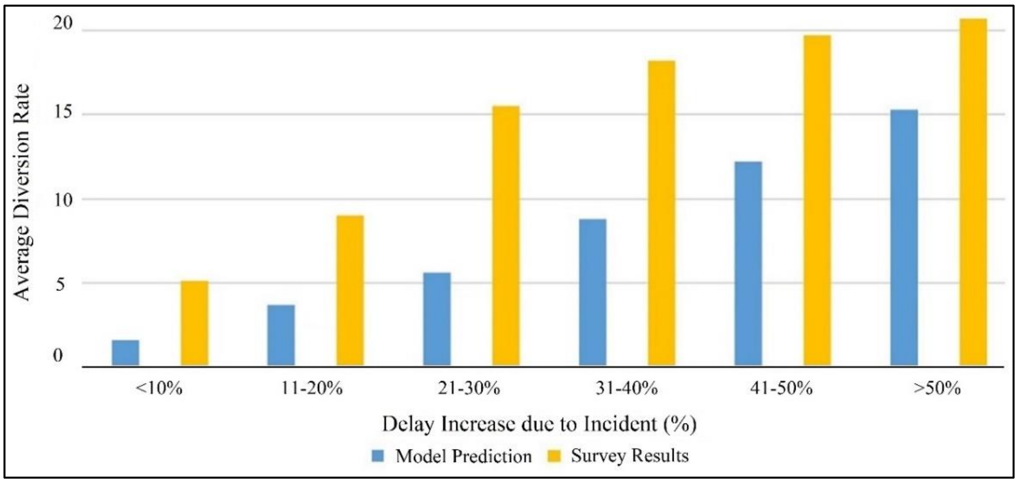

Figure 4. Diversion Rates as a function of incident delay

CONCLUSION

This paper evaluates the trip re-routing potential of route guidance apps and the impact of traffic diversion on roadway facility usage, congestion, and prevailing speeds. Comprehensive commuter navigation surveys were conducted to understand drivers' preferences and the factors affecting route choice decisions. A Multiple Linear Regression Model was used to predict actual traffic diversion rates. Results from the surveys showed that across all types of roadway facilities, the use of the applications led to a large increase in the actual use of the facility. The results showed that 56% and 26% of drivers consider diverting if the travel is mostly for regular commute trips and infrequent trips, respectively. It was found that navigation applications had a strong re-routing potential as smartphone users followed the suggested route and were likely to divert 20% to 39% of the time. The majority of the technology users would comply with the application and follow the re-routing 60% to 80% of the time. Drivers accept a routing change when the delay per hour trip is approximately 15 to 30 minutes. The use of navigation applications led to an overall increase in drivers' alertness and speeds. Finally, the survey results were consistent with the regression model and showed that the actual diversion rates ranged from 1% to 20%.

DISCLOSURE STATEMENT

There is no financial interest or benefit from the direct applications of this research. The authors declare no conflict of interest.

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Life Span Prediction of Traffic Signal Controllers

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ABSTRACT

Traffic signal controllers are devices that regulate the timing and operation of signalized road intersections, promoting efficient flow and safety. Traffic signal controllers can fail for several reasons, but there is limited knowledge of signal controller failure mechanisms in previous research. Understanding the failure methods can help predict the lifespan of traffic signal controllers. This study was the first known attempt to analyze the full lifespan of a traffic signal controller using a fault tree model. The lifespan obtained from the literature ranged from 4 to 20 years, and fault tree analysis predicted an average lifespan of 12 years. In addition, a sensitivity analysis (±20%) was performed to address uncertainty with the inputs for fault tree analysis, which predicted a range between 9 and 15 years. Transportation agencies can use life span predictions to estimate funding needs and improve asset management practices.

INTRODUCTION

At major intersections, traffic signals determine the direction and flow of traffic. This highly technological equipment must continuously operate to ensure vehicles can pass through the crossing safely (Washington State DOT 2022). Traffic signal assets are the physical infrastructure necessary for traffic signals to work as planned (FHWA 2017).

After a traffic signal is installed and tested, the responsibility for its maintenance and operation usually falls upon the signal owner, unless they establish a maintenance contract with a company or other agency (PennDOT 2020). Transportation organizations at many levels of government have investigated and put asset management principles, techniques, and tools to use for transportation infrastructure. Previous work has typically concentrated on pavements and bridges (FHWA 2017).

The traffic signal controller is one of the most critical parts of the traffic signal assembly. The objective of this paper is to present a model for predicting the lifespan of a traffic signal controller, allowing repair and redeployment. This method is applied to a case study of traffic signals in Illinois.

