Overview: Improving Public Transportation using Geospatial Movement Data

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Abstract—

I. Introduction

A. Motivation

Providing affordable and sustainable options for commuters, public transportation is an essential component of urban mobility. The adoption of this methodology is essential for the development of sustainable urban environments, similar to those of cities 5.0, which focused on eliminating obstacles that residents encounter when using municipal facilities [5]. It reduces traffic congestion, air pollution, and carbon emissions.

One problem with public transportation is that there are sometimes no direct connections, which can lead to long transfer times, and that frequent delays can hinder the reliability of arriving on time. This can lead to public transportation becoming less popular and people becoming more likely to take a car instead to save valuable time. This has an adverse impact on the climate, which should actually be mitigated by public transportation.

Recently, transportation systems have evolved to include new modes of transportation that are increasingly personal, like e-scooters and taxi services including Uber. To maintain competitiveness, public transportation systems must adapt to the evolving landscape of individual transportation options by carefully planning new lines and, for example, by considering individual movement requests when bus services are provided [12].

Designing and optimizing public transportation networks is a complex and challenging task that requires detailed knowledge of people's travel patterns, preferences, and behavior. However, traditional methods of data collection and analysis have limitations in capturing the complexity and variability of people's travel behavior, leading to suboptimal public transportation systems.

In this context, advances in artificial intelligence and data science may also have created new opportunities for urban planners to better collect and analyze larger volumes of individual movement data. Investigating the impact of these new advances is also part of this work. Individual movement data provides information on individual's travel patterns, such as their origin and destination points, travel modes, travel time, and frequency. Regardless of the method used to analyze the data, effectively making use of it remains a challenge.

This leads us to the following research claim: "How can individual geospatial movement data aid public transportation planning and minimize environmental impacts?"

B. Outline of contribution

Firstly, we plan to review relevant methods for collecting data on connections that are highly requested and ones that are underused. For that, we're planning to compare techniques such as GPS tracking systems, sensors, public movement data, and other approaches. Afterward, we will investigate methods to highlight in-demand and efficient transportation connections using a diverse set of analysis techniques. Prioritizing what improvements best maximize customer satisfaction is also an important aspect of this. Machine learning, data mining and other predictive analytics can aid in getting a better overview of what is required to be done to sway from other means of transportation to certain ones that have a reduced impact on the environment.

C. Structure of the paper

This paper is structured as follows.

a) Introduction: The first chapter consists of three sections. While the Motivation describes why the problem is relevant, the Outline of Contribution touches on the contribution of this paper to the problem of improving public transportation systems using individual movement data. The last section, Structure of the Thesis, gives an overview of the structure of this paper.

b) Related Work: The related work chapter gives an overview of similar papers concerning relevant topics including public transportation planning, urban planning, and exploiting individual movement data.

c) Elaboration of Contribution: Our contribution to the domain of science. We give an overview of relevant data sources, data analysis techniques, and methods on how these can be effectively combined to aid public transportation planning.

d) Conclusion: Finally, in section Discussion of results we will summarize and discuss the main ways of analyzing and using geospatial data to the benefit of public transportation quality. Subsequently, the section Limitations specifies what constraints there are in the optimization of public transportation. Section Future Work will explore potential future work in the field and highlight challenges ahead that need to be overcome.

II. Related Work

A. Data Acquisition

In this section, we will look at how the data effectively empowers algorithmic approaches to improving Public Transportation Planning and the limitations and data quality of the different approaches.

1) Surveys: How surveys are used to gather data.

Evaluating service quality in public transportation is a multifaceted task due to its inherent complexity. The public transportation system comprises numerous attributes that need to be assessed comprehensively. These attributes encompass factors such as punctuality, reliability, comfort, cleanliness, safety, affordability, and staff behavior, among others. Recognizing this broad range of attributes is essential for effectively evaluating service quality.

Survey data used for analyzing service quality in public transportation often exhibit imprecision, subjectivity, and heterogeneity. This can be attributed to the diverse perspectives and experiences of passengers. The researchers in [17] emphasize the need to address these challenges when interpreting survey results and drawing meaningful conclusions.

The paper critically examines different methodological approaches for evaluating service quality in public transportation based on customer satisfaction surveys. These approaches encompass various aspects such as data collection, data analysis, and interpretation of results.

The researchers highlight the significance of sound data collection techniques in survey-based evaluations. This includes considerations of sampling methods and survey design. Proper sampling methods ensure representative respondent selection, while thoughtful survey design facilitates the gathering of accurate and relevant data. These factors contribute to the overall quality and reliability of survey results.

To analyze the collected survey data effectively, researchers employ diverse statistical techniques. The choice of analytical techniques depends on the research objectives and the nature of the data. The paper discusses the implications of using statistical techniques for analyzing survey data, emphasizing the need for appropriate methods that align with the research goals.

Interpreting survey results is a crucial step in understanding the overall service quality in public transport. The researchers suggest that evaluating both attribute-performance ratings and attribute-importance measures provides a more comprehensive understanding of passengers' global evaluation. This holistic approach facilitates the identification of key attributes that significantly impact customer satisfaction.

Survey-based methods for evaluating service quality in public transportation also face several challenges. Ensuring an adequate sample size is essential to obtain reliable and generalizable results. Researchers must carefully consider the representativeness of respondents to avoid biases and enhance the validity of survey findings. Achieving a high response rate is crucial for the success of surveys. Low response rates can introduce selection biases and compromise the overall quality of the data. The reliability and validity of measures used in surveys are critical for accurate data collection. Researchers should employ established measurement scales and validate them to ensure the robustness of survey instruments.

2) Smart Cards: Smart Cards (1) are used by some public transportation systems on entry and exit of vehicles, which can be exploited to re-trace movements.

The authors of [10] published a literature review about smart card data mining. They used the four databases ScienceDirect, Web of Science, American Society of Civil Engineers, and SpringerLink. Appropriate articles had to be published in English, use smart card data, and relate to passenger destination estimation. After searching and selecting the literature, 20 papers were reviewed.

