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Developing a Multi–Dimensional Framework for the Deployment of Free-Floating Shared Mobility Services

Mohamed Besheer Abouelela

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The important thing in life is not the triumph, but the fight; the essential thing is not to have won, but to have fought well.

Pierre de Coubertin

Abstract

The growing urbanization puts unprecedented pressure on the urban environment and its infrastructure, particularly the urban transportation system. Current means of increasing road capacity to cater to the increased travel demand are not optimal; as stated by Lewis Mumford, “Adding car lanes to deal with traffic congestion is like loosening your belt to cure obesity.” Innovative solutions benefiting from the current advancement of information and communication technologies (ICT) have the potential to mitigate such problems. Among such solutions, shared mobility services (SMS) can potentially absorb the increase in travel demand and reduce the current traffic externalities.

SMS is a group of services that give users the option to share rides with other users, or to access different types of vehicles, and to pay for their actual use; it can be succinctly described as a pay–per–use system where users are charged based on the time or the distance they use such services. By doing so, users are relieved from the burdens and responsibilities of car ownership and increase their travel sustainability as they reduce overall vehicle idle time, energy consumption, greenhouse gas (GHG) emissions, and vehicle utilization rate. SMS exists and operates in several forms and schemes. Some of the most popular ones are free-floating (dockless) services; the popularity of these services is reflected in their burgeoning demand. However, free-floating shared services were introduced abruptly to the urban environment without advanced planning, which created several problems that could negatively impact the urban environment.

A motivation would therefore be to investigate these new services so that they are better integrated in the urban environment. As to the best of the author’s knowledge, this has not been yet looked at in previous research. The aim of this dissertation would therefore be to provide in–depth understanding of the SMS interactions with the different elements of the urban environment, namely i) the meteorological conditions, ii) the built environment characteristics, iii) the population’s sociodemographic attributes, iv) the available modes of transportation , and v) the SMS characteristics and the interaction within the SMS.

Accordingly, this work looks at different perspectives of SMS, by considering their interactions with aforementioned elements, to facilitate their integration in the urban environment; this has been explored and validated throughout six research papers. In the first paper, spatiotemporal demand patterns and factors impacting them were assessed, using shared E-scooter trip data from five North American cities. The findings of this study showed that the patterns are similar in all cities despite their differences and reinforced the need to predict SMS demand for more efficient operation. As a result, the second paper developed a framework to predict SMS demand for a long–time horizon, based on the concept of transfer learning and using open-source data.

The third study investigated the synergies between the different SMS, estimating the expected shift in the number of trips from carsharing to shared E-scooters, and the resulting savings in energy and vehicle kilometer traveled. In the fourth study, the role of personality traits and attitudes on carsharing adoption and use were investigated. Both of these studies utilized different surveys data from Munich, Germany
The fifth study evaluated the relationship between shared E–scooter and public transportation (PT), notably showing the potential of the latter to extend PT accessibility. The final study assessed the need for SMS, and evaluated its equitable use for different population groups, showing that SMS is not always the optimum solution, and the equitable use problem of SMS might be related to the urban structure and not to SMS. Finally, the findings of the different studies enabled the development of a five–stage framework that could be used for the planning and deployment of SMS. The proposed framework gradually targets the implementation of the services by thoroughly investigating the population's need for SMS (stage I). If SMS were needed, a pilot project is adopted (stage II), and if successful, a full deployment of the service is implemented (Stage III). During the full deployment stage, the service's interaction with other elements of the urban environment is monitored (stage IV). Finally, the lessons learned from the different stages are extracted so that they can be transferred for the implementation of future projects (stage V).

Zusammenfassung

Die zunehmende Verstädterung setzt die städtische Umwelt und ihre Infrastruktur, insbesondere das städtische Verkehrssystem, unter einen noch nie dagewesenen Druck. Die derzeitigen Möglichkeiten, die Straßenkapazität zu erhöhen, um die gestiegene Verkehrsnachfrage zu befriedigen, sind nicht optimal; wie Lewis Mumford sagte: "Zusätzliche Autospuren, um die Verkehrsüberlastung zu bewältigen, ist, als würde man den Gürtel lockern, um Fettleibigkeit zu heilen." Innovative Lösungen, die von den aktuellen Fortschritten der Informations- und Kommunikationstechnologien (IKT) profitieren, haben das Potenzial, solche Probleme zu entschärfen. Zu diesen Lösungen gehören die Dienste der geteilten Mobilität (SMS), die potenziell den Anstieg der Verkehrsnachfrage auffangen und die derzeitigen externen Effekte des Verkehrs reduzieren können.

SMS ist eine Gruppe von Diensten, die den Nutzern die Möglichkeit bieten, Fahrten mit anderen Nutzern zu teilen oder auf verschiedene Fahrzeugtypen zuzugreifen und für deren tatsächliche Nutzung zu bezahlen. Sie können kurz als Pay-per-Use-System beschrieben werden, bei dem die Nutzer auf der Grundlage der Zeit oder der Entfernung, die sie solche Dienste nutzen, bezahlt werden. Auf diese Weise werden die Nutzer von der Last und der Verantwortung des Autobesitzes befreit und erhöhen die Nachhaltigkeit ihrer Reisen, da sie die Leerlaufzeit des Fahrzeugs, den Energieverbrauch, die Treibhausgasemissionen und die Auslastung des Fahrzeugs insgesamt verringern. SMS gibt es in verschiedenen Formen und Systemen. Einige der beliebtesten sind Free-Floating-Dienste (dockless); die Beliebtheit dieser Dienste spiegelt sich in ihrer steigenden Nachfrage wider. Free-floating-Dienste wurden jedoch ohne vorherige Planung abrupt in das städtische Umfeld eingeführt, was zu verschiedenen Problemen führte, die sich negativ auf die städtische Umwelt auswirken könnten.