BACKGROUND

A comprehensive literature review of past studies and research on traffic signal controllers was conducted. This section summarizes the findings, highlighting the importance of lifespan estimates for lifecycle planning, and describing other signal controller lifespan prediction models.

Importance of Lifespan Estimation

The estimated lifespan of signal components can help plan funds for future replacement, as well as understand current value. Lifecycle planning is estimating the cost of managing an asset class or asset sub-group throughout its life while considering how to keep costs as low as possible while maintaining or enhancing the condition (FHWA 2017). For example, some agencies, like the Connecticut DOT, typically replace traffic signal components at specific intervals (Connecticut DOT 2019). Lifecycle planning relates to the valuation of infrastructure across its lifespan, developing investment strategy, and the concept of tort liability. Lifespan estimates from the literature are shown in Table 1.

Table 1. Expected lifespan for traffic signal controllers

Signal Component	Expected life, years [Source(s)]
Signal Controller	20 (San Jose DOT 2010)
	15 (PennDOT 2020, Colorado DOT 2016, Kloos and Bugas-Schramm 2005)
	5-10 (Minnesota DOT 2020)
	7 (Minnesota DOT 2020)
	13.5 average, 4-20 Range (Markow 2008)
	8.2 for the state, 9.6 for the County, 9.8 for the City/Municipality, with 9.4 as the national average (FHWA & ITE 2019)

Industry Actions

The federal government and nearly all states have approved tort claim legislation allowing them to be held liable for the negligence but not the intentional wrongdoing of government personnel (ITE & IMSA 2010). If an agency neglects its traffic signal system, it may be subject to tort liability claims for negligence. Therefore, planned maintenance is valuable and advantageous to the organizations that apply it (FHWA & ITE 2019). The longer an agency leaves a traffic signal maintenance task unaddressed, the greater the chance of a mishap resulting from a faulty signal system.

To reduce liability, several state transportation agencies are assessing the financial needs to improve the management of their traffic signal systems. For example, the Minnesota Department of Transportation's (DOT) investment strategy for traffic signals called for spending $157 million over ten years with a goal of ≤ 2% of traffic signals beyond their useful life (Minnesota DOT 2019). Similarly, the Connecticut DOT determined that to get 80% of traffic signals in the state of good repair, it would take $45 million per year (Connecticut DOT 2019). These types of estimates are important to convey the investment needs to decision-makers.

Deterioration Curves and Lifespan Prediction.

Life expectancy refers to the duration between a specific point in the life of an asset and the time when it becomes necessary to remove or replace it. The date of manufacture, the day the asset is put into service, and the current date are commonly utilized when determining the asset's remaining life. The starting point can usually be determined precisely; however, agencies should take caution in estimating the endpoint. There are several ways an asset can reach the end of its life.

- The asset might function well until it fails suddenly.
- The asset could function well until the end of its life, then become obsolete when a new, stricter standard is approved.
- The asset could have decreasing function until the end of its life, then become obsolete based on age.
- The asset could decrease its performance as a function of usage. After the usage threshold is passed, it reaches the end of its functional life. For example, a structural component could fatigue or corrode over time until it lacks the strength to safely perform its function.
- When certain components of an asset can be repaired without requiring a complete replacement, an asset's life can be extended by maintenance/repair. (NCHRP 2012).

Different signal components deteriorate at various rates and have varying degrees of impact on traffic signal functionality (FHWA 2022). Therefore, an asset-specific maintenance strategy is required for traffic signals and the key components.

Mathematical models can approximate the deterioration curves of traffic signal assets. For example, a life expectancy model can be used to determine the lifespan of traffic signal controllers (NCHRP 2012). In particular, the Weibull survival probability model, the Cox survival probability model, and fault tree analysis are valuable tools for assessing the life of a traffic signal controller.

The Weibull model allows for a variable rate of deterioration. Because the failure rate of traffic signal controllers is believed to increase with age, this model has been used by previous researchers. The functional form of the Weibull curve is presented below:

$$y\ (g) = e^{-\left(\frac{g}{\alpha}\right)^{\beta}}$$

Where y(g) is the probability of the asset remaining in a non-failed state at a specific age, assuming no maintenance actions are performed between year 0 and that age g; β is the shaping parameter, which determines the initial slowing effect on deterioration (e.g., when the galvanized coating is performing well); and α is the scaling parameter (NCHRP 2012).

