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Equity in Active and Shared Transportation: An Investigation of Barriers and Individual and Contextual Factors

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Abstract

To achieve the goal of encouraging more people to use sustainable modes of transportation, thereby reducing carbon emissions, it is necessary to understand the equitable distribution of active and shared transportation among demographic groups. This study investigated which individual and contextual factors influence perceptions of barriers to public transit, micromobility, and carpool. A non-parametric method (extreme gradient boosting decision tree) was employed to accurately model these relationships and rank the importance of the factors. To enhance model interpretability, Shapley Additive Explanations (SHAP) was employed to explain the model outcome. Three metropolitan U.S. regions—Greater Los Angeles, Greater Houston, and Virginia and Washington D.C.—were selected as the application regions for this developed methodology. Based on the findings, it was found that people who drive for most of their trips are more inclined to perceive the reliability of public transit as unsatisfactory and have a lack of familiarity with micromobility. Women are more prone to perceive public transit as unsafe, uncomfortable, and inaccessible, and minority groups are least likely to be unsatisfied with public transit, suggesting that they might be more willing to endure inadequate transportation service. Thus, ensuring that these groups feel that they have the right and ability to speak up about their experience and concerns is critical. This research provides insights for transportation agencies to develop equitable improvement and communication strategies for active and shared transportation systems, which is imperative for the widespread adoption of sustainable modes for all people regardless of demographic characteristics.

Keywords

Equity in Transportation AME10, planning and analysis, sustainability and resilience, transportation and society, transportation demand management, transportation equity

Social equity relates to how benefits and costs are distributed and whether that is considered fair and reasonable. Transportation planning policies may significantly affect equity, including the cost imposed on people as well as whether people can easily use the various mobility services. It is especially important for people to have equitable access to active and shared transportation, which will also significantly improve sustainability (*1*). According to a report by the Intergovernmental Panel on Climate Change, taking public transportation reduces CO_2 emissions by 45%, decreasing pollutants in the atmosphere compared with driving alone (*2*). It is the responsibility of transportation researchers and practitioners to assess equity impacts in transportation planning.

Active transportation is any form of human-powered transportation, including rolling, biking, and walking. Shared transportation includes public transit (such as buses and light rail), car sharing, bike sharing, and carpooling. Active and shared transportation equity, in its most basic meaning, refers to the equitable distribution of active and shared mobility services across space and among social groups. For instance, it has been

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discovered that Black women are particularly prone to experiencing transportation difficulties since they typically do not own cars, do not have relatives or friends who can accompany them, or live alone in isolated areas (*3*). Because of a lack of equitable distribution of services and infrastructure within the transportation system, individuals are limited or unable to connect to resources, jobs, and services efficiently, furthering their economic and social isolation. When they do travel, issues including road safety, unreliability, and a lack of access to shared and active transportation may cause them discomfort or prevent them from using these services.

Although considerable earlier research has been done to analyze the barriers to active and shared transportation in general, at least two significant gaps still exist. First, integrating barrier considerations into transportation decision-making remains difficult because of a lack of understanding of the most significant barriers such as accessibility, safety, and health risk, as well as who are most likely to face these barriers. Transportation agencies might prioritize the service or equity improvement plan by asking questions such as whether accessibility is the most significant issue of public transit in general, or which demographic factors are most likely to lead to unsatisfactory public transportation accessibility. As a result, there is a need to identify the most critical barriers and important linked aspects with these perceived barriers. Second, the lack of behavioral patterns has been observed in previous studies. Those who have used single-occupancy vehicles (SOVs) regularly, for example, are more likely to be unfamiliar with other options, and therefore to have a negative impression of them or a strong aversion to using them (*4*). While they receive the same level of service as others, their lack of knowledge may act as a significant deterrent to using or even exploring the alternatives. Understanding the behavioral factors that are more likely to lead to a perceived barrier can help transportation providers enhance their communication with potential users.

This paper intends to fill a research gap by identifying the most significant barriers and ranking individual and contextual factors that have the most influence on people's perceived barriers to active and shared transportation. In this paper, three types of active and shared transportation are studied: carpool, public transit, and micromobility. To collect travelers' perceptions about these barriers, a comprehensive online survey was designed and three urbanized regions in the U.S. were selected for the application areas: Greater Los Angeles, Greater Houston, and Virginia and Washington, D.C. (Virginia & D.C.) region. These regions were chosen as each has different multimodal transportation programs and varying adoption rates. In the study, participants were asked to select the barriers—accessibility, cost, safety, reliability, comfort, familiarity, and health risk—that prevent them from using carpool, public transit, and micromobility. This paper employed a non-parametric method called extreme gradient boosting decision tree. This method was used to identify the highest-contributing factors to the perceived barriers to carpooling, public transit, and micromobility. A model interpretation metric called Shapley Additive Explanations (SHAP) was utilized to explain the model outcome. The findings provide transportation authorities with a better understanding of how programs in different regions may result in different equity impacts.

This paper is organized into six sections. The following section discusses the literature on barriers to active and shared transportation. The data collection efforts and analysis methods used in this research are described next. The study results are then presented. Following that, the policy implications and recommendations stemming from the results of this research are discussed. The paper concludes with a study overview with primary research results and limitations.

Literature Review

Active and Shared Mode Barriers and Social Factors

One of the main barriers preventing individuals from using active and shared transportation is lack of physical access or excessive walking distance to connect (*5–7*). One study developed a public transit equity impact simulation platform based on investment using a combination of mathematical and optimization techniques (*8*). To promote equity, they used this platform to assess the trade-off between equity and transit operators' investments in purchasing electric buses, on-route charging stations, and in-depot charging stations for the under-served neighborhood (*9*). They discovered that improvements in equity will increase significantly on a logarithmic scale as investment increases. However, this study only considered the effects of investment on low-income people, neglecting the negative consequences that investment may have on women or minorities that have a history of unequal access to transit services (*10*, *11*). Minorities, for instance, have a higher likelihood of having limited access to multimodal transportation options (*12*). In particular, one study of Houston's transportation systems discovered a lack of frequent service, with 40% of local bus passengers lacking access to a vehicle to get about the city and 60% of local bus users being minorities (*13*). These numbers are significantly higher than the U.S. average, where only 8% of U.S. households lack access to a vehicle, according to an analysis of American Community Survey data for 2020, and where only 24% of the U.S. population is made up of minorities, according to data from the 2021 census (*14*, *15*).

The issue of safety is also one of the barriers that inhibit people from using multimodal transportation, especially for women and gender minorities. Online surveys and focus group studies have found that women of color and gender minorities are more likely to feel insecure or face frequent harassment when using public transportation (*11*, *16*). Studies revealed that women are more likely to feel vulnerable and unsafe using bicycles, and are thus less likely than their male counterparts to use bike sharing (*17*, *18*). Scooters are a relatively recent and popular mode of transportation (*19*). Although they have the advantage of being a convenient and affordable option for the "last mile" (i.e., to/from transit station) and other short trips, they still raise an equity issue. For instance, women are more inclined to believe that scooters are less safe (*20*). These findings indicated that more efforts are needed to make women feel comfortable with the use of micromobility such as cycling and scootering.

Another significant challenge to people using active and shared transportation is cost, especially for low-income populations (*21–23*). In particular, one study found that low-income transit riders travel shorter distances and make a higher share of transit trips during off-peak periods than higher-income riders, which makes them pay significantly higher per-mile transit fares than more affluent riders (*24*). Another study analyzed equity from the funding allocation perspective and found that municipalities located in remote areas or with higher poverty levels experience a lower highway expenditure rate per local mile (*25*).

Despite all these findings pointing to clear linkages between social and contextual factors and mode barriers, more comprehensive comparisons are needed to understand how well transportation systems serve travelers from different ethnic, gender, and income groups. Identifying the most vulnerable populations can make it easier for agencies to develop targeted plans and determine priorities. As a result, in this paper, a comprehensive survey was developed to understand the perceived barriers of carpool, public transit, and micromobility among travelers from different ethnic, gender, and income groups. Comparing the findings between the three metropolitan areas can help transportation agencies better understand how to prioritize the important issues in the improvement plans for active and shared transportation such as carpooling, public transit, and micromobility.