Three models were considered in more detail: Trip Chaining Model, Probability Model, and Deep Learning Model. While papers from China, America, and England focused on using the Trip Chaining Model, research in Korea, Australia, Chile, and Netherlands is focused on validating the Trip Chaining Model. The Probability Model is mainly used in China and the Deep Learning Model in China and Korea.

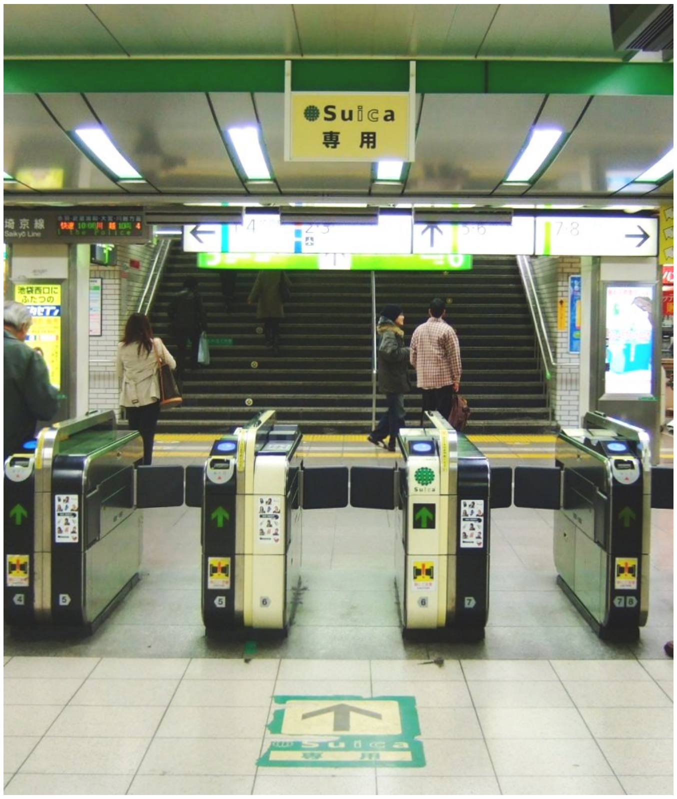

Fig. 1. A Smart Card Gate for Public Transportation Entry https://commons.wikimedia.org/wiki/File:Ja_JR_Ikebukuro_Sta._(North_entrance).jpg

The Trip Chaining Model is applied to create the tables of origin and destination trips. It has been improved based on three basic assumptions: There is no alternative means of transportation between two successive trips, passengers do not walk a long distance when interchanging, and passengers finish their last trip of the day when they started.

The Probability Model calculates the probability of getting off at a stop, considering the travel distance and the number of passengers. It was additionally figured out that the travel distance of the passengers corresponds to the Poisson Distribution. This model was further improved by adding transfer capacity using the number of bus routes and land use level using the number of passengers in the area as factors.

Two Deep Learning Models are referenced. First, an artificial neural network with the entry number as the input variable and the exit number as the output variable. However, a large dataset is needed to train the model appropriately. Moreover, complex public travel behaviors cannot be explained. Second, a model that estimates exit rates considering smart card data and land use data. Transaction variables and land use variables are used as input, which after two hidden layers result in a classification based on a softmax function.

Comparing the three models, the Trip Chaining Model just requires smart card data, is quite simple, and can predict the destination of each passenger, but is difficult to validate. The Probability Model considers extensive factors, but it can only derive the total number of passengers boarding and alighting. With the Deep Learning model, comprehensive factors are considered, it can assign an exit station to each passenger, and it can be validated by real-time data. However, this model can only be used with smart card gates at exit and entrance, and it requires huge amounts of data.

The sample size of the studies ranges from 396 with a matching rate of 88.74%, to 6 000 000 with a matching rate of 90%, to 38 000 000 records and a matching rate of 83.01%. Therefore, data quality and matching rate cannot be derived from the sample size. The data showed the problem of missing data, illogical values and duplicate transactions. Another problem is that many trips cannot be successfully matched. Some reasons for that could be that the walking distance is too long or too short, or that passengers use other means of transportation.

Five studies (25%) had matching rates below 70%, eight studies (40%) had matching rates between 70% and 90%, and four studies (20%) had matching rates above 90%.

Many researchers do not include a sensitivity analysis or a validation, which makes it hard to classify the quality of the studies.

As technology advances, more types of data (GPS, mobile phone, etc.) can be used to identify exit stations. New algorithms that handle this data are needed.

3) *Phone Data, GPS Data:* Through the commoditization of mobile phones, a vast amount of GPS, cell tower data can be obtained.

The paper by Huang, Cheng, and Weibel [8] analyzes the approaches taken in other papers regarding mobile phone data for transportation research. Traditional surveys suffer from poor data quality due to recall bias and low response rates. Mobile phone network data have varying resolution depending on the network coverage from meters to kilometers of resolution, but they are ubiquitous and can capture mobility patterns on a considerable scale. Most studies use Call Detail Records as the main source of mobile phone data, which contain information about the time, duration, and location of calls and text messages.

Events that can be used to analyze mobility patterns to infer mobility patterns include:

- Event-driven
  - Call Detail Records: time, duration, and (cell) location of calls and text messages; content varies
  - Internet Protocol Detail Records: the same as Call Detail Records, but for internet usage
- Network-driven
  - Power on/off events
  - movement to a new location area (stand-by)
  - handover to a new cell tower (active)

– using the phone (calling, texting, data); unlike the other events, this does not include receivers
– periodic updates

Network-driven data is denser with events reaching a frequency of 90s, whereas event-driven data is sparser with events reaching a frequency of 1–2 hours. Spatial accuracy is worse than GPS, but depending on the environment, a resolution of a few meters is possible. Nevertheless, the accuracy can also drop to multiple kilometers. The authors argue that analysis is still feasible because of the high frequency of the data and possible enrichment with other data sources. In the survey, 7 papers used event-driven data and 15 used network-drive data.