Es wäre daher wünschenswert, diese neuen Dienste zu untersuchen, um sie besser in das städtische Umfeld zu integrieren. Nach bestem Wissen und Gewissen des Autors wurde dies in der bisherigen Forschung noch nicht untersucht. Ziel dieser Dissertation ist es daher, die Wechselwirkungen zwischen SMS und den verschiedenen Elementen des städtischen Umfelds, nämlich i) den meteorologischen Bedingungen, ii) den Merkmalen der bebauten Umwelt, iii) den soziodemografischen Merkmalen der Bevölkerung, iv) den verfügbaren Verkehrsmitteln und v) den Merkmalen der SMS und der Interaktion innerhalb der SMS eingehend zu untersuchen.

Dementsprechend befasst sich diese Arbeit mit verschiedenen Perspektiven von SMS, indem sie deren Interaktionen mit den oben genannten Elementen berücksichtigt, um ihre Integration in die städtische Umwelt zu erleichtern; dies wurde in sechs Forschungsarbeiten untersucht und validiert. In der ersten Arbeit wurden die räumlich-zeitlichen Nachfragemuster und die sie beeinflussenden Faktoren anhand von Daten zu gemeinsamen E-Scooter-Fahrten aus fünf nordamerikanischen Städten bewertet. Die Ergebnisse

dieser Studie zeigten, dass die Muster in allen Städten trotz ihrer Unterschiede ähnlich sind und untermauerten die Notwendigkeit, die SMS-Nachfrage für einen effizienteren Betrieb vorherzusagen. Infolgedessen wurde in der zweiten Studie ein Rahmen zur Vorhersage der SMS-Nachfrage für einen langfristigen Zeithorizont entwickelt, der auf dem Konzept des Transferlernens basiert und Open-Source-Daten verwendet.
Die dritte Studie untersuchte die Synergien zwischen den verschiedenen SMS und schätzte die erwartete Verlagerung der Fahrten von Carsharing auf gemeinsam genutzte E-Scooter sowie die daraus resultierenden Einsparungen an Energie und gefahrenen Fahrzeugkilometern. In der vierten Studie wurde die Rolle von Persönlichkeitsmerkmalen und Einstellungen bei der Einführung und Nutzung von Carsharing untersucht. Für beide Studien wurden verschiedene Umfragedaten aus München, Deutschland, verwendet.
Die fünfte Studie untersuchte die Beziehung zwischen gemeinsam genutzten E-Scootern und dem öffentlichen Nahverkehr (ÖPNV) und zeigte insbesondere das Potenzial des ÖPNV, die Zugänglichkeit zu erweitern. Die letzte Studie untersuchte den Bedarf an SMS und bewertete deren gleichberechtigte Nutzung für verschiedene Bevölkerungsgruppen. Dabei zeigte sich, dass SMS nicht immer die optimale Lösung ist und dass das Problem der gleichberechtigten Nutzung von SMS möglicherweise mit der städtischen Struktur und nicht mit SMS zusammenhängt.
Schließlich ermöglichten die Ergebnisse der verschiedenen Studien die Entwicklung eines fünfstufigen Rahmens, der für die Planung und Einführung von SMS verwendet werden könnte. Der vorgeschlagene Rahmen zielt schrittweise auf die Einführung der Dienste ab, indem der Bedarf der Bevölkerung an SMS gründlich untersucht wird (Stufe I). Wenn ein Bedarf an SMS besteht, wird ein Pilotprojekt durchgeführt (Stufe II), und wenn es erfolgreich ist, wird der Dienst vollständig eingeführt (Stufe III). Während der Phase der vollständigen Einführung wird die Interaktion des Dienstes mit anderen Elementen des städtischen Umfelds überwacht (Phase IV). Schließlich werden die aus den verschiedenen Phasen gewonnenen Erkenntnisse ausgewertet, um sie für die Durchführung künftiger Projekte zu nutzen (Phase V).

Acknowledgements

Sometimes, not most of the time, I thought I would never reach this point, the point of writing my thesis acknowledgment, but I always remembered what Dale Carnegie once said: "most of the important things in the world have been accomplished by people who have kept on trying when there seemed to be no hope at all."
It has been quite a journey, not long, not short, not easy, not complicated. Defiantly, the scientific work is my own work stemming from my own ideas, learning process, and interaction with other people and research; however, this work would never materialize without the presence of many people in my life.
Unfortunately, I cannot mention everyone; but I would like to thank my supervisor Prof. Dr. Constantinos Antoniou, not only for being an excellent academic supervisor but for being an excellent human being, the kind we need in our lives.
Dr. Ing. Christelle Al Haddad, my colleague and the best lab friend ever, you believed in me sometimes more than I believed in myself; and yes, when all this work started, it was a pandemic, and we (me wildly) underestimated it. Christelle, thank you for the support.
As this dissertation is all about shared mobility, I need always to thank the person who pushed me in this direction, Prof. Alejandro Tirachini, not only for the push but for the ever-going support and feeling that he is always there for me.
I want to thank all the current and former members of the TSE group for their help, support, and always exciting lunch discussions. Manos (Prof. Dr. Ing. Emmanouil Chaniotakis), Dr. Ing. David Telmo Durán-Rodas, and Prof. Dr. Margarita Martínez Díaz thank you for always being there; knowing you always have my back is priceless. Also, the DTN and its members, and the supportive Prof. Dr.-Ing. Benjamin Büttner, the head of the DTN.
I cannot thank my family enough for their immense support that did not stop for a second during the graduate school journey or at any point in my life.