Another study gap is a lack of understanding of people's perceptions of health risks and how this influences their decision to use public transportation. According to Pew Research Center data, Americans who are low-income, Black or Hispanic, immigrants, or under 50 are more likely to use public transportation on a regular basis and also less likely than other groups to have access to a car (*26*). Studies found that people who still relied on public transportation during COVID-19 were disproportionately low-income, essential employees, and/or Black or Latino (*27*). In addition, these people were less likely than other groups to have access to a car and more likely to use public transportation regularly even when transit services were cut during the pandemic, which made public transportation less accessible (*26*, *28*). The pandemic exacerbated the disparity by exposing riders who rely on public transportation to a higher risk of being infected by the disease than other groups (*29*). However, few research studies have examined different demographic groups' perceptions of health risks associated with multimodal transportation. Further research into the demographic segmentation of perceptions could aid transportation agencies to better understand the equity issue which arose during the pandemic and improve services for all travelers. In this paper, the individual and contextual factors that influence the perceptions of health risk of using public transit, micromobility, and carpool, were also investigated.

Understanding the Perception of Barriers Toward Active and Shared Transportation

While spatial and temporal analysis is useful for studying the theoretical equity effects of multimodal transportation, people may perceive or experience the barrier differently, even if they have similar physical access or general level of service. In particular, a few studies evaluated the adoption of multimodal transportation such as walking or bike share; disadvantaged groups (e.g., low-income and racial/ethnic minority) benefit less than advantaged groups, even with the same walking environment or bike facilities built mainly to increase access for under-served neighborhoods (*30–32*). One survey study was conducted to evaluate a program that provided free public transit passes to K-12 students. While many students who did not use regional transit service to commute to school frequently reported utilizing it more for after-school activities as a result of the pass, fewer Latinx youth reported knowing about the program after it was implemented, indicating that communication efforts may have been insufficient (*33*). More research is needed to determine why some people use specific modes of transportation infrequently. Surveys, for example, could be a useful way to collect information about people's direct attitudes toward various modes of transportation, which could assist transportation researchers and practitioners in better understanding what communication methods or service improvement plans are needed (*6*, *34*). As a result, survey was selected as the main tool in this research to collect information about people's perceived barriers.

Besides a perceived unsatisfactory service level, some reasons for not using multimodal transportation could be an individual's behavioral patterns or psychological factors. Two cross-sectional surveys were administered before and after the shared e-scooter program on Virginia Tech's campus in Blacksburg, VA. The findings revealed that younger riders, particularly undergraduate students, were more likely to use e-scooters and that the gap between pre-launch intention to ride and actual riding behavior was greatest for older age groups, women, and university employees (*4*). More research is needed to better understand the reluctance to use various mobility options and how they are related to people's behaviors. For example, one study found that, for those who have always gone everywhere by car, the status quo bias—the tendency for one to keep doing what one has always been doing—could be a significant psychological blocker preventing infrequent or inexperienced users from giving public transportation a try (*35*). In this way, adjusting communications, besides enhancing services, can alleviate the bias against alternative mobility options and potentially increase ridership.

Estimating Mobility and Travel Choices

Several recent empirical studies have shed light on the relationships that underlie the correlations between travel preferences and factors such as demographics, environment, and trip characteristics. Statistical models, such as logistic regression and linear discriminant analysis, have been widely employed to understand travel behavior in the past literature (*36*). For example, logistic regression has been used to understand the relationship between socioeconomic variables such as car ownership, gender, income, and travel mode choices (*36*, *37*). Machine learning models have also been used to estimate travel preferences and choices in an effort to more accurately reflect the non-linear relationship (*38*). The Extreme Gradient Boosting (XGBoost) classifier is an effective method for forecasting binary variables such as preferences and choices (*39*, *40*). For instance, one study found that, when predicting mode choice, the XGBoost model performed better than the linear model (92.7%) with a prediction accuracy of 94.5% (*41*). XGBoost classifier is a tree-based model that can solve multicollinearity issues among independent variables—in the case of this research, individual and contextual variables—and this method is better at capturing their possible non-linear impact on perceived barriers than linear models (*42*, *43*). When it comes to accurately capturing non-linear relationships, XGBoost outperforms traditional decision-tree-based algorithms such as the random forest approach because it learns where it fails to predict at each iteration and improves it at the next iteration. The random forest approach lacks a process to iteratively reduce the error.

One limitation of XGBoost is that it is difficult to interpret the results. Particularly, XGBoost is unable to explicitly produce the positive or negative impacts of each variable as can conventional statistical models. SHAP has been used to understand the output of models whose outputs cannot be directly interpreted to understand how various factors affect prediction results (*44*). SHAP improves the interpretability by estimating the positive or negative relationship for each factor with the dependent variable from the outcome of the model such as XGBoost. This technique has been used extensively in traffic safety studies, including crash injury prediction, to better interpret risk factors (*45*, *46*). In recent years, SHAP has also been used to estimate and interpret transportation mode preferences from a variety of data sources, including smart cards and travel surveys (*47*, *48*).

The purpose of this work is to address the above-noted gaps in the existing literature by developing an approach to identify the most significant barriers such as perceived health risk, and ranking individual and contextual factors, including the frequency of using SOVs (SOV frequency), that have the most influence on people's perceived barriers of carpool, public transit, and micromobility. A comprehensive survey was conducted to collect information about people's perceived barriers to their most frequent trips in three U.S. urbanized regions. Because of the advantages in model fit and interpretability, XGBoost and SHAP were utilized to evaluate the survey results. The findings can assist transportation agencies in setting priorities for tackling the barriers to carpooling, taking public transit, and micromobility.

Data Description

Application Regions

Three urbanized regions were selected as the application regions: Greater Houston, Texas (including Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, and Waller County), Greater Los Angeles, California (including Ventura, San Bernardino, Riverside, Los Angeles, and Orange County), and Virginia & D.C. region. The grounds for choosing these three regions for applications are that they each have different multimodal transportation programs and varying adoption rates.

The major transportation agencies, operators, and programs are introduced in the following paragraphs. Comparing perceived barriers in these three metropolitan areas would provide transportation officials with a better understanding of how programs in different regions might result in different equity impacts.

Greater Houston Area

Public Transit. Among the top five most populated metropolitan areas in the U.S., Greater Houston has the second-lowest public transit ridership rate. According to the 2019 American Community Survey, only 2% of all workers in the Greater Houston area commute by public transit (*49*).

Micromobility. One of the largest bike-share programs in the Greater Houston Area is Houston BCycle. In the central Houston areas, it had over 100 stations and 700 bikes available to passengers in 2021.

Carpool. To encourage employees to carpool, METRO STAR, a carpool and vanpool service in the Greater Houston Area, offers a variety of transportation benefits plans to businesses. By doing so, employees can arrive on time and experience less stress while driving, and there will be less traffic on the road and in the parking lot (*51*). According to the 2013 census data, the percentage of carpool commuters was 14% in the City of Houston (*52*).

Greater Los Angeles

Public Transit. The majority of Los Angeles County's transportation system is planned, operated, and funded by the Los Angeles County Metropolitan Transportation Authority (LA Metro). To improve mobility and reduce traffic congestion, LA Metro provides a range of employee incentives, including the Metro Annual Transit Access Pass (ATAP) and Metro Small Employer Pass (SEP) program, to businesses in LA County (*53*). According to American Community Survey in 2019, the percentage of public transit commuters in Greater Los Angeles was 4.8% (*49*).

Micromobility. The Downtown Los Angeles Pilot Program and Santa Monica Breeze are the two bike-share programs in Los Angeles County, and both have experienced rapid expansion in recent years. Breeze Bike Share began in Santa Monica in November 2015, and in 2016 and 2017 it expanded to Beverly Hills, West Hollywood, and University of California, Los Angeles. Metro Bike Share began in downtown Los Angeles in July 2016, and in 2017 it expanded to the Port of Los Angeles, Venice, with more bikes installed at metro stations in Santa Monica. Both programs provide two different types of plan for casual users, who mostly utilize bike sharing on an as-needed basis, as well as members who are regular or long-term. In addition to its bike-share programs, Los Angeles introduced the biggest dockless mobility pilot program in the U.S. in 2019. Around 10 million trips on scooters were made in the first year to get to work or school, get to the doctor or childcare, or to use the transit system (*54*).