Only a minority of the covered papers mention the methods for data cleaning and filtering, such as removing outliers and identifying home and work locations. Preprocessing is necessary for possible outliers, low-frequency location events, and oscillating cell tower switching. Cleaning-approaches explained by papers include pattern-based (2 papers), speed-based (2 papers), and hybrid methods (1 papers). None of the studies evaluated their preprocessing, making it difficult to evaluate the approaches.

Furthermore, the authors review the methods for trip identification and transportation mode detection from mobile phone data. Trip identification involves finding a single stage of a trip, usually using a single mode-of-transport. Methods include geo-referencing-based (41%), rule-based (14%), frequency-based (9%) and spatio-temporal clustering (9%). Geo-referencing-based methods use a reference dataset to identify transportation hubs. Rule-based systems, for instance, use temporal thresholds to identify trip starts and ends. Frequency-based methods use the frequency of location events at a location to identify significant locations. Typically, spatio-temporal clustering methods group close spatially and temporally close events together to make data less noisy and use rule-based methods on this data.

The authors also review the methods for transportation mode detection from mobile phone data. Transportation mode detection methods vary in granularity, from coarse (car, public transport, walk) to fine (bike, bus, train, etc.), with most opting to ignore difficult-to-distinguish modes such as bike and bus tram. Algorithm approaches include rule-based (82%), clustering (14%), and statistical (4%). However, there is little evaluation of the accuracy and reliability of these methods. Most papers used a Rule-based approach (18 of 22). Another three papers used clustering, for instance with k-means and hierarchical agglomerative clustering, based on travel speeds and durations. The Last paper used a Hidden Markov Model (statistical method) to infer travel behaviors based on past information. Clustering may have a lower granularity than other methods because by definition it will bundle different datasets.

ML-based approaches are not used in the papers, because of the lack of labeled data, unlike GPS-based approaches. The authors argue data cleaning should become advanced and use more recent advances. Mode detection should also adopt supervised learning and fuzzy logic, which work well with GPS data. Real-time detection should also be explored. In addition, they argue for a benchmark dataset to compare different approaches, but acknowledge that this could be difficult due to the lack of standardized data formats. Furthermore, mode detection should adopt supervised learning and fuzzy logic, which work well with GPS data. The data may also be socioeconomically biased towards people with mobile phones, which may not be representative of the population. The phone data approach appears to have great potential, but given the conclusions of the paper it is hard to judge the approach effectively.

On the other hand, the topic of data acquisition by using GPS Data is explored in Lin and Hsu [11]. One of the topics that can be explored using this data is the inference and prediction of individuals' movements. This can be done by applying various techniques to analyze the spatial and temporal patterns of the data. Some techniques are:

- Locations inference: This involves identifying the frequent locations visited by an individual, such as home, work, or school. This can be done by clustering the GPS points based on their proximity and duration.
- Modes of transport: This involves determining the type of transportation used by an individual, such as walking, biking, driving, or taking public transit. This can be done by analyzing the speed and stops of the GPS points, and using machine learning algorithms to classify them.
- Trajectory mining: This involves discovering the common routes or patterns of movement followed by an individual. This can be done by using cluster-based or graph-based methods to build a temporal list of significant locations, and then finding frequent sequences or patterns among them. Trajectory mining can be used to gain insights into the mobility patterns of individuals, and can be used to predict future locations.

As highlighted by the authors of Mazloumi, Currie, and Rose [14], it is also important to consider the insights that may be gained with these data acquisition methods, and how they might allow one to develop new quality metrics and give concrete suggestions to improve local public transportation systems. One of the factors that affect the user satisfaction of public transportation systems is the travel time variability, which is the variation in travel times for the same journeys over a particular route. Travel time variability goes beyond just the waiting or mean travel times, and can be used to measure the reliability of public transportation systems, and may be an important factor in rider satisfaction. Travel time variability measures how reliable and dependable public transportation is and eases traveler decision-making, even in the face of high waiting times. The authors have not researched what the exact impact of this metric is empirically, but their arguments are sound. To quantify and analyze travel time variability, analytical approaches using GPS data installed on buses were employed by the authors. By applying statistical methods such as shape analysis, standard deviation and percentiles, the distribution and characteristics of travel time variability and possible causes were identified. In their study, travel time variability was influenced by various spatial and temporal factors. Independent of the timing, land-use allocations and route-length were found to be the most significant factors, suggesting that bus services could improve this metric most easily by splitting bus routes. The number of stops and signals also had a large impact, peaking at the AM-travel peak. The impact of signals could be reduced with better traffic management, like priority lanes. Driver schedule management by drivers also had an impact, and could be improved by improving their execution. The results aren't statistically significant, but the results also suggest a positive impact on travel time variability.

As for the shape, peak travel time variability was found to follow a normal distribution, and off-peak travel time variability tended more towards a log-normal distribution. Analyzing GPS bus travel behaviors has allowed the authors to provide suggestions that can help make stakeholders improve the situation.

4) Case Studies: Case studies on the impact of how public transportation is used in practice.

The paper [19] presents a noteworthy case study that focuses on the practical application of geospatial movement data in public transportation. The authors introduce PubtraVis, a dynamic and interactive visualization tool developed to measure and display the operational characteristics of the transit system in Calgary, Canada.

PubtraVis comprises six visualization modules that provide valuable insights into various aspects of transit system operation. These modules cover key characteristics such as mobility, speed, flow, density, headway, and analysis. By leveraging General Transit Feed Specification data, the authors demonstrate the utility of this dataset in creating effective visualization tools for analyzing and communicating transit system performance.

The study underscores the significance of utilizing General Transit Feed Specification data for developing visualization tools like PubtraVis. By harnessing this comprehensive and standardized data source, transit operators, city authorities, and the general public can gain a holistic understanding of public transit planning and operation. The interactive nature of PubtraVis facilitates effective communication by enabling stakeholders to explore and interpret the visualizations effortlessly.