Declaration

I hereby affirm that this dissertation is entirely my work without any use of undisclosed sources or assistance. Therefore, to the best of my knowledge and conviction, this dissertation does not incorporate any previously published or authored materials from any other individual except where duly referenced with accurate citations. This encompasses all ideas obtained directly or indirectly from printed books, articles, and various online sources, as well as my translations from materials in a different language.

Munich, 5^{th} August, 2023

Mohamed Abouelela

Contents

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Acronyms

ANN	Approximate Nearest Neighbor.
API	Application Programming Interface.
Apps	Mobile Phone Application.
B2B	Business–to–Business.
C2C	Consumer–to–Consumer.
EFA	Exploratory Factor Analysis.
GBDT	Gradient Boosting Decision Tree.
GHG	Green House Gas.
GIS	Geographical Information Systems.
GTFS	General Transit Feed Specification Files.
HCM	Hybrid Choice Model.
ICLV	Integrated Choice and Latent Variable Model.
ICT	Information and Communication Technologies.
LISA	Local Indicators of Spatial Association.
LITA	Local Index of Transport Accessibility.
LR	Linear Regression.
LSTM	Long Short-Term Memory Neural Network.
ML	Machine Learning.
ML	ordered Logit Model.
PLS	Partial Least Square.
PMI	Potential Mobility Index.
POI	Points of Interest.
PT	Public Transportation.
SEM	Structural Equation Model.
SMS	Shared Mobility Services.

SP	Stated Preference.
SVR	Support Vector Regression.
VKT	Vehicle Kilometer Travelled.
ZINB	Zero-Inflated Negative Binomial Model.

1 Introduction

1.1 Motivation

Our cities are growing at an unprecedented rate; according to the United Nations Population Division, by 2050, 67% of the world population will be living in cities, as compared to 33% in 1955 [1]. Such an increase in urban population will significantly impact the urban environment, specifically urban transportation systems, and will lead to various challenges. Among the expected challenges are: the increase in traffic externalities, the increase of the strain on the infrastructure, specifically transportation infrastructure, the increase of the gap between the transportation supply and demand, the increase in the demand for urban spaces, such as parking spaces, the increase of safety concerns related to travel, and finally the inequitable use of transportation systems [2, 3]. Urbanization is generally coupled with increased vehicles on the road, fuel consumption, travel time delays, commuters' frustration, and pollution such as air and noise pollution [4, 5]. Urban transportation significantly contributes to air pollution and greenhouse gas (GHG) emissions, and urbanization exacerbates this problem as more vehicles are on the road, emitting pollutants and further contributing to climate change [6, 7, 8].
The expected increase in urban population and travel demand would increase the strain on the urban transportation infrastructure, which is hard and expensive to expand to accommodate the growing demand. Urbanization often outpaces the development of transportation systems, resulting in fragmented or inadequate networks that might lead to inefficient travel routes, longer commuting times, and limited access to various parts of the city [9]. Also, public transportation (PT) supply struggles to keep up with the rising demand, leading to overcrowded vehicles making commuting uncomfortable and time-consuming [10]. Urban space's complexity and management also challenge urbanization due to limited land availability. One side of this problem is the unavailability of parking spaces leading to illegal parking, congestion, and frustration for residents and visitors [11]. The increased risk of accidents, pedestrian injuries, and cyclist collisions rises when more vehicles compete for limited road space is another expected outcome of rapid urbanization [12]. Finally, urbanization can exacerbate transportation inequities. Certain population groups, such as low-income communities, may face limited access to affordable and reliable transportation options [13], which would hinder these groups' access to essential services and opportunities and worsen their economic situation in the long run.

On the other hand, technological advancements in recent decades have been unprecedented, contrasting with historical trends where significant progress took centuries or even millennia to occur. This acceleration is attributed to the rapid growth of digital technology and the internet, leading to what is known as the "exponential growth of technology" or "Moore's Law" [14]. The internet and global communication networks have facilitated the rapid spread of knowledge, collaboration, and innovation [15]. These networks have fueled swift technological progress, resulting in transformative improvements and breakthroughs that impact various aspects of our lives. However, it is essential to approach these advancements responsibly, considering the potential challenges and ethical concerns that may arise while ensuring their beneficial impact on humanity [16].

Technological advances have collectively led to the so-called "shared economy" rise. Shared economy, sharing economy, or collaborative consumption, refers to the economic model in which individuals or businesses share access to resources, goods, or services rather than owning them through digital platforms to facilitate the sharing, renting, or lending of underutilized assets, such as vehicles, accommodations, tools, or skills, among a community of users [17, 18]. The sharing economy is a shift away from traditional ownership-based models and their subsequent burdens. The shared economy promotes efficiency, sustainability, and cost-effectiveness by maximizing the utilization of resources and enabling peer-to-peer transactions; also, it is characterized by increased connectivity, trust, and peer-to-peer interactions, offering new opportunities for providers and consumers in various sectors [19].