Carpool. LA Metro provides numerous carpool and vanpool services for commuters, including Metro Vanpool and RideMatch, which match commuters who share the same travel time and route and are looking to save money. According to the 2013 census data, the percentage of carpool commuters was 12% in the City of Los Angeles (*52*).

Virginia & D.C

Public Transit. The Washington Metropolitan Area Transit Authority (Metro) operates the country's third-largest heavy rail system and the sixth-largest bus system (*55*). Virginia also has several publicly funded transit providers, including bus and paratransit services, a subway system that covers northern Virginia, and a light rail system called The Tide.

Micromobility. Capital Bikeshare D.C. is one of the five major bike-share systems in the U.S., with Citi Bike in New York, Citi Bike in Miami, Divvy in Chicago, and Hubway in Greater Boston. According to a research study, these five systems accounted for 85% of all bike-share rides in the U.S., whereas Capital Bikeshare accounted for 5% of the five programs (*56*).

Carpool. OmniRide Ridesharing is one of the major ride-matching services operating throughout Northern Virginia and the District of Maryland that allows commuters to find a carpool or vanpool and connect those who live and work near one another and who have similar work hours. According to the 2013 census data, the percentage of carpool commuters was 17% in D.C. (*52*).

Based on data from the 2020 U.S. census American Community Survey, additional statistics about vehicle ownership, median household income, and the percentage of non-white people have been collected, and these are summarized in Table 1 (*57*). Greater Los Angeles has the highest vehicle ownership and median household income among the three metropolitan areas. Virginia & D.C. have the highest percentage of non-white people.

Survey Design

A survey was designed to understand the barriers to public transit, micromobility, and carpool. Surveying is a relatively efficient way to obtain samples with acceptable levels of accuracy compared with focus groups. This method has also been used in many previous audience segmentation studies (*58*, *59*).

Amazon Mechanical Turk (MTurk) was employed for distributing the surveys as it is a prominent platform that

Table 1. Selected Census Statistics of the Application Regions

	Percentage of households with one or more vehicles	Median household income	% non-White people
Greater Houston Area	91.7	$53,600	49
Greater Los Angeles	87.9	$71,358	51
Virginia & D.C.	83.6	$64,994	54

can collect responses swiftly. In this study, MTurk was employed for surveying because the data quality is comparable to that of traditional survey techniques (*60*, *61*). MTurk samples have also been demonstrated to be just as diverse in relation to demographics as samples from digital mobile surveys (*62*). Because of these qualities, MTurk has been used in several travel studies to better understand people's mobility preferences and opinions (*63*, *64*).

The survey was distributed to the study's application areas through MTurk in October 2021 and lasted for a month to reach the effective sample size. The effective sample size was calculated based on the formula proposed by G.D. Israel (*65*). This approach has been used to calculate the effective sample size in past transportation data collection endeavors, such as travel preference surveys (*66*, *67*). The effective sample size was calculated based on the confidence level (set as 90%), the margin of error (set as 5%), and the degree of variability (set as 50%). For example, if the true proportion of 40% of the population believes that using public transit poses a substantial health risk, the estimated proportion from the survey would be between 40% −5% and 40% + 5% with a 95% confidence level. The degree of variability was set as 50% to be more conservative, as it assumes a greater level of variability in the survey than 20% or 80%, which would require a higher number of samples. In total, 351, 292, and 268 valid responses were collected in the Greater Los Angeles, Greater Houston, and Virginia & D.C. regions, respectively, after identifying the inconsistencies among the answers to various questions and removing respondents who provided "Prefer Not to Answer" in at least one question. The distribution of the responses based on respondents' home zip codes collected from the survey in the three application regions is shown in Figures 1 to 3.

The design of the survey for the application of this research was based on the methods in the current literature on understanding people's barriers to using active and shared transportation (*20*, *68*). Based on these findings, the survey questions were designed to capture seven types of barrier: unsatisfactory comfort, not familiar, unsatisfactory reliability, unsatisfactory cost, unsatisfactory health risk, unsatisfactory safety, and unsatisfactory accessibility. To keep it from being overly long, and to narrow the scope of this research, not all associated variables were questioned in the survey. The details of the survey are summarized in the following paragraphs.

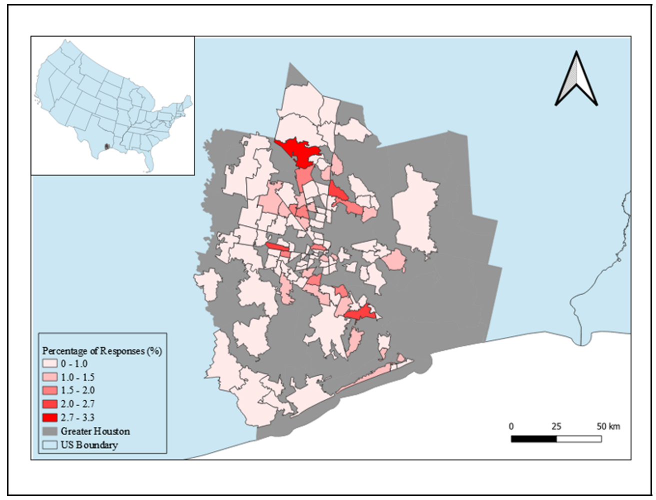

Figure 1. Response distribution in Greater Houston.

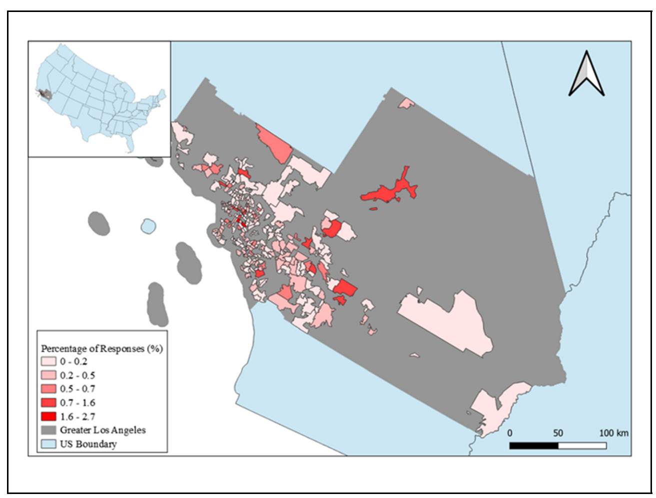

Figure 2. Response distribution in Greater Los Angeles.

Trip characteristics: Respondents were asked to consider trips taken with the highest frequency and to provide information about their trip purpose and departure time of that trip. These variables are considered contextual factors in this study. The choices of the trip purpose include commuting, pick-up/drop-off, grocery/shopping,

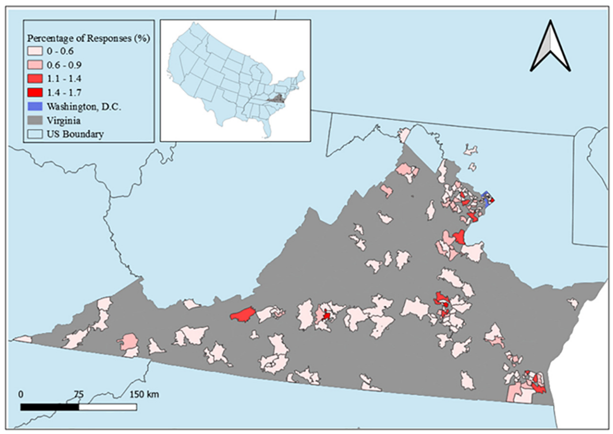

Figure 3. Response distribution in Virginia & D.C.

social/leisure, and errands. The choices of the departure time include midnight (12:00–4:59 a.m.), morning (5:00–9:59 a.m.), noon (10:00 a.m.–12:59 p.m.), afternoon (1:00–5:59 p.m.), and evening (6:00–11:59 p.m.).

Mobility options barriers: Respondents would check all barriers among unsatisfactory accessibility, reliability, safety, health risk, comfort, cost, and familiarity that currently prevent them from using each of the following modes of transportation for the trip that they make the most frequently.