The authors emphasize that PubtraVis serves as a valuable tool for showcasing the dynamic nature of transit vehicles across the entire network at a glance. This capability aids in identifying areas of improvement and optimizing public transportation services. By visually representing operational characteristics such as mobility, speed, flow, density, and headway, PubtraVis supports evidence-based decision-making and encourages collaboration between different stakeholders involved in public transit planning and management.

Hall, Palsson, and Price [6]: In a comprehensive study on the impact of ride-hailing services on public transit, researchers have provided valuable insights that can be instrumental in improving public transportation using geospatial movement data. The study, which focused on the effect of Uber on public transit, used transit agencies as the unit of observation. On average, a Metropolitan Statistical Area with public transit was found to contain approximately 2.21 transit agencies. The data on transit ridership was sourced from the National Transit Database, which records monthly ridership for virtually all transit agencies receiving federal funding.

The researchers gathered data for each Metropolitan Statistical Area on the entry and exit times of each Uber service. To estimate Uber's level of influence, they used data from Google Trends on the share of Google searches for "Uber" at the Metropolitan Statistical Area level. This approach is similar to the one used in previous studies and provides a reliable estimate of Uber's market penetration. The authors suggested that Uber's ability to fill gaps in their coverage is valuable, making Uber a strong complement to public transit. This finding is particularly relevant for improving public transportation, as it highlights the potential benefits of integrating ride-hailing services with traditional public transit systems.

In their conclusion, the authors noted that Uber has a mixed effect on public transit, with larger transit agencies experiencing negative impacts and smaller ones benefiting. This finding suggests that the integration of geospatial movement data from ride-hailing services like Uber can have different effects depending on the size and characteristics of the transit agency. The study also presented several robustness tests, including block bootstrapping and placebo tests, further strengthening the validity of their findings. These insights can be instrumental in guiding future research and policy decisions aimed at improving public transportation using geospatial movement data.

Oostendorp and Gebhardt [18] published a case study on intermodal public transportation. Berlin was clustered in three categories: decentralized neighborhoods, urban neighborhoods, and well-connected neighborhoods. Three study areas were selected for each category. 1098 participants took part in the case study with relatively equal participation numbers across the different groups. The gender distribution was rather balanced as well, and the average age was 47.8 years.

As for the case study results, only 16.5% said they never combine different modes of transportation on a trip. 70.7% combine different means of public transportation, 33.1% use bike and public transport, and 15% rely on car and public transportation. Other combinations are not used frequently, which is why intermodal transportation behavior can be strongly associated with public transportation. This strong link can be highlighted by the fact that the use of unimodal public transportation is much lower than intermodal, while unimodal bike and car use is much higher than the combination of these with public transportation.

As may be assumed, spatial differences in the use of particular forms of intermodal combinations can be detected. While in the “urban neighborhoods” an increased use of bikes and public transportation and in the “decentralized neighborhoods” one of car and public transportation can be observed, in the “well-connected neighborhoods” a combination of different public transportation modes can be seen.

Regarding the use of intermodal combinations in terms of trip purposes, it can be seen that trips to work or education account for the highest share on a daily basis. However, looking at the general distribution, it can be seen that the use for leisure activities, shopping and private matters is higher than trips to work or education.

Furthermore, the study investigated how sociodemographic and socio-economic factors influence intermodal travel behavior, which reasons are most important for using intermodal combinations, and how important various services and features are at interchanges. The study underscores the importance of public transportation for intermodal travel behavior.

B. Public Transportation Planning

In this section, we shall look at general information on Public Transportation Planning.

1) Basics: How public transportation planning works in practice and the traditional processes used therein.

Loidl et al. [13]: In the realm of transportation modeling, geospatial analyses have emerged as a significant tool, accounting for the function of similarity, spatial dependency, and spatial heterogeneity. A key component of this modeling approach is the Traffic Analysis Zones, which play a pivotal role in the Four-Step Model of transportation modeling. The delineation of these zones, however, introduces the Modifiable Areal Unit Problem, a phenomenon that describes the effect of scale and spatial zoning on model or analysis results.

Geographic Information Systems can be used to assess the effect of scaling and zoning and to delineate optimized Traffic Analysis Zones, thus addressing the Modifiable Areal Unit Problem. However, traditional transportation modeling often overlooks the spatial association or dependency between Traffic Analysis Zones or other spatial entities. This oversight underscores the need for tighter integration between transportation modeling, Geographic Information Systems, and Geovisual Analytics, a need that the authors of the paper anticipate will be met in the near future.

McLeod, Scheurer, and Curtis [15]: The main takeaway from [15] is that public transportation networks should be legible, coordinated and frequent with transfers available to serve a diverse range of trips in urban areas. The paper emphasizes the importance of multidestination lines, especially for orbital trips, and the extension of lines to the city periphery to maintain line speed. Demand-responsive modes, such as bike sharing, ride sharing, autonomous cars, and demand-responsive buses, can complement formal public transportation systems by accommodating sporadic travel demand patterns and serving as the “first mile” or ”last mile” of trips. The authors suggest that transfers and multiple modes of transportation should be incorporated into land use and urban design policy, particularly near transfer nodes. The implementation of transformative public transportation futures requires a regionally oriented approach and interagency collaboration to achieve sustainable travel outcomes.

Redman et al. [20]: Public transportation has been recognized as a sustainable alternative to private car use, and understanding the aspects of public transportation service quality that attract car users is crucial for enhancing its usage. A comprehensive synthesis of current knowledge in this field reveals two main questions that need to be addressed: What quality attributes of public transportation services are attractive to users? What changes in quality attributes of public transportation services would encourage a modal shift from private motor vehicles to public transportation?

The quality attributes of reliability and frequency have been identified as core determinants of general public transportation demand and satisfaction levels. However, public transportation improvements are often implemented before considering the quality attributes they potentially address. This approach could be adjusted to enhance the general effectiveness of public transportation quality improvements on car-user demand for, and satisfaction with, public transportation services.