Transportation is a prominent sector within the sharing economy; in this context, it is called shared mobility services (SMS). It encompasses various services that enable individuals to share rides or gain access to different types of vehicles based on their needs. Some examples of SMS are: popular ride-hailing platforms like Uber (`Uber.com`), Lyft (`Lyft.com`), and Didi Chuxing (`Web.Didiglobal.com`), which allow people to share rides with others using their private vehicles, carsharing services such as Zipcar (`Zipcar.com`) and platforms like Turo (`Turo.com`) enable individuals to share their cars for short periods. Shared micromobility such as bike-sharing and scooter-sharing services are also part of this sector, allowing users to rent bikes, E-bikes, mopeds, or standing scooters for convenient short-distance travel [20], some of the leading providers for shared micromobility are Lime (`Li.me`), and Tier (`Tier.app`). SMS has gained rapid momentum due to its focus on sustainability and potential social, economic, and environmental benefits. At the individual level, shared mobility provides convenient on-demand travel, easy payment systems, perceived safety, and eco-friendliness [21]. On a larger scale, shared mobility can positively impact cities and society by reducing vehicle idle time, lowering CO_2 and GHG emissions, decreasing energy consumption, alleviating congestion, saving travel costs, and optimizing curbside space utilization. It also presents a quick solution to transportation issues, especially in areas with limited access to public transportation [22, 23]. Therefore, SMS could play a

significant role as a countermeasure for urbanization, as it could act as a quick fix for rational transportation systems problems and be a sustainable replacement in some situations under specific conditions.
Expanding the current transportation infrastructure may not always be the optimal solution. Infrastructure projects might face several challenges, requiring huge investments and lengthy processes to materialize [24, 25, 26]. Innovative mobility services such as Shared Mobility Services (SMS) supported by the advances in information and communication technologies (ICT) represent an opportunity and sustainable solution that would cope with increasing urbanization rates. However, the introduction and integration of SMS into the urban environment were poorly planned due to the sudden deployment and incomplete understanding of the service characteristics. It came with various challenges, such as but not limited to the increase in safety concerns, fleet-size control, attracting users from active modes of transportation towards motorized modes, and inequitable use [27, 28, 29]. Therefore there is a need to investigate and understand how to plan and deploy SMS efficiently, effectively, and sustainably in the urban environment considering all the services' outcomes, positive and negative, to maximize the positive outcomes and minimize the negative ones and to make sure that these services and the opportunities they bring are equally allocated to all the members of the society.

1.2 Problem definition and objectives

SMS are trending popular means of transport, and their exponential demand growth, e.g., reflect their popularity, ride-hailing [30], bike-sharing [31], and shared E-scooters [32]. However, in several cases, SMS were introduced without appropriate prior planning, causing several problems and challenges due to the novelty of SMS and our incomplete knowledge about how to integrate them effectively in the urban environment. Integrating shared mobility services in the urban environment faces several challenges, mainly tied to the systems' governance and management. These operational problems are more avid and critical for vehicle-sharing systems (scooter sharing, bikesharing, and carsharing), especially for the subcategory of free-floating systems (dockless), compared to other forms of shared mobility. Some of these problems are fleet size management, spatial and temporal demand prediction and estimation, fleet geographical distribution and redistribution, deciding on the optimal pricing schemes, use equity, accessibility of the service, operational hours, and geographical limits, zonal fencing [27, 28, 29, 33, 34, 35].
The current level of knowledge required to deploy and integrate SMS, especially the free-floating systems, which are the main focus of this research, within urban environments optimally still needs to be completed. The SMS deployment process is complex and challenging due to its multidimensional nature that should consider: i) meteorological conditions, ii) built environment characteristics, iii) population's sociodemographic attributes, iv) available modes of transportation , v) SMS char-

acteristics, and interaction within the SMS; the previous dimensions' relation with SMS should also be evaluated and considered from different stakeholders' viewpoints to ensure the efficient integration of SMS in urban environments and to target optimum outcomes for all stakeholders.
Therefore, the main objective of this dissertation is to understand the SMS' interactions and relationships with the different elements of the urban environment, including the relationships within the SMS. Therefore, we formulated several research questions (**RQ**) to address the various objectives (**O**) as follows:

O-1 Understand how SMS are used and factors impacting their use based on:

O-1.1 Exploring spatiotemporal, hourly, daily, and seasonal demand patterns. Answered by **RQ-3.1** .

O-1.2 Exploring the differences in SMS trip characteristics in different locations. Answered by **RQ-3.2** .

O-1.3 Defining exogenous factors impacting SMS demand, including meteorological conditions, infrastructure, land use, and residents sociodemographics impacts on the demand. Answered by **RQ-3.3** .

O-1.4 Assessing the relationship between SMS, and PT. Answered by **RQ-3.3** , and **RQ-7.2** .

O-2 Design a framework to predict the demand for SMS considering based on the concept of transfer–learning using open source data; this framework could be used for service operation and management. Answered by **RQ-4.1** , **RQ-4.3** , and **RQ-4.4** .

O-3 Understand the individual characteristics of SMS user and their preference and use patterns for SMS:.

O-3.1 Define the differences between user and non-user for SMS. Answered by **RQ-6.1** .

O-3.2 Define factors impacting the adoption of SMS, and the shift from traditional modes of transport to SMS. Answered by **RQ-6.2** , and **RQ-6.3** .

O-3.3 Define factors impacting the choice between SMS; using carsharing, and shared E–scooter as a case study. Answered by **RQ-5.1** .

O-3.4 Define the factors impacting the choice between the different payment schemes; using carsharing as a proxy for other free–floating SMS. Answered by **RQ-6.4** .

O-4 Understand the synergies between the different SMS, in terms of factors impacting their choice, and the expected modal shift. Answered by **RQ-5.2** .

O-5 Explore the role of knowledge about SMS on adoption and use. Answered by **RQ-6.5** .

O-6 Assess the equitable use of SMS. Answered by **RQ-8.1** .