- Carpool: Traveling in one's own or other vehicles with one to three other people (excluding rideshare services such as Uber and Lyft, and/or their shared services UberPool and LiftLine)
- Public Transit: Rail or bus
- Micromobility: Walk, bike, scooter, or other shared modes

The definitions of the aspects for the respondent to select are shown in the following bullet points. These definitions were also shown to the respondents for them to fully comprehend their meaning.

- Accessibility: How easy it is to access this mode, including whether you have physical access to it and if the entire journey duration, walking distance, and other factors are acceptable.
- Reliability: How people feel this mode is running on time.
- Safety: How people perceive a personal or road-safety-related risk when using the mode.
- Health risk: How people perceive a health risk when using the mode.
- Comfort: How comfortable people feel when using the mode.
- Cost: How satisfied people are with the fare, parking cost, and so forth.
- Familiarity: How familiar people are with the mode, or how easy people feel it is/would be to find out how to use the services.

In addition, respondents were asked questions such as SOV frequency, socio-demographic characteristics, mask-wearing frequency, and vaccination status. These variables are considered as individual factors in this study. The demographics of the survey respondents are shown in Table 1. When comparing the participant demographics with those of the 2020 American Community Survey Data, there is a higher proportion of participants who are between the ages of 18 and 44 and hold a college degree or higher (*69*). Table 2 shows the respondents' characteristics distribution.

Methodology

This study focused on identifying, ranking, and explaining the impact of the individual and contextual factors on the perceived barriers. While traditional statistical models, such as logistic regression and linear discriminate analysis, have been employed as common methods to understand travel behavior in the past literature, two fundamental limitations exist (*36*). First, most conventional statistical models use parametric techniques. Methods known as "parametric methods" assume that data come from a population with a probability distribution that is based on a specified set of parameters. Certain probability distribution and set of parameters could be found to fit the data, but the data might not always necessarily have been generated from that distribution. This could lead to a less ideal quantification of the relationship and, as a result, a biased understanding of the behavior patterns from the data (*70*). As a result, to better discover the non-linear relationship, it is vital to use a more advanced modeling framework.

A nonparametric method is a mathematical approach for making statistical inferences without considering the underlying assumptions on the particular probability distribution of the data under investigation. As a result, the nonparametric method is more accurate at estimating variables than the parametric method because it represents the relationship between independent and dependent variables under fewer constraints. Some non-parametric approaches, such as the decision tree model, have been employed for understanding travel behavior without placing distributional assumptions on the data. The factor importance value of each variable can be estimated based on how much it contributes to creating the decision tree. The extreme gradient boosting decision tree—a variant of the decision tree model—has been shown in travel choice

Table 2. Respondents' Characteristics Distribution

	Greater Los Angeles ($n = 351$) (%)	Virginia & D.C. ($n = 292$) (%)	Greater Houston ($n = 268$) (%)
Gender			
Woman	46.1	55.2	55.2
Man	47.2	42.8	44.8
Non-binary	6.7	2.0	0.00
Hispanic, Latino, or of Spanish origin			
No	65.7	94.4	79.7
Yes	34.3	5.6	20.3
Ethnicity (multiple choice)			
Asian	19.3	8.2	6.2
White	67.7	76.6	67.5
Black or African American	11.1	17.2	22.9
American Indian or Alaska Native	5.3	0.8	2.1
Native Hawaiian or Other Pacific Islander	1.2	0.9	1.4
Age			
18–34	49.8	47.2	56.7
35–44	28.0	29.2	26.4
45–54	14.4	14.8	11.9
55–64	5.4	6.4	3.8
65 +	2.4	2.4	1.2
Income			
$1 to $9,999	6.0	2.0	4.6
$10,000 to $24,999	13.4	10.8	8.4
$25,000 to $49,999	20.9	24.4	27.2
$50,000 to $74,999	23.5	24.0	28.7
$75,000 to $99,999	17.5	18.0	10.3
$100,000 to $149,999	10.6	13.2	14.9
$150,000 and greater	8.1	7.6	5.9
Education			
Less than high school	0.6	0.0	0.4
High school	22.6	23.6	20.7
College	57.5	54.4	56.7
Post college	19.3	22.0	22.2
Vaccination			
Fully or partially vaccinated	83.4	80.8	73.0
Not vaccinated	16.6	19.2	27.0
Mask wearing			
Always	58.5	49.8	44.1
Often	21.0	26.9	25.1
Sometimes	14.8	13.1	12.6
Rarely	4.8	6.5	11.2
Never	0.9	3.7	7.0
Single-occupancy vehicle (SOV) frequency			
For most of my trips	76.0	84.9	83.7
For some of my trips	17.1	8.6	14.0
For very few of my trips	3.2	2.0	1.4
I don't use or have a car	3.7	4.5	0.9
Trip purpose			
Commuting	52.4	58.4	56.3
Pick-up/drop-off	10.6	10.6	9.3
Grocery/shopping	17.1	19.6	20.0
Social/leisure	13.7	7.3	11.1
Errands	6.2	4.1	3.3
Departure time (multiple choice)			
Morning (5:00–9:59 a.m.)	59.8	69.0	67.9
Noon (10:00 a.m.–12:59 p.m.)	24.7	11.4	20.0
Afternoon (1:00–5:59 p.m.)	22.2	20.0	20.5
Evening (6:00–11:59 p.m.)	7.4	9.8	11.6
Midnight (12:00–4:59 a.m.)	5.8	2.4	2.3

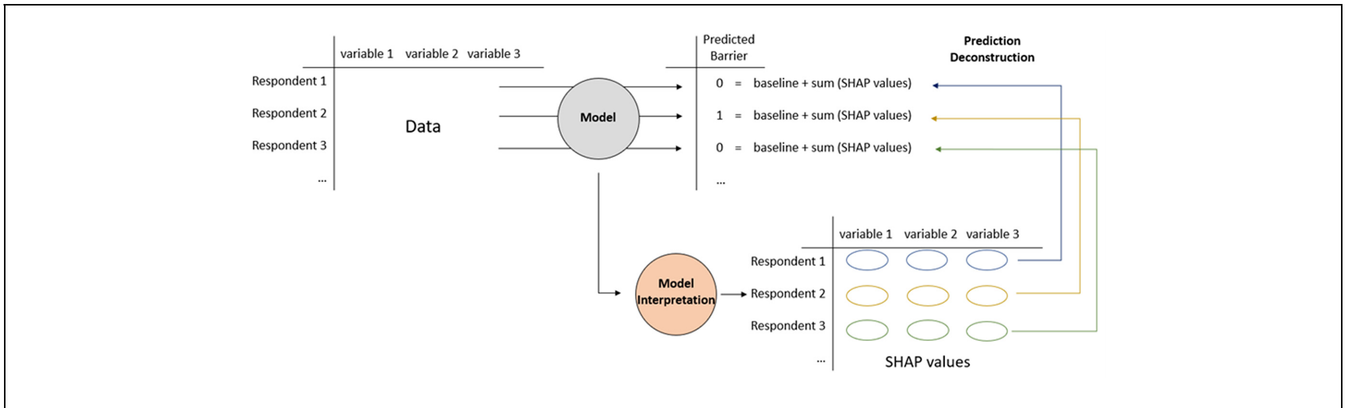

Figure 4. Using Shapley Additive Explanations (SHAP) as an interpretation technique to explain positive or negative correlations between barriers and individual and contextual factors from the model.
Source: Adapted from the study by Knapič et al. (*71*).