Access to a private motor vehicle is a significant hindrance to an individual’s demand for public transportation services. To attract private car users, it is important to determine or enhance the underlying motivations for using private vehicles and translate these into attributes that are emulated by public transportation services. The authors conclude that public transportation services have the potential to attract private car users by improving the quality of the service, but the specific improvements depend chiefly on the context and particularities of each targeted sample and individual motivations for using private motor vehicles.

2) AI: How AI can be used to enhance public transportation planning:

The paper [21] attempts to incorporate the evolving field of artificial intelligence into urban design. They elaborate on several fundamental aspects that boost the importance of urban planning: sustainability, living, economy, disasters, and the Environment. The first step towards environmentally responsible and socially inclusive communities is thoughtful urban planning. It enhances the quality of life for all citizens and, on the other hand, also bolsters the resilience and adaptability to natural disasters or other unforeseen challenges.

Four key trends are what the authors come up with, that will lead the future of AI in urban planning. New configuration representation techniques are the first of these and involve the organization and design of structures, streets, and public spaces in cities. The goal is to create a functional, visually appealing and sustainable urban environment that meets the needs of residents and businesses.

Secondly, there are new generative learning approaches. Those Learning approaches are about leveraging AI's ability to analyze extensive amounts of data and identifying patterns exceeding human understanding. They will not only enhance the efficiency of urban planning but also promote stimulate innovation and sustainability.

Third of all, we have human-machine collaborative planning vs. conversational AIs (something like Chat-GPT) that aim for a synergistic relationship between urban planners and AI-assisted tools. The goal here is to combine AI's analytical capabilities with human expertise to ensure a more inform and balanced decision-making.

The last step is to make said AI-assisted urban planning fairness-aware. To achieve that, we need to consider all the needs and aspirations of citizens, reducing the risk of biased or discriminatory outcomes. The incorporation of artificial intelligence can aid in enhancing the justice and inclusivity of cities by placing fairness and equity at the forefront of urban planning.

C. The Future of Public Transportation

This section discusses which future or existing methods and systems should be used more or could have a positive impact.

1) Micro-Mobility: Covers the impact of last-mile/micro-mobility (e.g. e-scooters).

The paper [16] introduces which services and infrastructures are necessary for the integration of micro-vehicles into public transportation. For this, 48 articles from around the world are analyzed.

Since increased use of micromobility reduces CO2 emissions, this paper summarizes recommendations for successfully integrating micro-vehicles into public transportation. Communities and municipalities should provide an infrastructure that can grant safe and efficient use of micro-vehicles. User-friendly parking facilities for micromobility close to public transportation stations must also be ensured. In addition to the structure of the road network, the types of uses in the surroundings of stations also influence the choice of transportation modes. Educational and cultural facilities and also green spaces in the street networks play an important role in increasing the use of micromobility. For micromobility, real-time data in technologies is unavoidable to increase the usability and user-friendliness of micromobility sharing systems. General assurance of quality and maintenance of vehicles allows preserving safety and satisfaction of users and attracting new users. Collaborative planning and development of micromobility and public transit promotes the integration of micro-vehicles. To be able to guarantee the safety regulations, small fines should be introduced. Road sections should be reserved for micromobility and illegal parking on them should be strictly punished. In order to increase the popularity of micromobility, incentives must be established. On the one hand, prices should be presented clearly, and any discounts should be considered. On the other hand, companies that promote micromobility should be supported. Campaigns and training can help bring attention to the issue and increase the popularity it needs.

The authors of [2] recognize the potential benefits that last-mile/micro-mobility services, such as e-scooters, can offer in urban transportation systems. These services aim to bridge the gap between existing public transportation infrastructure and the final destinations of passengers. By incorporating the findings from their predictive models, the authors contribute to the understanding of how shared mobility, particularly e-scooters, can positively impact urban transportation.

The utilization prediction models developed in the study provide insights into the demand patterns and usage trends of shared-e-scooter fleets. By accurately forecasting fleet utilization, urban transportation planners and operators can optimize the allocation of resources, ensuring that e-scooters are available when and where they are needed the most. This optimization can lead to improved last-mile connectivity and enhanced overall public transportation efficiency.

The utilization prediction models rely on the analysis of geospatial movement data, which captures the spatial and temporal patterns of shared-e-scooter usage. This data, combined with machine learning algorithms, enables the identification of factors influencing fleet utilization, including weather conditions, holidays, events, and other relevant variables. The integration of these variables into the models allows for a more comprehensive understanding of the factors affecting the demand for last-mile/micro-mobility services.

By leveraging open-source big data and machine learning techniques, the authors demonstrate the potential for data-driven decision-making in the realm of shared mobility. The utilization prediction models serve as a valuable tool for urban transportation planners and policymakers to assess the impact of e-scooters on public transportation systems. The findings from this research can guide the implementation of effective strategies to optimize the integration of last-mile/micro-mobility services into existing transportation networks.

2) Ride-pooling: Ride-pooling as an evolution of bus services and shared mobility.

Zwick and Axhausen [22]: Ride-pooling, a service offered by Transportation Network Companies like Uber and Lyft, represents a significant development in the future of individual public transport. This service, which complements traditional ride-hailing, has the potential to reshape urban mobility by providing a shared transportation mode that can increase the efficiency of vehicle usage.

However, the adoption of ride-pooling is not without its challenges. One of the main concerns is the potential increase in vehicle kilometers traveled in urban areas. This increase can be attributed to deadheading (the movement of a commercial vehicle in service but without passengers), induced trips, and the supplanting of more sustainable modes of transport. These factors highlight the need for careful planning and regulation to ensure that ride-pooling contributes positively to urban mobility and does not exacerbate traffic congestion or environmental problems.

In the context of improving public transportation using geospatial movement data, the spatial and temporal assessment of ride-pooling demand is crucial. A case study conducted in Germany demonstrated the potential of geospatial analysis in predicting ride-pooling demand. This approach can provide valuable insights for transportation planners and policymakers, helping them design more effective and sustainable transportation systems. Future research in this area could further explore the integration of geospatial movement data in transportation modeling and planning, particularly in the context of emerging transportation modes like ride-pooling.