The fulfillment of these objectives define the interactions and relationships needed to be understood between SMS and other elements in the urban environment. To maximize the benefits of the findings and to consolidate them in more practical way, the following framework was developed:

"A data-driven free–floating–SMS deployment framework based on lesson learnt from current operation data, users and non-users surveys, and SMS evaluation methodological frameworks."

The primary reliance of this dissertation was on open-source data, with the exception being individual-level information utilized when necessary. The main objective of using open-source data was to facilitate a decision-making process that is transparent, reproducible, and informative for all stakeholders involved.

1.3 Contributions

This dissertation summarizes the author's work [32, 36, 37, 38, 39, 40] that was done to understand the interactions and relationships between SMS and the different elements of the urban environment. The following contributions were made throughout the different case studies, and the methodological frameworks, and they can be split into theoretical, methodological and practical contributions:

- **Theoretical contributions:**
  - Developing the concept of population quarters to identify the transport-disadvantaged population group [36].
  - Developing a concept to estimate the modal shift combining choice model with real data and weather data [40].
  - Designing of two stated preference experiments to estimate the impacts of introducing new SMS on the existing one, and factors impacting choice of different SMS payment schemes [37].
- **Methodological contribution:**
  - Using open-source data, developing a methodology to predict the number of trips per vehicle per day based on transfer learning. This framework could be used to organize the deployment of SMS and fleet control processes for both operators and authorities [32].

- Developing a methodology to examine the relationship between the SMS and PT by exploring the different external factors that impacts the distance between shared E-scooter and PT stations as an indicator of using scooters to extend the accessibility of PT [39].
- Developing a framework to evaluate the equitable use of SMS using accessibility as the center of the methodology and the main indicator of the equitable use, to ensure planning a just transport system. The framework also evaluates the equity-related outcomes of SMS deployment for the different population groups, modes replaced by SMS, and geographical locations [36].

- **Practical contributions:**
  - Understanding and comparing shared E-scooter spatiotemporal demand patterns in different cities and the factors impacting them, also comparing trip and demand characteristics during pilot projects and complete deployment projects [38].
  - Defining and quantifying the synergies between the different SMS by estimating the factors that impact the adoption, shift from carsharing to shared E-scooter [40].
  - Estimating the percentage of carsharing trips that E-scooter might replace under different scenarios and conditions, and the subsequent saves in motorized-Kilometer and energy [40].
  - Quantifying factors that impact the adoption of carsharing, shifting from other modes, choice of different payment schemes, and knowledge about carsharing service [37].
  - Understanding the importance of the different aspects of carsharing services, such as physical offer bundles and digital platform ratings on carsharing use from users' and non-users' perspectives [37].
  - Understanding the difference in travel behavior between SMS users and non-users [37].
  - Quantifying the percentage of the population that would benefit from the deployment of SMS and quantifying the percentage of trips for the different modes that shared E-scooters would replace to gain additional accessibility to the different opportunities [36].
  - Developing a framework that can be used to deploy the SMS building on the lessons learned from the developed frameworks and case studies examined in this dissertation, Chapter 9.

1.4 Dissertation structure

The upcoming chapter of this dissertation, Chapter 2, gives a brief background of the current research on SMS, the used methods, and the data. Chapter 3 to Chapter 8 summarizes the three case studies the three frameworks, and the details of the case studies are shown in the different appendices. Finally, Chapter 9 provide the overall discussion for the findings, proposed framework to deploy shared mobility based on the dissertation findings, recommendation for future research, limitations, and the conclusion. Figure1.1 shows the overall structure of the thesis. Figure1.1 shows the overall structure of the thesis.