The Cox Survival Probability Model is similar to the Weibull survival probability model; however, it introduces a multiplier to the survival probability, taking into consideration explanatory variables. The functional form of the Cox model is presented below (NCHRP 2012):

$$y_{1_g} = e^{\left(-1.0\,\times\,(g/\alpha)^{\beta}\right)} \times\ e^{(b_1X_1 + b_2X_2 + \cdots + b_nX_n)}$$

Where y_{1g} is the probability of the asset remaining in a non-failed state at a specific age, assuming no maintenance actions are performed between year 0 and age g, β is the shaping parameter, and α is the scaling parameter. The variables X_n are explanatory variables such as traffic volume or location. They can be continuous variables or discrete (e.g. 0 or 1). The coefficients b_n are determined by linear regression or can be estimated simultaneously as the Weibull shaping parameter. The multiplier can shift the survival probability either upward or downward. The multiplier has no effect if all the explanatory variables are zero (NCHRP 2012).

Fault Tree Analysis (FTA) is a method that uses logical reasoning and visual diagrams to evaluate the likelihood of an undesired event occurring because of various contributing events and their combinations (U.S. Nuclear Regulatory Commission 1981). The FTA differs from regression models in that it focuses on the causal relationship between contributory events and undesirable events (Xu, et al. 2018).

A typical fault tree includes several different logic symbols. In a fault tree, a rectangle represents either a top event or an intermediate event. The top event is the undesirable event that we are investigating. All the paths in the fault tree lead towards this top event. On the other hand, an intermediate event serves as both the input event for the event above it and the output event for the event below it. At the bottom of the fault tree, a circle symbolizes a basic event that triggers the occurrence of a fault.

The two fundamental fault tree gates are the OR and AND gates. The Boolean symbol "+" is equivalent to the OR-gate. When one or more input events connected to an OR-gate take place, the event above the OR-gate also takes place. The Boolean sign "•" is equivalent to the AND-gate. Only when all input events connected to an AND-gate co-occur does the event above the AND-gate occur. For additional information on this method, readers are encouraged to review (U.S. Nuclear Regulatory Commission 1981).

Although asset life estimations are crucial for cost-effective asset management, asset life is an uncertain value that might lead to suboptimal judgments. Inaccurate life estimates put a company at risk of making poor project prioritization decisions. On the other hand, risk-informed decisions enable organizations to weigh degrees of confidence against expenses (NCHRP 2012).

METHODS

The study utilizes documents with information on the lifespan of traffic signal components, the Weibull-distributed survival probability model, and the Fault tree model with return period probabilities to analyze the lifespan of signal controllers. The data from the literature review serves as validation data for the predictions.

To fill the research gap in understanding the root causes for replacing a traffic signal controller, this study used fault tree analysis to investigate how different events interact, leading to traffic signal controller replacement. Fault tree analysis has not been used previously for associating the causes for signal controller replacement. Furthermore, few studies have used fault tree analysis for modeling transportation system failures (Xu, et al. 2018). Based on information collected about traffic signal systems and possible failure modes, a fault tree was developed for the traffic signal controller, see Figure 1.

The initial goal of the research was to determine the variation in probabilities of all the basic events shown in the fault tree to determine the probability of signal controller replacement, i.e., end of life. However, during the data collection process, the authors were not able to obtain documentation for the failure or replacement of traffic signal controllers in Illinois. Therefore, the authors identified probability distributions to represent the physical failure and obsolescence rates for the devices.

Data from the literature provided multiple estimates of the lifespan of the signal controllers. Expected lifespan data obtained from literature was presented previously. Unfortunately, these lifespans did not differentiate between types of failure (e.g., vehicle collision, lightning, obsolescence). Furthermore, previous studies have not considered repair and redeployment practices. For example, some agencies will repair traffic signal controllers, when possible, and redeploy those controllers.

The average life of a signal controller is affected by both physical factors and obsolescence. These failure mechanisms are not mutually exclusive, so researchers assumed the product of the likelihoods as the probability that both occur simultaneously ($P_{both}=P_{obsolete}$x $P_{phyiscally\ damaged}$). When estimating the combined failure likelihood, mutual exclusiveness was addressed.