Liu, Zhang, and Yang [12]: The paper [12] proposes "bus ride-sharing" which is similar to car-sharing but tackles problems such as demands for recurring, long-distance and low-cost trips, since a lot of similar low-capacity services like carpooling or taxi ride-sharing do not. An example of that would be the immense number of people in a metropolis going to work every day. They currently have to choose between traditional public transportation like train, relying on taxi-ridesharing or using their car. All of those are either ecologically/economically suboptimal or time-consuming/unreliable. In practice, the bus ride-sharing would work like this: the rider uses an online bus-hailing service to share his or her trip demand and waits for it to gather enough people to then be picked up. The provider continues by assigning a driver to riders after integrating the matched ride request. The authors analyzed 65065 taxi-trip instances from one day in Shanghai and concluded that bus ride-sharing can provide better cost performance and on-demand bus services for every ride request. Moreover, the amount of oil used is reduced by 92 % and the number of vehicles by 96 % compared to regular cars.

Abduljabbar et al. [1]: In the paper [1] the authors discuss applications of artificial intelligence in road transportation. Therefore, they discuss bus planning, shared mobility, on-demand bus-services and autonomous vehicles.

Several AI techniques are described (mainly neural networks). These models can predict the speed and the traffic flow partly accurately. This will require large amounts of data from the population based on their daily route choices. Big data can also be provided by recent ride-sharing services such as Uber and Didi Chuxing. Through these, AI can not only prevent empty vehicles, but also create real-time prediction for bus passengers on the bus and at the bus stop.

Shared mobility offers the possibility of reducing individual traffic and thus air pollution. Particularly noteworthy are shared bikes and cars, and generally on-demand services. AI can increase user satisfaction in shared mobility. Uber uses AI not only for route-based pricing and for destination prediction, but also to detect fraudulent drivers.

Besides the possibility of using AI to reduce the waiting time of the passengers of the bus, AI can also be used for autonomous buses. These have been tested mainly in China, but also in Singapore and the USA.

Another way to use AI in public transportation is flexible on-demand bus services. These combine the direct connection of a cab with the efficiency of buses. The systems use real-time traffic data and passenger input to find the fastest route and stop only at locations requested by passengers.

AI offers the opportunity to improve public transportation and simplify route planning. However, the limitations of AI should also be considered, such as the fact that neural networks are "black boxes" because the relationship between input and output are developed without the knowledge of the system's internal operations.

3) Improvements to Existing Systems and Technologies: There are several potential improvements to existing public transportation technologies and systems that can enhance their efficiency and convenience.

Bast, Brosi, and Storandt [3]: The future of individual public transportation is being shaped by advancements in technology and data analysis. One such advancement is the visualization of large transit networks in real-time, which is a topic explored by the authors of the paper.

This real-time visualization is made possible through the use of General Transit Feed Specification data, a common format used to represent public transit schedules and related geodata. The authors developed a framework based on General Transit Feed Specification data to visualize the public transit of the entire world, highlighting the potential for technology to revolutionize the way we view and interact with public transportation systems.

However, the creation of a worldwide live map presents significant challenges, primarily due to the vast amount of data required for the application. The authors of the paper discuss these challenges and present a client/server infrastructure for real-time movement visualization. In this infrastructure, the server manages transit data, receives requests, and outputs information that enables the client to display vehicles on the screen. This approach demonstrates how technology can be used to manage and interpret large datasets, providing valuable insights for public transportation planning.

In addition to these technological advancements, the authors also discuss the potential of their server as a powerful tool to validate and minimize General Transit Feed Specification feeds. This highlights the importance of data validation and optimization in improving public transportation systems. By ensuring the accuracy and efficiency of data, transportation planners can make more informed decisions and develop more effective strategies for improving public transport.

III. Elaboration of Contribution

A. Data Acquisition

Common data-sources in the public transportation space are surveys, mobile phone data, GPS tracking and smart-cards. Surveys require a lot of thought and effort to carry out successfully [8]. Through the wide spread of mobile phones, the data from cell towers has become a desirable source of movement data. In dense population centers, accuracy of locations can reach as far as a few meters, but data can be unreliable and only have kilometer-level precision in sparsely populated areas. Current approaches are lacking benchmark data, which makes it hard to give any recommendations on the use of this data, and whether it is a usable source of data. Phone data may also be skewed towards more affluent public transportation users, since they may be more likely to own a phone. [8]

GPS tracking is much more cumbersome to collect, as it requires setting up tracking, but the accuracy of location data tends to be high. Besides tracking passengers, it may also be used to track the travel of public transportation vehicles, allowing to judge their reliability of arriving on time. [11]

Smart cards are systems used by some public transportation that provide to control the exit and entry of passengers. Such systems may require to scan a card on entry/exit of public transportation vehicles, which can be recorded. Like with phone data, not all passengers may use the system and, for instance, instead buy paper-tickets on demand or pay for passage directly. This method is only usable if the local transport systems are actually using a smart card system. Depending on the location, it is possible that the collected data is fairly limited, and either only the entry or exit into the system is recorded and the data needs to be enhanced to get a glimpse at full travel behavior. [10]

GPS and phone data tend to be analyzed in similar methods, though the use of AI is less applicable to phone data given the lack of benchmark data. First, data needs to be cleaned of outliers and low-accuracy data, like vehicles moving at impossible speeds. To identify transport hubs, clustering methods like k-means or even more efficient algorithms. To identify trips, it is also paramount to detect the used mode of transport, which in other papers was also based on clustering, or just rule-based methods. Rule-base methods may simply detect the mode-of-transport based on the travelling-speed. Given all this data, it is possible to cluster it again on a higher level to detect trip-level information. [8, 11] The missing entry and exit stations for smart-card data is often obtained by using AI-methods, and AI-methods also find use with GPS-data. [10, 11]

Whereas the analysis of surveys and smart card data directly leads to trip information, GPS, and phone data are usually analyzed through multiple stages. First significant locations are determined, then movements are assigned to a mode of transport, later to be joined into trips. [10, 11, 8]

Smart-Card data may be the most reliable when both entry and exit are recorded, but this is only possible if the local cities support it, and such systems are not in use everywhere or may be severely limited. GPS data seems strictly preferable over phone data, unless it is too difficult to obtain the required level of data. Surveys may be a good last-resort if the other data collection methods are not applicable to the current domain. For all given methods of data collection, it is also paramount to consider privacy, since unless great care is taken, individuals movements' could become exposed. The importance of this has become greater in the advent of recent privacy legislation like the EU General Data Protection Regulation law (GDPR).