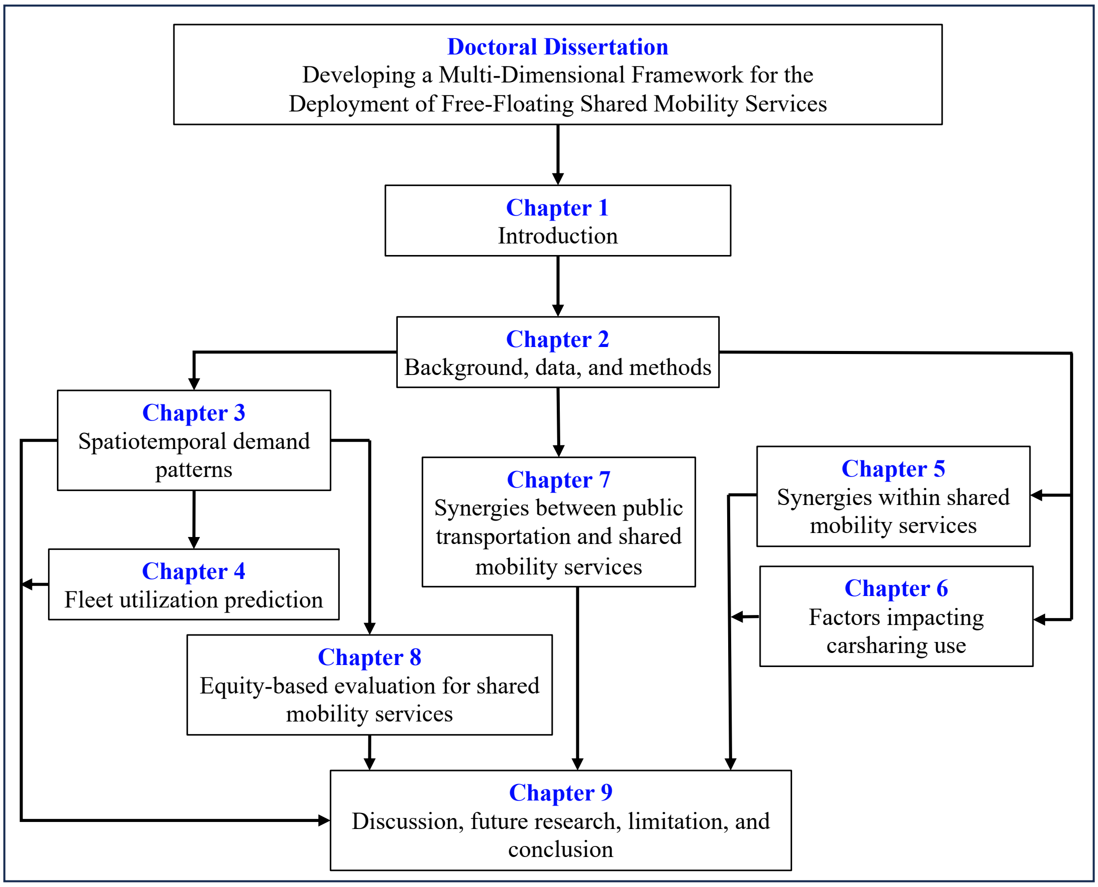


Figure 1.1: Thesis Structure

Chapter 1, Introduction: this chapter introduces the research motivation, defines the problem statement, research objectives, and dissertation structure.

Chapter 2, Background, data, and methods: this chapter gives an overview on the current literature related to the study of SMS, and then describe the data sources and methodologies used in the different case studies.

Chapter 3, Spatiotemporal demand patterns: this chapter focuses on understanding and comparing the spatiotemporal demand patterns and factors impacting them for shared E–scooter in five North American cities.
The content of this chapter has been published in: *Abouelela, M., Chaniotakis, E., & Antoniou, C. (2023). Understanding the landscape of shared-e-scooters in North America; Spatiotemporal analysis and policy insights. Transportation Research Part A: Policy and Practice, 169, 103602.*. The article is presented in Appendix A [38].

Chapter 4, Fleet utilization prediction: this chapter presents a framework using open-source data to predict the demand and the daily number of trips per vehicle (scooter) per day in order to manage the SMS fleet dynamically, building the framework around the concept of transfer learning.
The content of this chapter has been published in: *Abouelela, M., Lyu, C., & Antoniou, C. (2023). Exploring the Potentials of Open-Source Big Data and Machine Learning in Shared Mobility Fleet Utilization Prediction. Data Science for Transportation, 5(2), 5.* The article is presented in Appendix B [32].

Chapter 5, Synergies within shared mobility services: this chapter presents the interactions between the different SMS using a stated preference experience, focusing on factors impacting the shift from carsharing to shared E–scooter and quantifying the shift in terms of the number of scooter trips that replaces carsharing trips for the different trip distances.
The content of this chapter has been published in: *Abouelela, M., Al Haddad, C., & Antoniou, C. (2021). Are young users willing to shift from carsharing to scooter–sharing? Transportation Research part D: Transport and Environment, 95, 102821.*. The article is presented in Appendix C [39].

Chapter 6, Factors impacting carsharing use: this chapter presents a stated preference experiment that was designed to understand the user's behavior when choosing between the different operators of SMS, in this case for carsharing services. The experience tested the impacts of user's attitudes and personality traits on the different service use aspects, and the service aspects such as application rating and offers bundles impacts on the service use were tested.
The content of this chapter is under revision: *Abouelela, M., Al Haddad, C., & Antoniou, C. (2023).Personality and Attitude Impacts on Carsharing Use. Under revision.* The article is presented in Appendix D [37].

Chapter 7, Synergies between public transport and shared mobility services: this chapter presents a methodological framework that was built around the Approximate Nearest Neighbor (ANN) algorithm, which was used to examine the relation between Shared E-scooter use and public transportation.
The content of this chapter has been published in: *Abouelela, M., Al Haddad, C., & Antoniou, C. (2021). Are e-Scooters Parked Near Bus Stops? Findings from Louisville, Kentucky. Findings.* The article is presented in Appendix E [40].

Chapter 8, Equity-based evaluation for shared mobility: this chapter presents a methodological framework to assess the equitable use of SMS, using shared E–scooter as a case study, and it quantifies the impacts of scooter introduction on population, and the expected modal shift.
The content of this chapter is under revision: *Abouelela, M., Durán-Rodas, D., & Antoniou, C. (2023). Do we all need scooters? An accessibility–centered spatial equity evaluation approach. Transportation Research Part A: Policy and Practice.* The article is presented in Appendix F [36].

Chapter 9, Discussion, future research, limitations, and conclusion: this chapter presents and discusses the findings across the different case studies and the developed framework for SMS deployment. Additionally, it contains the directions for future research, and final conclusion.

2 Background, data, and methods

This chapter overviews shared mobility services background and the current research landscape regarding them. The remainder of the chapter presents the data used in the following chapters and the procedures followed for data processing. Finally, the details of the methodologies used in the following chapters are explored.