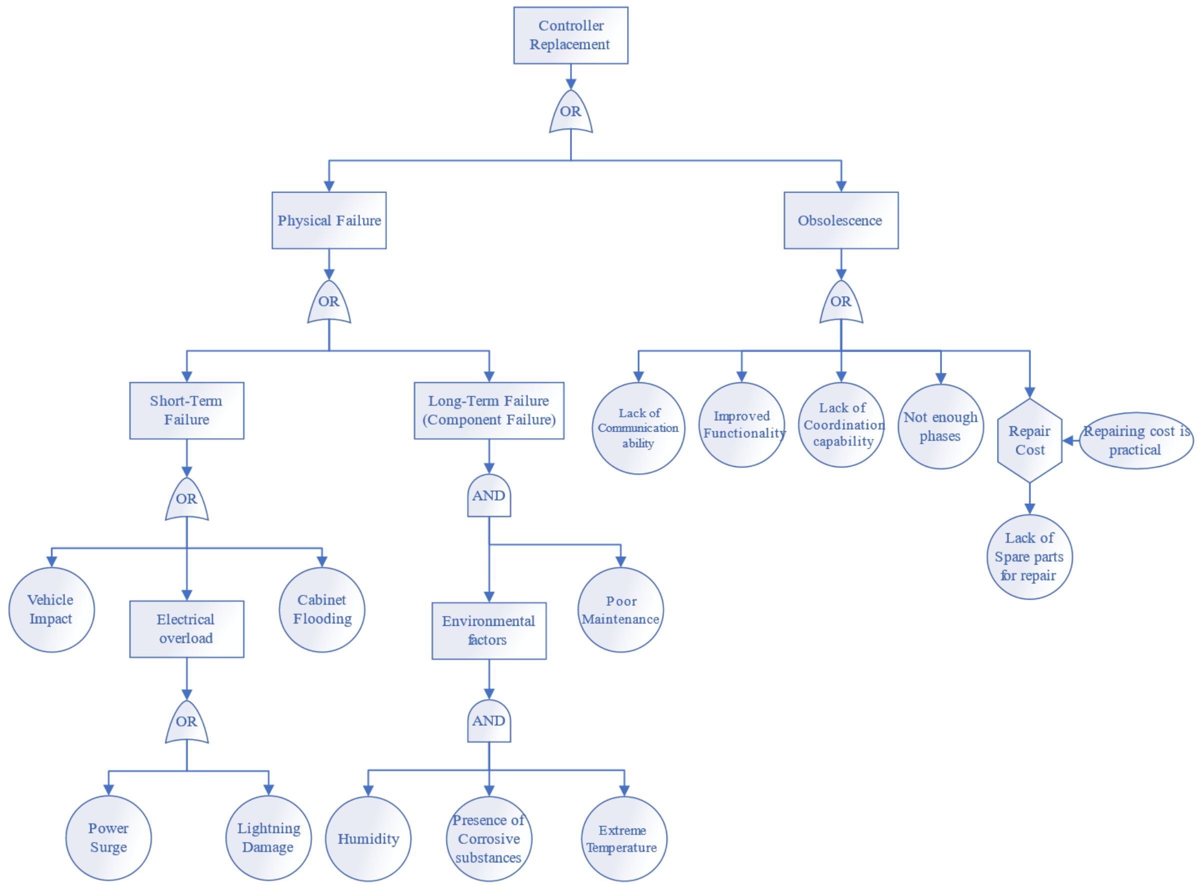

Figure 1. Fault tree diagram for traffic signal controller replacement

Lifespan before Obsolescence.

If an event occurs independently and randomly over time, and the mean rate of occurrence remains constant each time period (e.g. one year), the number of occurrences in a given period will follow the Poisson Distribution (Siegel and Wagner 2022). The probability mass function for Poisson Distribution is:

$$P(r) = \frac{(\mathrm{\mu t})^{\mathrm{r}}}{\mathrm{r!}} e^{-\mathrm{\mu}t} = \frac{\left(\frac{\mathrm{t}}{\mathrm{T}}\right)^{\mathrm{r}}}{\mathrm{r!}} e^{-\frac{t}{T}}$$

Where r is the number of occurrences for which the probability is computed, t denotes the time of interest, T denotes the return period, and μ=1/T is the counting rate.

The Poisson Distribution was chosen to represent the likelihood of obsolescence for several reasons. Foremost, it represents the random occurrence of traffic signal controller obsolescence, which is appropriate for predicting the variety of contributing factors (See Figure 1). In addition, the Poisson Distribution assumes the mean equals the standard deviation, which also agrees with the broad range of lifespan until obsolescence.