B. Public Transportation Planning

The integration of Geographic Information Systems and transportation modeling offers a significant advantage in addressing spatial dependencies and heterogeneities, which traditional transportation modeling often overlooks. This approach allows for a more nuanced understanding of Traffic Analysis Zones and the Modifiable Areal Unit Problem, leading to more accurate and effective transportation planning. However, its disadvantage lies in its complexity and the need for advanced technical expertise, which may not be readily available in all planning agencies.

On the other hand, the principles of urban public transportation planning are more straightforward and can be implemented without the need for advanced technical expertise. These principles emphasize the importance of legibility, coordination, and frequency of services, as well as the integration of multidestination lines and extension of lines to the city periphery. However, this approach may not fully account for spatial dependencies and heterogeneities, which could limit its effectiveness in certain contexts.

Both approaches share a common emphasis on the importance of coordination and integration in transportation planning. However, they differ in their focus, with the GIS-based approach focusing more on spatial aspects, while the urban public transportation planning approach focuses more on service aspects.

The integration of demand-responsive modes has the advantage of accommodating sporadic travel demand patterns and serving as the “first mile” or ”last mile” of trips. However, this approach requires a high level of coordination and integration with existing public transportation systems, which could be challenging to achieve in practice.

The focus on quality attributes of public transportation services that attract car users offers the advantage of enhancing the attractiveness of public transportation for car users. However, this approach requires a in-depth understanding of user preferences and behaviors, which could be challenging to obtain and may vary widely across different contexts.

In essence, each of these approaches offers unique advantages and faces specific challenges. A comprehensive approach to public transportation planning would ideally integrate these approaches, taking into account both spatial and service aspects, and focusing on both system efficiency and user satisfaction. However, the specific strategies for integration would depend on the context and particularities of each targeted sample and individual motivations for using private motor vehicles.

In light of these shared themes, the integration of artificial intelligence (AI) into public transportation planning emerges as a promising approach. AI's ability to process and analyze large volumes of geospatial data in real-time allows for a more dynamic, responsive, and user-centric model of public transportation planning. By leveraging AI's predictive and analytical capabilities, planners can better anticipate demand, optimize routes, manage fleets, and ultimately enhance service quality. The following section elaborates on the role of AI in public transportation planning, drawing on several studies that have significantly contributed to this emerging field.

A significant area of focus is the use of data for transport planning. One body of work employs an analytic platform leveraging AI to process and analyze smart card data, providing valuable insights for transport planning [22]. This approach's ability to handle large volumes of data and provide real-time analysis is a significant contribution to the field. However, it contrasts with another study that focuses on transport mode detection using mobile phone network data [8]. Here, the categorization of mode detection algorithms into rule-based heuristics, clustering, and statistical analysis, along with the emphasis on data cleaning methods and trip identification approaches, adds a unique perspective to the discussion.

In parallel, a comprehensive review of AI applications in public transportation planning provides a valuable context for understanding the state of the field [1]. It highlights the growing trend of AI adoption in transport planning and the various AI methods used in the field, including machine learning, data mining, and optimization algorithms. However, it also cautions about the challenges of data privacy and the need for interpretable AI models. This broad overview contrasts with other research that delves into specific aspects of AI in transportation, such as the use of Agent-Based Models (ABMs) [13]. Here, the importance of representing spatial heterogeneity and emergent traffic patterns is highlighted.

The necessity of customer satisfaction surveys in assessing the quality of service in public transportation is also emphasized in one study [17]. The use of both objective and subjective information in assessing service quality provides a user-centric perspective, complementing the data-centric approaches of other research. This focus on understanding user perceptions and experiences in public transportation planning adds a valuable dimension to the discussion. However, it contrasts with another study that explores the quality attributes of public transportation services that attract users and encourage a modal shift from private motor vehicles to public transportation [20]. Here, understanding the factors that influence transportation mode choice and improving these quality attributes is seen as an effective strategy for promoting public transportation use.

C. The Future of Individual Public Transportation

There are several key components to lead cities into a future-proof public transportation system.

First of them is the need for micro-mobility services. With the usual public transportation modes such as train or bus, not every location can be reached coherently. In addition, spending money and time on, for example, a cab to reach one's intended destination is rather undesirable and has a negative impact on the environment anyway. The best ways to provide transportation for the last mile of a trip are e-scooters or bike-sharing, both part of said micro-mobility services. [16, 2]

The big advantage of micro-mobility is the sheer amount of flexibility, with micro-vehicles potentially being available all over the city, even in parts not well-connected by train or bus. Together with the affordability and the negligibility of the environmental impact, a very solid complementary mode of transportation can be achieved. However, this also causes some problems, such as the general safety. Inexperienced or reckless drivers may lead to collisions with pedestrians, cyclists or other vehicles. The risk of injuries and accidents may further increase with the lack of helmet or other protective clothing requirements. A solution could be introducing small fines for careless driving and reserving road space for micro-vehicles.

Ride-pooling and ride-sharing are different approaches to expand and reduce the burden on public transportation.