2.1 Background

2.1.1 Shared economy

The progress in information and communication technologies (ICT) has fostered the facilitation of sharing goods, skills, space, and services directly between consumers and providers through digital platforms, websites, and smartphone applications (Apps). This direct exchange occurs between providers and consumers without the involvement of intermediaries in what is commonly known as the sharing economy or collaborative consumption. Unlike traditional business models, digital platforms do not physically possess goods or offer services; instead, they connect and match individuals, owners, and providers with consumers. By streamlining coordination processes and sometimes circumventing costly government regulations related to obtaining operational licenses, these platforms help reduce services costs [19, 41, 42]. In addition to financial advantages esteeming from the cost reduction, social benefits derived from fostering social cohesion and connecting people, and environmental benefits resulting from increased efficiency in resource utilization and reduced energy consumption are the main motivations to participate in the shared economy [43, 44]. However, impacts of shared economy in a broader context accounting for its entire life cycle and interaction with the different societal elements are hard to evaluate and quantify [45]. Also, it is necessary to highlight that the motivations for participating in the sharing economy may vary across different sectors, sociodemographic groups, and among users and providers. Also, benefits gained might not be equally distributed among the different members of the society, and several inequitable outcomes might result, e.g., large-size providers might profit more than small-size providers due to their significant capital assets [46].

2.1.2 Shared mobility

Definition, potentials, and challenges

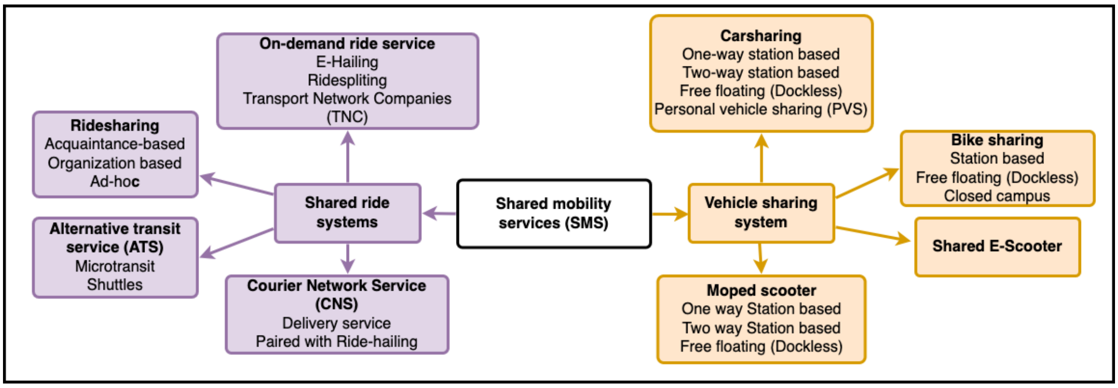


Figure 2.1: Shared mobility services

Transportation is one of the main sectors of the shared economy; in this context, it is referred to as shared mobility. Shared mobility offers travelers short-term access to various modes of transportation based on their travel needs [47]. The term shared mobility is an umbrella encompassing a wide range of services, including but not limited to shared E-scooter, bikesharing, carsharing, and ridesharing using vehicles of different sizes (such as carpooling and vanpooling, shuttle services, and microtransit. Furthermore, shared mobility extends its reach to the urban freight transport sector, where the delivery of parcels can be integrated with people's transportation, such as courier network services. [48, 49].
Shared mobility services (SMS) have various business models. These models can be categorized by the type of provider and the clients, with the two common models; Consumer-to-Consumer (C2C), also known as the Peer-to-Peer model, and Business-to-Consumer (B2C). C2C involves individual providers granting access to others to utilize their underutilized services, and goods, in this case, vehicles; an example of this model is BlaBlaCar (`Blablacar.com`) for ridesharing [50]. In the B2C model, a company owns the assets and provides access to users through membership fees and usage-based fees. Examples of this model include Lime scooters (`li.me`) and shareNow (`share-now.com`) for carsharing [51]. Other less common business models such as B2E, business to employee; B2G, business to public agency; and G2P, public agency to individual, also exist [52].
Figure 2.1 shows the main shared mobility services, which can be grouped into two main groups, shared ride services and shared vehicle services. Shared vehicle services, which are the focus of this dissertation, have three subgroups based on their operation schemes; round trip, where the vehicle is booked in advance, collected from a station, and returned to the same station. The second type is a one-way station based, where it is picked up from one station and returned to

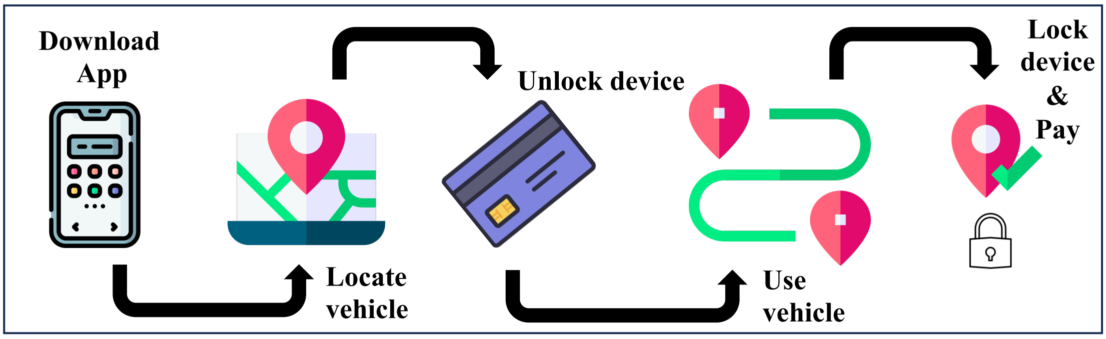


Figure 2.2: Shared vehicle use process

another station or a specific location, and finally, the free-floating type, where the vehicle is used within a geographical area [53]. The general idea of how to use the free-floating shared mobility services is explained in Figure 2.2, where the user needs to download an app, which he uses to locate the nearest vehicle of the service he plans to use, and once the user locates the most convenient vehicle, the user uses the app to unlock the vehicle, some times unlock fees applies in addition to the trip cost, and he uses a digital banking option to pay for the trip cost, which is calculated based on the actual trip cost; per minute of use or kilometer drove, and finally, the user locks the vehicle using the app.