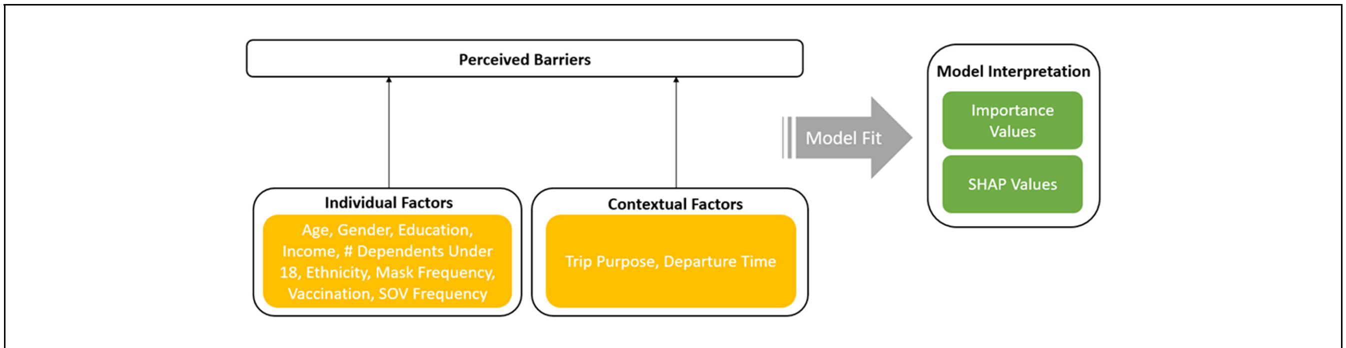

Figure 5. Modeling and interpretation framework.
Note: SHAP = Shapley Additive Explanations; SOV = single-occupancy vehicle.

and preference studies to outperform multinomial logit models and overcome the basic decision tree's overfitting problem through an iterative learning process (*39*, *47*). The model results, on the other hand, are not easily interpretable. Decision-tree-based models, in particular, are unable to produce the positive or negative effects of each variable as directly as traditional statistical models. As a result, in relation to analyzing the model outcome, a recurring concern is: How do different features affect prediction results?

Concerning the model interpretation, SHAP has been utilized to comprehend the output of models whose outputs are not directly interpretable. This analysis method deconstructs a prediction into a sum of contributions from each of the model's input variables and each individual observation to interpret the positive or negative impact of each feature and individual observation. In the case of this research, for individual prediction from the model outputs (i.e., whether they perceived a certain barrier exists), it can be decomposed by a baseline value and the sum of SHAP values of all attributes of that respondent. In this way, the average SHAP value of each attribute can be estimated, reflecting their positive or negative association with the dependent variable. This interpretation process is illustrated in Figure 4.

Based on this analysis, the XGBoost decision tree model was employed to identify and rank the impact factors of the perceived barriers to public transit, micromobility, and carpool based on the factor importance values. The SHAP values were used to determine whether each important factor has a positive or negative impact on the perceived barrier. The models are depicted in Figure 5.

The modeling implementation was carried out in Python using the XGBoost package. The mobility options' barriers are coded as binary variables, with 1 indicating "consider as a barrier" and 0 indicating "do not consider as a barrier." Ten-fold cross-validation is utilized to determine the hyperparameters of the XGBoost model to prevent overfitting and too much complexity also using the XGBoost package (*72*). The SHAP values were estimated from the XGBoost model outcomes using the SHAP package.

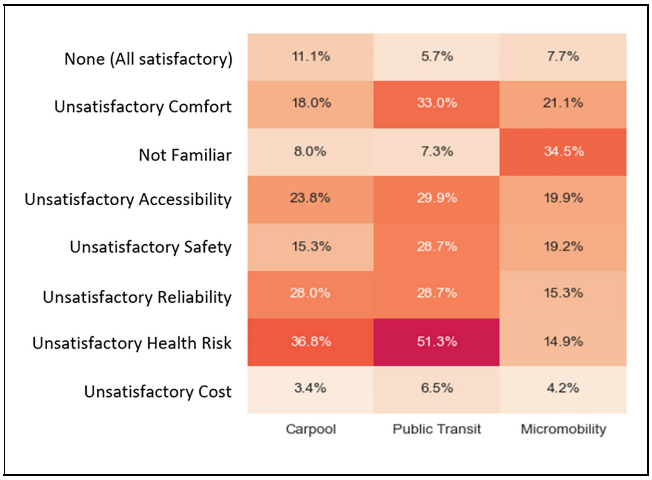

Figure 6. Greater Houston barrier distribution.

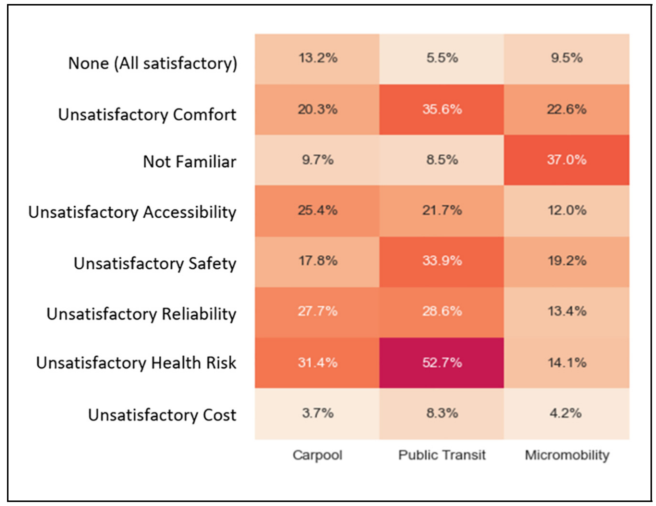

Figure 7. Greater Los Angeles barrier distribution.

There will be two outcomes for each variable, one indicating the feature's relative importance to other variables and the other showing its influence, either positive or negative, on the perceived barrier.

1) Importance Value: This score indicates how important each variable was in the construction of the XGBoost classifier. The more a variable is used to make key decisions to construct the XGBoost classifier, the higher its relative importance.
2) Average SHAP Value: To assess the positive or negative impact of each feature and each observation, a SHAP value is generated for each data point for each variable as a prediction is broken down into a total of contributions from each of the model's input variables and each individual observation. The average SHAP value, which describes the overall positive or negative impact a variable has on the XGBoost model, is the average of the SHAP values of all the data points for that variable.

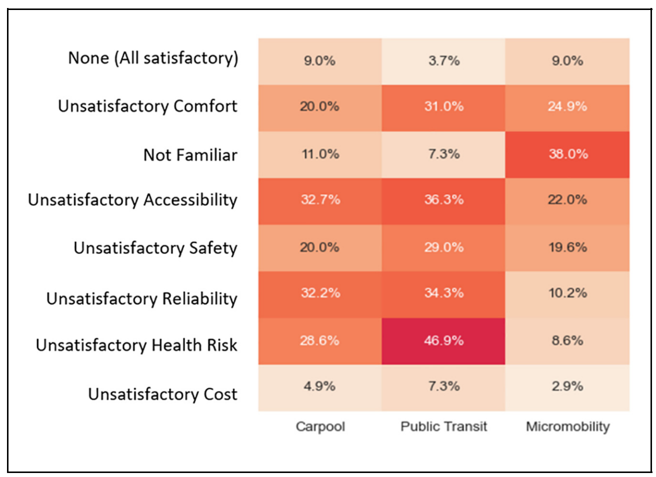

Figure 8. Virginia & D.C. barrier distribution.

Results

Barriers Distribution

The distribution of the barriers is shown in Figures 6 to 8. The X-axis represents mobility options, whereas the Y-axis represents perceived barriers. The percentages show the number of people who said the barrier was one of the reasons they did not use that mobility option.

Cost was not discovered to be a significant barrier in any of the regions. Major public transportation barriers include health concerns, reliability, comfort, safety, and accessibility, where health risk is considered the most significant barrier to public transit and carpool in all three regions, especially in Virginia & D.C. Carpool is also frequently hampered by reliability and accessibility issues. The most common impediment to micromobility is a lack of familiarity.

As a result, the analysis focused on these significant barriers, with the rest of Section 5 examining the individual and contextual impact on these barriers.