Lifespan before Physical Failure

The traffic signal controllers are placed inside a strongly built, waterproof-proof cabinet. Therefore, the primary physical deterioration mechanisms are temperature and humidity. There are other short-term failure mechanisms, such as vehicle crashes, cabinet flooding, and electric overload, as pointed out in the fault tree diagram. It reflects failures induced by random occurrences such as unpredictable environmental loads, human mistakes, abuse, and 'acts of God.' However, the mechanisms generating failures in electronics are mostly connected to component deterioration (Ebeling 1997). Therefore, this study has neglected the effect of short-term failures. Further, Motalab et al. found that the Weibull distribution closely represents the aging of electronics and recommended a shape parameter (beta) of 19.53 (Motalab, et al. 2013). For those reasons, a Weibull distribution with β=19.53 was chosen for this study. When selecting the scale parameter (gamma, γ), values greater than one were considered because they represent increased failure with age, and 1.4 was chosen because it represents a slight increase in failure probability over time and was the smallest shape parameter that created the expected shape of the Weibull distribution. Weibull distributions considered are shown in Figure 2, where the chosen curve is bolded.

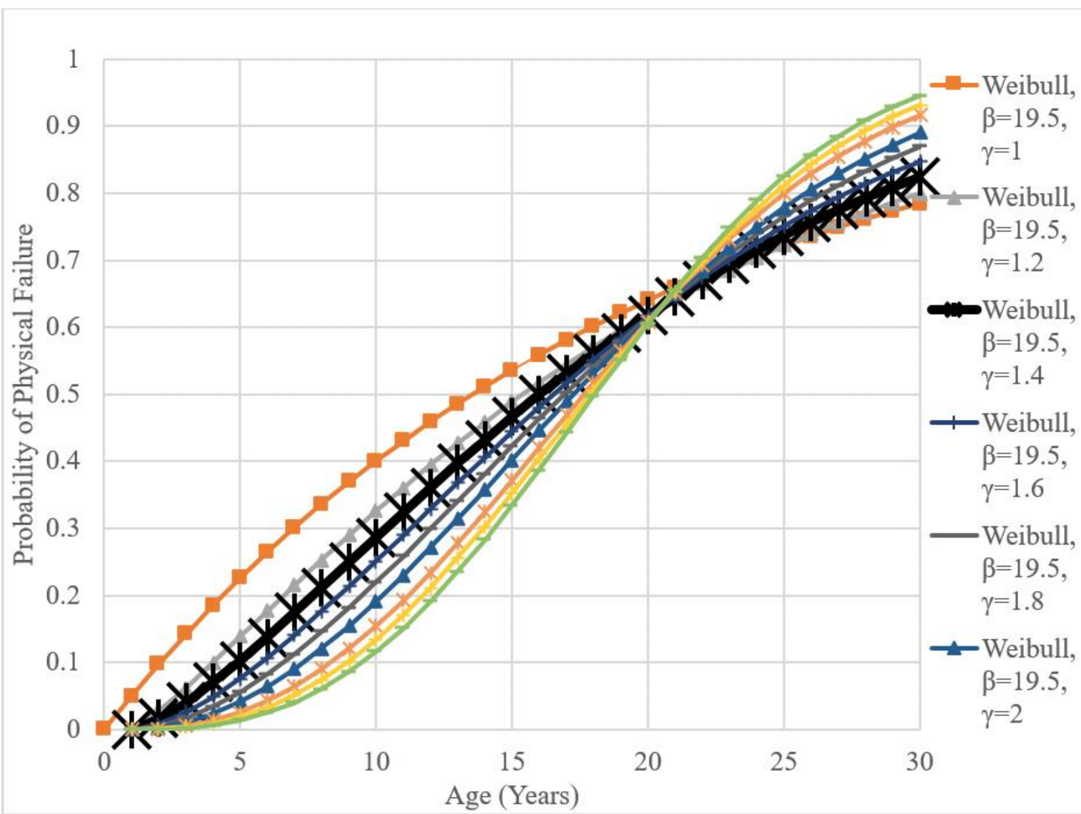

Figure 2. Weibull Scale Parameter Calibration

Expert Opinion

Data were obtained by interviewing signal controller manufacturers, distributors, and state Department of Transportation (DOT) personnel with strong experience with signal controllers. This effort was initiated after multiple unsuccessful attempts to obtain maintenance records documenting service life. Although state and local agencies have records about when controllers are replaced, many are repaired and returned to service. In addition, sometimes controllers are removed from service for software updates, retiming, or other reasons. Due to these factors, no records were available to track the life of signal controllers in Illinois. Instead, the researchers chose to collect expert opinions through interviews.

The interview questions and research methods were reviewed and approved by the Institutional Review Board (IRB) at SIUE (Approval # 1944). The interviewees were chosen because of their professional experience with traffic signal controllers. Four individuals participated in interviews, representing one traffic signal controller vendor, two traffic signal controller manufacturers, and one Department of Transportation Personnel.