Classic ride-sharing offered by companies such as Uber or Lyft brings a lot of quality of life with them and thus are hard to exclude from the future of public transportation. Nevertheless, they are arguably the worst mode of transportation discussed in this paper, considering the major impact on the environment and the cluttering of roads with more cars. [1]

In comparison to other means of micro-mobility, some strengths can be highlighted. Firstly being the guarantee of getting from point A to point B without needing to transfer at any given point or travel extended distances by foot. Safety concerns for both the vehicle and citizens are also much lower traveling via car instead, with cars having an accident rate of 7.6 per 1 million trips and e-scooters encountering 115 injuries per 1 million trips instead [4, 9]. Major strengths of micro-vehicles in direct comparison are environmental friendliness [7], independence from any other individuals and traffic jams, and not further increasing road congestion.

Another approach related to car-sharing is car-pooling, which retains many of the benefits while eliminating some of the drawbacks. The term describes multiple people getting together and driving in one car to a similar destination, and thus saving road space and gas. It is still possible to have the certainty to reach point B without many circumstances, and it's just as good in terms of safety. [22]

Additional benefits include social interaction and reduced stress on the driver, since participants can alternate driving the car. The two major advantages car-sharing offers over car-pooling are the sheer amount of quality of life and flexibility. It is not always possible to find fellow travelers, or one wants to save oneself the trouble of organizing the trip with them.

Bus-pooling is a proposed concept enhancing both pros and cons of car-pooling, making it a very solid option for recurring, long-distance trips, e.g. traveling to work every day. Using that concept achieves up to 92 % reduction in oil consumption and 96 % reduction in the number of vehicles on the road, while the quality of life with a well-planned schedule doesn't suffer too much, since you get picked up and dropped off at the same place every time. Spontaneous and one-time trips are generally very difficult to realize, because of the large amounts of people required to fill the bus properly. [12]

AI, in addition to improving bus schedules and public transportation planning, can facilitate the introduction of bus-pooling by deploying autonomous vehicles that can plan and drive autonomously and simultaneously. [1]

While so far, we have discussed complementary means of public transportation, real-time movement data and their visualization can help to highlight the importance of validating and optimizing the data. A map with the real-time position of the public transportation is also of great benefit to passengers, as they can always monitor where the bus or train is located, allowing them to plan their trip more accurately. However, the dependency on vast amounts of data and server resources may diminish the cost-effectiveness. [3]

IV. Conclusions

A. Discussion of Results

The exploration of geospatial movement data for the improvement of public transportation has revealed several key insights and potential directions for future research.

The contrast between traditional methods of data collection like surveys and modern approaches, such as the use of artificial intelligence and data science with phone and GPS data, has been a significant focus in recent research. Modern methods have shown great potential in capturing the complexity and variability of people's travel behavior, leading to better insights that can be used to obtain optimal public transportation systems. However, to gain those insights large quantities of data are required, and the data needs to match the local environmental conditions. For instance, phone data can be less valuable in less densely populated areas. It is of utmost significance to employ the appropriate methods of data collection.

Public transportation planning has made remarkable progress in the last couple of years, shifting part of the workload from humans to AI. The collective contribution of research works in that area advances our understanding of the application of AI in public transportation planning. They provide a solid foundation for future research, addressing different aspects of the problem, investigating various AI methods, and suggesting promising directions for further exploration. In addition to public transportation planning, AI could also simplify the integration of bus-pooling by autonomous vehicles. The differences in their approaches and focus areas highlight the breadth and depth of the field, while their shared focus on improving public transportation planning through AI underscores the importance of this area of research.

Comparing the different means of individual public transportation shows the necessity of all of them to exist concurrently, it's just a matter of individual needs and possibilities. While bus-pooling beats out ride-sharing and ride-pooling in almost all of the mentioned categories, it's much less flexible and thus not utilizable in every situation. Micro-Mobility on the other hand provides superior flexibility, affordability and environmental friendliness, but has safety issues and is not suitable for long distance-trips. Insights in how strategies for improving public transportation can be made more efficient are offered by real-time movement data and their visualization. It can also be a benefit for passenger satisfaction, but is depended on vast amounts of data and server resources.

B. Limitations

Despite a careful approach, this paper is not without its limitations. The selection of papers used in the analysis, while extensive, may not capture the full diversity of possible approaches because public transportation is a broad field. Additionally, the methods used to analyze the data, while powerful, may not be suitable for all types of data or the subtleties of other research objectives.

Many public transportation systems are also in private ownership and may not wish to disclose details in their planning, so public data limits our insights. Government entities can also be less forthcoming and hesitant to implement new planning approaches.

Less available data leads to worse understanding of passenger behavior and prevents the usage of real-time visualization. For both approaches, a large amount of sensitive data is needed and therefore regions with less available data may be limited in improving their public transportation planning.

Since public transportation in cities is already planned, integrating the complementary means of transportation into city planning is a difficult task. Changing any aspect of an in-place public transportation is a very slowly paced task and can lead to various unforeseen difficulties.

C. Future Work

The future of this research field holds great potential. The exploration of modern data sources and analysis techniques, as well as their application in various urban contexts, promises new opportunities in public transportation planning. The integration of artificial intelligence in urban planning, in particular, is an area that needs to be further explored. The main objective is to create a functional, visually appealing, and sustainable urban environment that caters to the needs of residents and businesses, while fostering innovation and sustainability, as forecasted in the cities 5.0 project.

A significant area of focus for future research is the examination of the role and impact of last-mile/micro-mobility solutions, such as e-scooters, in urban transportation systems. The hypothesis is that an increased utilization of micro-mobility solutions can lead to a reduction in CO_2 emissions. Strategies for the integration of micro-vehicles into public transportation systems are proposed, which include ensuring the safe and efficient use of micro-vehicles, establishing user-friendly parking facilities in proximity to public transportation stations, and leveraging real-time data technologies to enhance the usability and user-friendliness of micro-mobility sharing systems.

The importance of collaborative planning and development of micro-mobility and public transportation is underscored, along with the introduction of minor penalties to ensure adherence to safety regulations, and the creation of incentives to boost the popularity of micro-mobility.

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