Public Transit Barriers

Table 3 shows the impact of the first six most significant variables identified by the model, which are considered the most important factors associated with the

Table 3. Individual and Contextual Impact on the Perceived Barriers of Public Transit

Greater Houston			Great Los Angeles			Virginia & D.C.		
	Importance value	Avg. SHAP value		Importance value	Avg. SHAP value		Importance value	Avg. SHAP value
Public transit—unsatisfactory accessibility								
Mask frequency	0.59	−0.10	#Dependents_0	0.47	0.06	Age_18–34	0.77	−0.05
#Dependents_0	0.50	0.03	Morning (5:00–9:59 a.m.)	0.41	0.15	Mask frequency	0.65	−0.10
Commuting	0.45	0.03	Asian	0.40	0.05	#Dependents_0	0.64	0.14
Gender_Woman	0.37	0.05	Gender_Woman	0.36	0.07	Black or African American	0.60	−0.10
Income_$100,000 to $149,999	0.36	0.01	Mask frequency	0.36	−0.11	Income_$75,000 to 99,999	0.58	0.02
Education_Post College	0.32	−0.04	SOV frequency	0.33	0.06	Education_Post College	0.49	−0.11
Public transit—unsatisfactory health risk								
Mask frequency	0.93	0.01	Mask frequency	0.76	0.06	Mask frequency	0.53	0.04
Age_18–34	0.40	−0.02	SOV frequency	0.43	0.00	Age_18–34	0.39	0.01
Income_$100,000 to $149,999	0.39	−0.02	Morning (5:00–9:59 a.m.)	0.41	0.03	Gender_Woman	0.39	0.03
Black or African American	0.33	−0.04	Asian	0.33	−0.03	Income_$100,000 to $149,999	0.35	−0.04
Morning (5:00–9:59 a.m.)	0.32	−0.04	Commuting	0.31	−0.01	Vaccination	0.31	−0.01
#Dependents_0	0.31	0.00	#Dependents_0	0.30	0.02	Education_Post College	0.29	0.04
Public transit—unsatisfactory safety								
Commuting	0.49	0.07	Age_18–34	0.54	0.03	Gender_Woman	0.72	0.09
Mask frequency	0.44	0.08	Noon (10 a.m.–12:59 p.m.)	0.42	0.04	Age_18–34	0.60	0.03
Education_Post College	0.44	−0.07	Gender_Woman	0.29	0.03	Mask frequency	0.57	0.10
Income_$100,000 to $149,999	0.44	0.01	American Indian or Alaska Native	0.29	−0.04	#Dependents_0	0.48	−0.03
Gender_Woman	0.37	0.05	Morning (5:00–9:59 a.m.)	0.27	0.03	Commuting	0.40	0.11
Vaccination	0.34	−0.03	Education_Post College	0.26	−0.03	Black or African American	0.36	−0.01
Public transit—unsatisfactory reliability								
Mask frequency	0.81	−0.17	#Dependents_0	0.79	0.11	Mask frequency	0.41	0.03
Age_18–34	0.43	0.04	Gender_Woman	0.49	0.04	Income_$100,000 to $149,999	0.40	0.05
Black or African American	0.32	−0.05	Mask frequency	0.34	−0.05	Pick-up/drop-off	0.36	−0.08
#Dependents_0	0.30	−0.08	Age_18–34	0.34	0.03	Education_High School	0.33	−0.04
Vaccination	0.30	−0.06	Evening (6 p.m.–11:59 p.m.)	0.33	−0.05	#Dependents_0	0.33	−0.01
Asian	0.30	0.01	Commuting	0.33	0.07	Income_$75,000 to $99,999	0.32	0.02
Public transit—unsatisfactory comfort								
SOV frequency	0.74	0.17	#Dependents_0	0.54	0.02	Mask frequency	0.59	−0.08
Mask frequency	0.64	−0.13	Mask frequency	0.44	0.05	Gender_Woman	0.37	0.03
Asian	0.58	−0.12	SOV frequency	0.43	0.06	Income_$25,000 to $49,999	0.33	−0.03
#Dependents_0	0.57	−0.01	Education_Post College	0.31	−0.03	Pick-up/drop-off	0.30	−0.05
Commuting	0.48	0.11	Gender_Woman	0.26	−0.02	Commuting	0.28	−0.01
Vaccination	0.48	0.02	Age_18–34	0.26	0.07	Evening (6 p.m.–11:59 p.m.)	0.27	−0.08

Note: SHAP = Shapley Additive Explanations; SOV = single-occupancy vehicle.

perceived barriers to public transit. The "Importance Value" represents the relative importance of the variable. The higher this value, the more this variable contributes to estimating the perceived barrier. The "Avg. SHAP Value" (average SHAP value) represents the overall positive or negative impact a variable has on the perceived barrier. For example, the average SHAP value of 0.05 of the variable "Gender_Woman" indicates that women are more likely to perceive public transit accessibility as unsatisfactory. Public transit is perceived as more inaccessible by women in Greater Houston and Greater Los Angeles. In Greater Los Angeles, Asians are more likely to be dissatisfied with public transportation accessibility. Furthermore, those who commute or take an early morning trip (5:00–10:00 a.m.) in Greater Los Angeles are more likely to be dissatisfied with public transit accessibility. Those who have completed post-college education are less likely to consider public transportation as inaccessible in Greater Houston and Virginia & D.C.

Mask frequency has the most impact on people's perceptions of public transportation's health risks. Those who use masks more often are more inclined to regard public transportation as posing a significant health risk. Those with a higher annual household income (i.e., those with an annual household income of more than $100,000) are less likely to see public transportation as posing a severe health risk in both Greater Houston and Virginia & D.C. Those who have been vaccinated are less likely to perceive that public transit is associated with health risks in Virginia & D.C. Although Asians are more likely to have limited access to public transportation in Greater Los Angeles, they are less likely to perceive health risks in using public transit. Those who leave during morning peak hours (5:00–10:00 a.m.) or those who use SOV frequently are more likely to believe that taking public transportation poses a significant health risk in Greater Los Angeles. In Greater Houston, Black or African American people are less likely to see public transportation as a health risk.

Women are more likely to feel public transportation is unsafe, particularly in Virginia & D.C., where women are the most important factor contributing to safety as a barrier to taking public transportation.

In all three regions, those without dependents are less likely to view public transportation to be unreliable. In Greater Houston and Greater Los Angeles, younger people are more likely to find public transportation unreliable. Furthermore, in Greater Los Angeles, women are more likely to find public transportation to be unreliable.

SOV frequency is one of the most prominent factors affecting the experience of inadequate comfort as a barrier in Greater Houston and Virginia & D.C. Additionally, those with a low income or who do not have any dependents are less likely to find public transit in Virginia & D.C. to be uncomfortable.

Micromobility Barriers

Table 4 shows the impact of the first six most significant variables identified by the model, which are considered the most important factors associated with the perceived barrier of micromobility. Unfamiliarity with micromobility is less common among those who wear a mask more often. Those who commute or travel early in the morning (5:00–10:00 a.m.) are more likely to report they are unfamiliar with micromobility. Those who do not have dependents (e.g., could be retirees or younger generations) in their homes are more likely to be unfamiliar with micromobility. Additionally, higher SOV frequency in Greater Los Angeles is more likely to result in an unfamiliar perception of micromobility.

Carpool Barriers

Table 5 shows the impact of the first six most significant variables identified by the model, which are considered the most important factors associated with the perceived barrier of carpool. In all three regions, women or Asians are more likely to find carpool inaccessible. Those who do not have any dependents are also more likely to find carpool inaccessible. In Greater Houston, higher-income people are more likely to find carpool inaccessible. In Greater Los Angeles, those with a higher SOV frequency are less likely to find carpool inaccessible.

Younger people, particularly those who are Black or African American, are less likely to believe that carpool is harmful to their health. Those who wear masks more frequently or have more than one dependent in the house are more likely to perceive the health risk of carpool, similar to the findings of the perceived health risk of public transportation. Those who use SOV regularly are more likely to believe that carpool poses a health risk. Additionally, women are more likely to perceive the health risk of carpool in Virginia & D.C. It was also discovered that families with multiple children are more likely to regard carpool as a health risk.

In all three regions, people who plan commuting trips are more likely to find carpool unreliable. In Greater Houston, people with higher income are more likely to find carpool unreliable, but in Greater Los Angeles, people with higher income are more likely to find carpool reliable. Carpool is perceived as unreliable by younger individuals in Greater Los Angeles and Virginia & D.C. In Greater Houston, African Americans are more likely to find carpool unreliable.