The response data from participants helped the researchers estimate the likelihood of the different modes of failure. This data was analyzed to obtain time ranges for obsolescence and physical failure of signal controllers. Both sources of information were deemed essential for predicting the overall lifespan of a signal controller.

Sensitivity Analysis

Due to uncertainty in the data and the multiple assumptions used to estimate controller lifespan, a sensitivity analysis was conducted. The average return period values for obsolescence (Poisson Distribution) and physical failures (Weibull Distribution) were both adjusted + by 20% and -20% to identify the effect on lifespan estimates. This range was chosen based on other published studies.

RESULTS AND DISCUSSION

This section discusses the observed results from probabilistic analysis and makes comparisons to previous studies. Explanations are offered about the differences and significance of the obtained results.

Documents with information on the lifespan of traffic signal components were screened and combined to obtain a range, mode, and average for the lifespan of the traffic signal controller. The range for the lifespan of traffic signal controllers was 4 to 20 years. Considering all studies equal, the mode was 15 years, and the average was about 11 years. This range from literature review serves as validation data for the data obtained from the two mathematical models.

The interview responses provided several helpful estimates about when signal controllers become obsolete. First, respondents estimated that new signal controllers are introduced every 14 years. Assuming signal controllers are purchased/installed randomly over time, the mean service time for a signal controller before the company stops producing the model will be around seven years. The manufacturer and independent technicians provide support for another 3-15 years after a signal controller model production is discontinued. Therefore, the range for obsolescence of a signal controller would be 10 to 22 years, with a mean of 16 years. This information was used to calibrate a Poisson distribution to represent the likelihood of obsolescence over time.

This distribution was chosen because of its memoryless property. As shown in Figure 4, 50% of signal controllers are estimated to be obsolete in approximately 15 years.

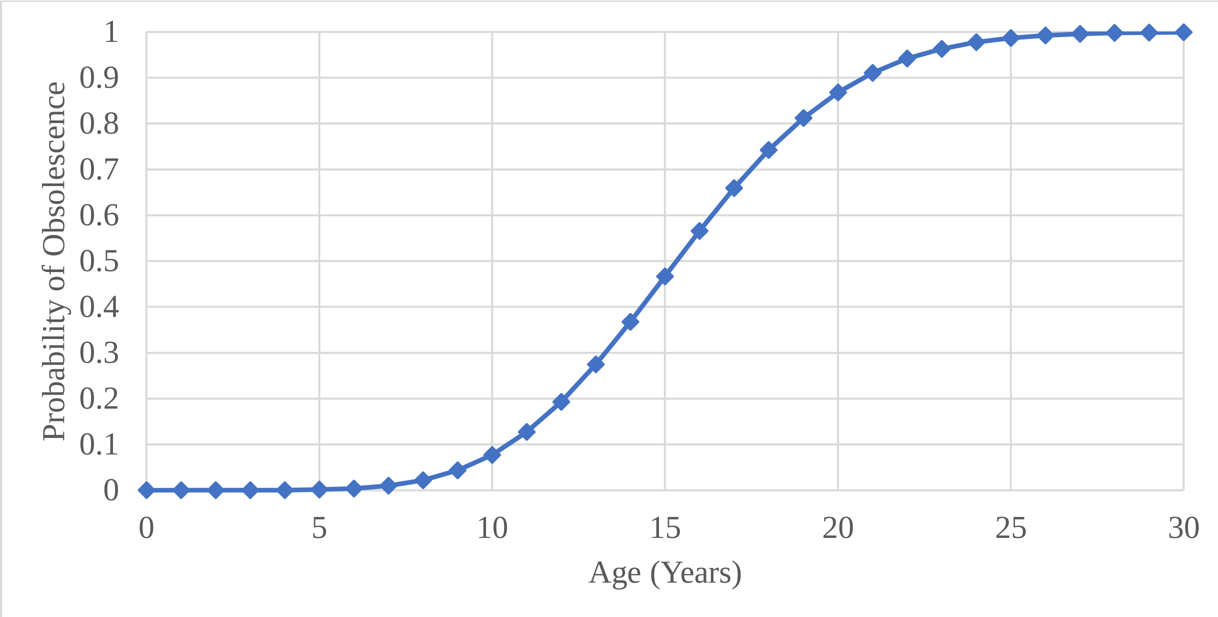

Figure 3. Likelihood of Signal Controller Obsolescence Over Time

The interview responses also provided input about the lifespan of signal controllers concerning physical failure. These include vehicle collisions, lightning strikes, and others shown in Figure 2. Interviewees shared that when a significant repair of the signal controller is needed, it may be at the end of its life. It was noted that approximately 10% of signal controllers are damaged each year. Initial assessment by signal technicians deems 20% of those damaged controllers unrepairable and the other 80% are sent for repair. Of those sent for repair, approximately 7% of the signal controllers are deemed irreparable for a variety of reasons including availability of parts. The remaining controllers are repaired and placed in service again. These estimates suggest that 2.5% of signal controllers reach the end of their life for physical reasons each year. The researchers recognize that declaring a signal irreparable in the physical sense is commonly based on the maintenance technician's judgment that repairing the controller at its current stage in life is economical. Overall, this information suggests that 50% of signal controllers will reach the end of their physical life in 19.5 years.

The researchers combined estimates from the literature and interviews to calibrate a Weibull equation representing the likelihood of physical failure over time. The probability distribution is shown in Figure 3.

The overall failure probability curves are presented in Figure 4. As shown, a variation of 20% in the average lifespan will result in a change in the average lifespan of approximately 3 years (~25%), from 9 to 15 years. These findings suggest that traffic signal controller lifespan estimates are sensitive to changes in the mean, supporting the need for better data and additional research on this topic.

Comparing these findings to other studies suggests general agreement. Markow (2008) was most similar, estimating an average life of 13.5 years. Several other studies predicted shorter

(Minnesota DOT 2020, FHWA & ITE 2019) and longer (PennDOT 2020, Colorado DOT 2016, Kloos and Bugas-Schramm 2005, San Jose DOT 2010) lifespans.

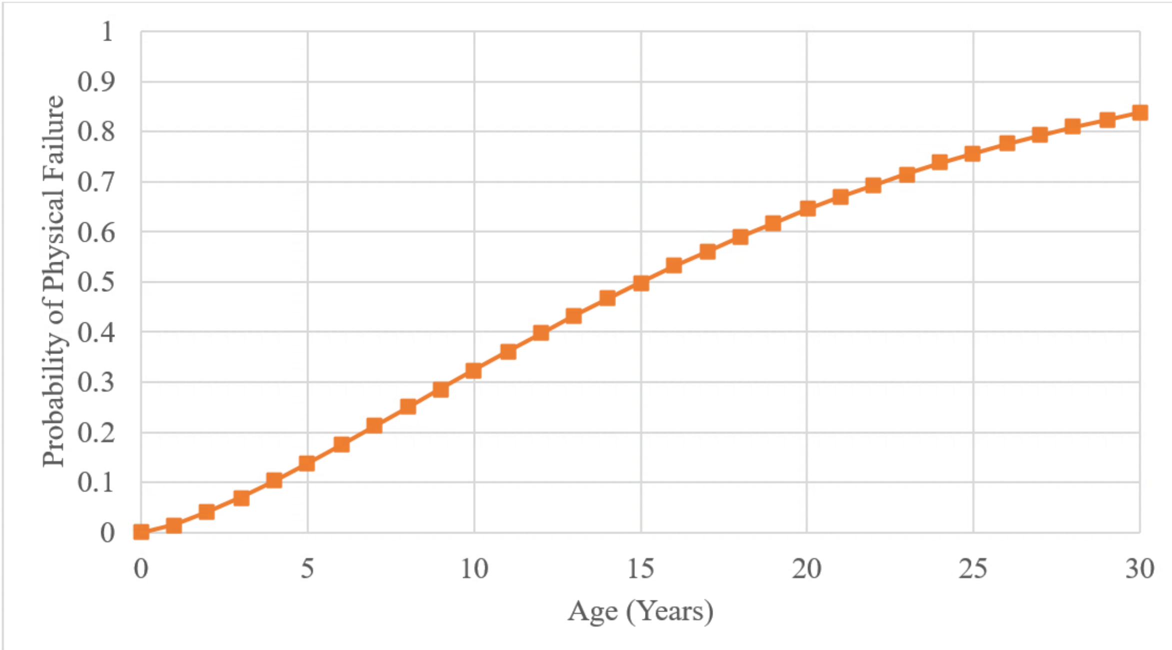

Figure 4. Likelihood of Signal Controller Physical Failure Over Time

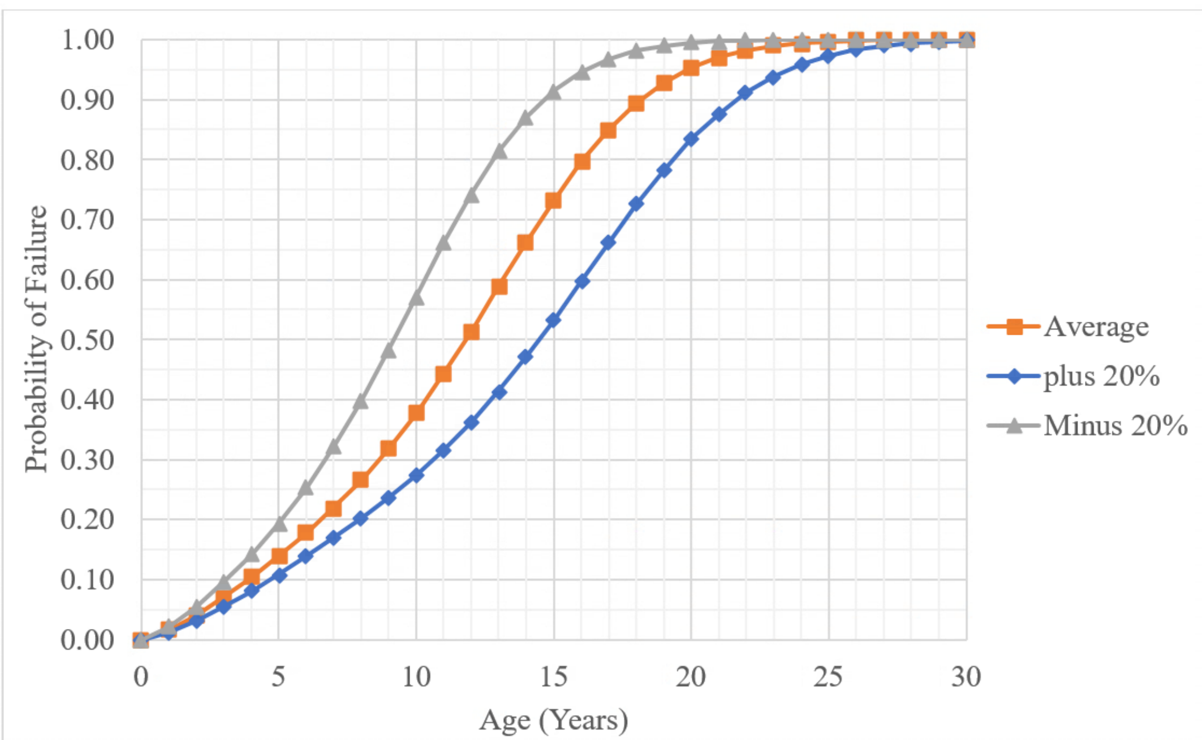

Figure 5. Probability of a traffic signal controller by physical decay and obsolescence

CONCLUSIONS

This study used probabilistic methods to estimate the lifespan of traffic signal controllers in Illinois. Previous research suggested signal controllers have a lifespan between 4 and 20 years, but none differentiated between total lifespan with and without repair. The key contributions of this study are 1) analyzing traffic signal controller failure mechanisms through fault tree analysis, and 2) considering repair in the traffic signal controller lifecycle.

The use of Fault tree analysis was a novel approach for the prediction of the lifespan of traffic signal controllers. It incorporated observed failure methods to predict the probability of overall failure. The use of the technique was especially appropriate because of the variations in the level of data on failure methods.