Table 4. Individual and Contextual Impact on the Perceived Barrier of Micromobility

Greater Houston			Great Los Angeles			Virginia & D.C.		
	Importance value	Avg. SHAP value		Importance value	Avg. SHAP value		Importance value	Avg. SHAP value
Micromobility—not familiar								
Age_18–34	0.55	−0.01	SOV frequency	0.71	0.12	Age_18–34	0.59	−0.04
Commuting	0.48	−0.07	Mask frequency	0.45	−0.02	Gender_Woman	0.59	0.02
#Dependents_0	0.48	0.04	Age_18–34	0.42	0.02	Mask frequency	0.57	−0.09
Mask frequency	0.48	−0.06	#Dependents_0	0.34	0.06	Commuting	0.56	0.03
Morning (5:00–9:59 a.m.)	0.47	0.10	Commuting	0.28	0.01	#Dependents_0	0.51	0.02
Vaccination	0.43	0.02	American Indian or Alaska Native	0.24	−0.05	Education_High School	0.35	0.01

Note: SHAP = Shapley Additive Explanations; SOV = single-occupancy vehicle.

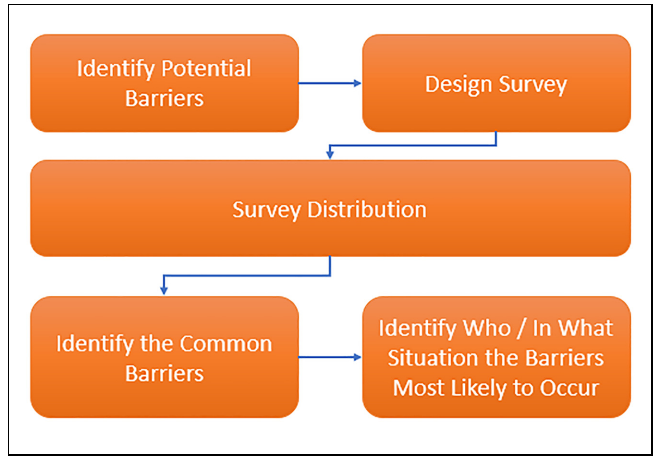

Figure 9. Method implementation procedure.

Discussions

Key Findings and Interpretations

A survey was designed for this study to learn about people's common barriers to public transit, micromobility, and carpool. Greater Houston, Greater Los Angeles, and Virginia & D.C. were selected as application regions. MTurk was utilized as the channel to distribute the surveys to these regions. Common barriers were identified, and the XGBoost model and SHAP were used to explore who (individual characteristics) or in what situation (contextual factors) certain barriers are more likely to occur. Future policymakers who seek to understand the equitable allocation of transportation services can use the implementation procedure proposed in this study to gain some insight. The procedure is illustrated in Figure 9. The primary findings and interpretations are reported in the following paragraphs.

Perceived health risk is the most significant barrier to shared mobility in the three application regions. Those who wear masks frequently are more likely to perceive a high health risk from using shared mobility options. This suggests that those who are more concerned about catching the disease are more concerned about shared modes.

The most significant factor inhibiting people from using micromobility in all the three application regions was discovered to be their lack of familiarity with it. There was also a lack of familiarity with bike-share found in the studies of other cities in the U.S. (*73*, *74*). For example, a survey in three cities in the U.S. (Philadelphia, PA; Chicago, IL; and Brooklyn, NY) found that a high percentage of respondents said they did not feel familiar enough with the bike share system to use it, especially for lower-income respondents of color (*75*). More education or promotion initiatives may be required to familiarize individuals with bike-share systems.

Table 5. Individual and Contextual Impact on the Perceived Barrier of Carpool

Greater Houston			Great Los Angeles			Virginia & D.C.		
	Importance value	Avg. SHAP value		Importance value	Avg. SHAP value		Importance value	Avg. SHAP value
Carpool—unsatisfactory accessibility								
Mask frequency	0.58	−0.10	Asian	0.53	0.08	Education_High School	0.76	−0.17
Gender_Woman	0.48	0.06	Mask frequency	0.42	0.07	#Dependents_0	0.64	0.06
#Dependents_0	0.47	0.12	#Dependents_2	0.36	−0.06	Age_18–34	0.51	−0.03
Commuting	0.41	0.07	SOV frequency	0.35	−0.07	Commuting	0.41	−0.02
Vaccination	0.34	−0.03	Age_18–34	0.33	0.06	Mask frequency	0.39	−0.07
Income_$100,000 to $149,999	0.31	0.05	Morning (5:00–9:59 a.m.)	0.33	0.06	Age_45–54	0.36	−0.02
Carpool—unsatisfactory health risk								
Mask frequency	1.12	0.19	SOV frequency	0.43	0.08	Mask frequency	0.74	0.14
Black or African American	0.50	−0.01	Age_18–34	0.42	−0.06	Commuting	0.44	0.02
#Dependents_2	0.46	0.03	Morning (5:00–9:59 a.m.)	0.39	0.04	SOV frequency	0.33	0.07
Age_18–34	0.44	−0.01	Mask frequency	0.38	0.05	Gender_Woman	0.29	0.05
Morning (5:00–9:59 a.m.)	0.41	−0.01	#Dependents_0	0.31	0.05	Education_High School	0.28	−0.05
Commuting	0.34	0.05	#Dependents_2	0.30	0.08	Age_18–34	0.28	−0.06
Carpool—unsatisfactory reliability								
Income_$100,000 to $149,999	0.59	0.06	#Dependents_0	0.45	0.04	Mask frequency	0.52	−0.06
Education_Post College	0.45	−0.10	Age_18–34	0.41	0.06	Commuting	0.46	0.09
Commuting	0.43	0.08	Mask frequency	0.37	−0.08	Morning (5:00–9:59 a.m.)	0.36	−0.03
Mask frequency	0.40	−0.07	Noon (10:00 a.m.–12:59 p.m.)	0.37	−0.04	Evening (6:00–11:59 p.m.)	0.34	−0.09
SOV frequency	0.35	−0.02	Income_$100,000 to $149,999	0.30	−0.05	Gender_Woman	0.32	−0.06
Income_$25,000 to $49,999	0.34	−0.07	Gender_Woman	0.28	0.02	Age_18–34	0.32	0.01

Note: SHAP = Shapley Additive Explanations; SOV = single-occupancy vehicle.

Women are more prone to perceive public transportation as unsafe, uncomfortable, and inaccessible, which is consistent with the previous findings that women are more at risk on public transit and the predominant victims of transit-based crimes (*76*). Furthermore, when women are the major caregivers for young dependents in the home, attaining transportation equity might be much more challenging (*77*). According to the LA Metro research "Understanding How Women Travel," women in Los Angeles are also more likely than men to travel during off-peak hours when transportation service may be curtailed (*78*). This could result in women experiencing more time poverty, having relatively little leisure time, even even if they have a high disposable income through well-paid employment. Because of time poverty, to compensate for the time wasted, women take on more part-time employment closer to home. Women's earning potential is consequently further lowered, and they are limited to fewer employment opportunities nearby (*79*). All of these findings indicate that more work needs to be done to improve the transit experience for women.

While gender equity has been identified from the survey results as a concern, it is also crucial to consider the impact of other individual and contextual factors. When compared with other factors, gender is usually relevant, but it is not always the most significant factor affecting the perception of barriers to using public transit. In relation to transit accessibility, it was discovered that, in Greater Houston, factors such as not having any dependents and commute trips were more important. This shows that commuters or those who do not have dependents are more likely to consider accessibility to be a barrier to using public transit. People without dependents were also found to be more likely to view accessibility as a barrier to using public transit in Greater Los Angeles and Virginia & D.C. One explanation for this would be that those without children tend to be younger generations who may not yet be able to afford to reside close to areas with good transit options (*80*, *81*). The findings of this study indicated that more research should concentrate on examining the accessibility of younger generations and comprehending their barriers to using transit, even though previous studies had shown that younger generations are more open to public transit than older populations (*82*). Contextual factors (morning trips) are also relatively important in Greater Los Angeles, which presents transit job accessibility issues. This finding is consistent with that from American Community Survey which found that there are more jobs in D.C. within a 10 min commute by public transit than in Greater Los Angeles and Greater Houston (*49*). In summary, the rankings allowed for the identification of specific groups of people and contexts, which enables transportation operators to conduct more focused improvement planning research on these factors.

In relation to safety, the gender factor only ranks as the most important in Virginia & D.C., but is less important in Greater Houston and Greater Los Angeles when compared with other factors such as commuting, income, and education. This suggests that women are the main demographic group experiencing safety barriers when using the transit system in Virginia & D.C. Los Angeles public transit has a higher safety level in relation to public transit safety and security events than Virginia & D.C. and Greater Houston. As a result, the transit agencies in Virginia & D.C. should think about improving their operations to increase safety and take into account the opinions of women.

In addition, African Americans and Asians are less likely to perceive health concerns and poor levels of comfort while using shared mobility choices, according to this study. They are likely to be more tolerant of shared mobility options probably because they are less likely than other groups to possess a car. As a result, they are more likely to be obliged to use public transit for commuting and other essential journeys, even if the service is poor (*26*, *83*, *84*).

Those who use SOV frequently are also more likely to see health risks, low comfort, and low reliability as impediments to taking public transportation or carpool. People with higher incomes are more likely to view shared mode as unreliable. This could be a result of their biased aversion to public transit or associated with a bad experience in the past. This is similar to previous research on car drivers' biased perceptions of public transportation quality, which found that the typical ratio of perceived public transit travel time to car travel time was 1: 2.3, with almost half of the difference owing to mistaken perceptions (*85*). To modify their current habits of driving and bias toward the alternatives, more communication or behavior change tactics or policies may be required (*86*, *87*).

Finally, contextual factors, such as the trip's purpose, may influence people's perceptions of mode selection. According to the findings from Greater Houston and Virginia & D.C., people planning a commuting journey are more inclined to consider carpool as unreliable. This is consistent with the findings, which show that carpool is less appealing because of significant uncertainty in trip duration and individuals' limited flexibility in arrival and departure timings (*88*).

The policy implications of the findings of this paper are presented in the following paragraphs.

Policy Implications

Consider the Input of Women. In relation to policy recommendations, this paper demonstrates the need to increase women's accessibility to public transportation as well as their entire travel experience. Transit schedules, which are currently primarily structured to support 9-to-5 workers, can provide more real-time and/or accurate schedule information, lowering additional wait times and improving comfort for those traveling outside of peak hours. Off-peak, family, and trip-chain fare discounts or incentives could also be offered. If children and trip chains are supported, for example, women can travel with their dependents for less cost and avoid paying a price for each leg of the journey.

In summary, overcoming gendered mobility barriers is both an environmental and a transportation decarbonization imperative. Women's needs and voices are not always taken into account in transportation design, planning, and operations, which is a missed opportunity to improve and accelerate progress toward gender equality and sustainable development goals (*89*).

Increase Accessibility for Different Ethnic Groups. The findings show that more Asians, particularly in Los Angeles, believe public transportation is inaccessible. According to the TransitCenter Equity Dashboard, Asian, Black, and Latinx transit riders have lower levels of job access (*5*). This type of geographical analysis might be used in transit planning to identify and target high-need groups, allowing transit service to be prioritized for those who need it most while also supporting jobs in communities of color. Furthermore, minorities are more likely to tolerate low-level transit services. Making people feel like they have a right to speak up about current concerns with public transportation is crucial, even if they do not grasp the value or necessity of doing so. Various ethnic groups may require different engagement plans to make their feedback more available.

Bike Educational Programs. People's lack of familiarity with micromobility may be associated with bike-share programs or riding and maintaining their own bikes. Bikeshare ridership could be increased by marketing and/or community education, as well as systemwide enhancements that focus on the nonfamiliarity issue found in our study. Educational programs should be available on how to ride their own or shared bikes, where to find repair shops, and how to follow safety rules. More how-to videos or infographics on the existing or newly introduced bike-share program or its enhanced features, as well as public biking events in which it is easy to participate, should be made available so that more people who are unfamiliar with bikes are engaged to feel comfortable trying cycling. More carbon savings might be obtained, and the sustainable target could be met by converting more drivers into occasional or habitual cyclists.

Communication to SOV Users. The results show that habitual SOV users are more prone to judge alternative modes as having inadequate comfort and reliability. While some may have had a bad experience with these transportation options, others may be predisposed in their favor. The status quo bias—the tendency for one to keep doing what one has always done—may be a substantial psychological barrier discouraging occasional or novice users from trying public transit (*35*). Besides improving public transit services, more communication could be carried out to address people's bias toward alternative mobility options. Applying behavioral science to gain a better understanding of people's bias and to shape the content, framing, and timing of communications and programs to persuade this population to try public transit again has also been suggested by previous research (*90*).

Limitations and Future Work

While these findings are important, there are some limitations that should be considered in future research. To begin, future research may include similar assessments that focus on particular barriers to certain programs to prioritize the improvement strategy. Additionally, future research could take into account more psychological factors or biases. This research can facilitate the development of more-targeted strategies to help people overcome some mental biases.

Second, because of data collection limitations, the analysis was limited to young and middle-aged people. According to research that examined the demographics of MTurk respondents, over 60% of them are under the age of 40, making them much younger than the general population of the U.S. (*91*). As a result, other channels for distributing surveys could be employed to provide a more thorough analysis of the older generations. Additionally, only one month's data was collected, and this limits the capacity to adequately examine the issues presented by various mobility services throughout several COVID infection waves. Additionally, it is possible to overstate the influence of COVID-related factors. More iterations of the survey should be conducted in future research to provide the most up-to-date and informative policy implications.

Third, focus groups or unstructured interviews can be used as a supplementary channel to understand people's barriers and pain points, allowing researchers and practitioners to find ideas and topics that have not previously been examined but are relevant to current or potential users. These interviews could also be used to confirm the study's findings, such as whether certain barriers exist for a certain set of people. Overall, these issues, that were beyond the scope of this study, should be considered in future work to further the current state of the literature on this topic.

Fourth, this study focused on a certain subset of equity-related issues to avoid making the survey excessively lengthy and subject to high variations given that the sample size is relatively small. In particular, only relatively common trips are included in the trip purposes while other trips, such as those for work training or health care, are not. Future studies should take into account the barriers perceived by seniors and individuals with disabilities.

Conclusions

This study aims to identify and rank the individual and contextual factors that have the most impact on people's perceptions of the barriers to active and shared transportation. The XGBoost decision tree model was employed to identify and rank the impact factors of the perceived barriers to public transit, micromobility, and carpool. The SHAP values were utilized to show how each important factor influences the perceived barrier. This approach not only increases model fit compared with the traditional statistical models such as the logit model, but also makes the model results more interpretable. This research provides critical insights for a more equitable distribution of active and shared systems. Transportation agencies can utilize this framework to develop and prioritize improvements and communication strategies. The major findings are summarized in the following bullet points:

- One of the major barriers to using micromobility may be unfamiliarity. Educational programs will be needed to promote this mode of transportation.
- According to the results of the significant individual factors, women and minorities are more likely to encounter inadequate transportation services. As a result, their experiences should be enhanced and their perspectives should be given more weight and attention.
- A high frequency of SOV use could lead to a generally negative impression of other alternatives. More work may be needed to confirm whether bias exists—if so, additional efforts to mitigate the bias should be considered.
- The results from the significant contextual factors suggest that trip purpose could affect individuals' perceptions of the barriers. People who are planning a commuting trip are more likely to view carpooling as unreliable, according to findings from Greater Houston and Virginia & D.C.
- When examining the relative importance of factors across various metropolitan regions, it can be seen that some factors are more important in some regions than others. For instance, it was discovered that, in Virginia & D.C., being a woman is the most significant factor in relation to the transit safety barrier, but this was not the case in Greater Los Angeles and Greater Houston.

The survey and analysis methods employed in this study could help transportation authorities identify issues presented by transit, carpool, and micromobility and choose areas where the mobility services should be improved at the individual and contextual levels. The findings from this study are expected to advise transportation agencies about the significant issues in active and shared transportation systems and the characteristics that most significantly contribute to these issues, with the ultimate goal of building more equitable transportation systems that engage a diverse group of people and achieve a long-term sustainable goal.

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Author Contributions

The authors confirm their contribution to the paper as follows: study conception and design: M. (Melrose) Pan; data collection: M. (Melrose) Pan; analysis and interpretation of results: M. (Melrose) Pan, A. Ryan; draft manuscript preparation: M. (Melrose) Pan, A. Ryan. All authors reviewed the results and approved the final version of the manuscript.

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