This study was also unique because it considered the repair and redeployment of traffic signal controllers. Both obsolescence and physical failure mechanisms were included, where obsolescence was simulated using Poisson's probability distribution curve, and physical failure was approximated with a Weibull distribution. The value of the return period for probability distribution was obtained from expert opinion during a series of interviews of personnel experienced with manufacturing, distributing, and field monitoring of traffic signal controllers.

This study estimated an average lifespan of 12 years. To address uncertainty with the inputs, a sensitivity analysis (+/- 20%) predicted a range between approximately 9 and 15 years. This method estimates signal controller lifespan considering multiple failure mechanisms and practices such as repairing signal controllers.

Future research should incorporate maintenance records that track the actual life of signal controllers, including those repaired and returned to service. In addition, detailed information about lightning strikes, vehicle collisions, and other events could improve the accuracy of physical failure mechanisms.

Traffic Signal asset management is a deliberate and purposeful approach to managing, maintaining, and improving traffic signal physical resources. Transportation agencies understand the need for a component-specific management plan due to the varied deterioration rates of components and the severity of impact on the system. This study is one such effort for the lifespan prediction of traffic signal controllers. Data availability was the most significant limitation in developing life expectancy models for traffic signal controllers. It is difficult to build or validate a mathematical model without observed records. However, during the literature review, it was noted that transportation agencies have started to focus on this problem. When a management system is in place, funding will play a vital role in whether the agencies can better manage their traffic signal assets.

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