The utilization of shared mobility has been encouraged by various factors, primarily aiming to achieve sustainability goals and attain social, economic, and environmental benefits. Positive potential impacts are expected from shared mobility; on the individual level, increase in the convenience of travel based on the increase of freedom of movement, as they are on-demand service, ease of use, ease of payment, perceived safe, and environmental friendliness [21, 54]. The benefits are not limited to the individual level but can be scaled up to the city and societal levels. Compared to private passenger cars, SMS are considered more sustainable as they have the potential to reduce vehicle idle time, minimize the environmental impact by lowering CO_2 and greenhouse gas (GHG) emissions, decrease energy consumption, reduce congestion, save travel costs, and utilize public spaces more efficiently [22, 23]. Also, SMS could be used as a quick fix for various transportation problems, such as maintaining, upgrading, and constructing transportation infrastructure needs significant investments and a long time to materialize, which is not always a viable solution; one example is extending the transportation system's accessibility to suburban areas with inefficient public transportation's access [55, 38]. SMS could also reduce the demand and congestion on roads, as well as the vehicle kilometer traveled (VKT), such as in the case of pooled rides, but under specific conditions to be considered, such as not replacing public transportation trips and replacing low occupancy vehicles [56]. Alonso-Mora et al. [57] concluded that shared rides could reduce the number of cars on city roads; similar promises could be achieved using carsharing services, as private cars are idly parked for around 90% of the time [58]. Transport for London (TfL) sees carsharing services as complementary to public transportation services [59], that its use correlated with the increase in public transportation use [60]. Overall, SMS are attractive to implement as establishing its infrastructure is considered relatively quick and economically viable [61]. The attractiveness, popularity, and succession of shared mobility are reflected by attracting demand from traditional travel alternatives, which is evident through the substantial growth in ridership, as seen in ride-hailing services [30], bike-sharing initiatives [31], and the use of shared e-scooters [32].

Challenges related to the introduction of shared mobility must be addressed. An example of their challenges is the increase of safety concerns, such as the case of shared E-scooters, as half of the reported accidents related to scooter use involved severe injuries, and fatal accidents were reported in the USA [62, 63]. Janssen et al. and Gössling et al. [64, 65] summarized shared mobility deployment problems as fleet-size control, capping and organization, permit cost, and attracting users from active modes. Regarding emissions net effects, Moreau et al. [66] performed a life cycle assessment for a free-floating shared E-scooter (scooters) system and showed that over their entire life cycle, scooters produce more CO_2-equivalent per passenger-kilometer than the modes they replace. At the same time, scooters were also found to attract users from environmentally friendly modes [67], such as walking and biking, generating empty vehicle kilometers traveled (VKT) during redistribution and maintenance processes [68]. Therefore, integrating shared mobility services into urban environments encounters numerous challenges, primarily related to their governance and systems management. Among these challenges, vehicle-sharing systems (such as scooter sharing, bikesharing, and carsharing), particularly free-floating systems, face more pronounced and critical operational issues than other forms of shared mobility. The critical problems revolve around fleet size management, spatial and temporal demand prediction and estimation, fleet distribution and redistribution across geographical areas, determination of optimal pricing schemes, ensuring equity of use, addressing service's accessibility, operational hours, and implementing geographical limits (zonal fencing) [27, 28, 29, 33, 34, 35]. While increased mobility and accessibility are expected outcomes of the addition of shared mobility to the urban environment, this increase in mobility and accessibility should be equally allocated to all the members of society. According to the first article of the Universal Declaration of Human Rights, all humans have equal rights [69]. These rights cannot be acquired or accessed equally for all the members of the society without the availability of different means of mobility that is accessible to all the society's members regardless of their gender, income, ethnicity, or education level; otherwise, some groups would be excluded from the participation in the daily life activities, creating a so-called social exclusion situation. The equitable use of shared mobility is not always achievable and can lead to social exclusion situations for specific population groups [70]. The inequitable use of shared mobility is widely expected from its unique setup as users, in general, should have digital skills, a smartphone, and digital banking access; otherwise, they will be excluded from using the service by default [71]. Also, shared mobility might only be affordable to some population groups, and the spatial coverage of shared mobility might be limited to areas with high demand, primarily near the downtown, and ignoring areas located in the city's suburbs [72]. Notably, the aforementioned challenges directly stem from the travel demand aspect, highlighting the importance of understanding the factors that influence demand and the need for demand prediction to enhance shared mobility operations, the evaluation of the equitable use of the services, understanding the synergies with the different modes in the urban environment, such as PT and in between the shared services themselves.

Shared mobility study framework

Data sources

The study of SMS relies heavily on data in the diverse analysis, processing, and modeling stages. Once the study objectives, research questions, and hypotheses have been defined, the required data to fulfill the research objective is identified, and the collection process follows. In shared mobility related-studies, the data collection methods primarily depend on the study's objectives rather than being directly related to the service itself. Commonly, five primary data sources are utilized: surveys, open-source data, mobile phone data, GPS data, and combinations thereof [73].
When collecting specific individual-level information, such as sociodemographic data, travel patterns, and motivations for using various services, surveys, online and face-to-face interviews, and travel diaries are commonly employed. For instance, online surveys have examined the demographics of bikesharing users [74, 75] and carsharing program members [76]. Online surveys have also been used to identify motivations for using different services, such as ridesharing and carsharing [77]. Face-to-face interviews have been employed in the study of shared mobility as well. Tirachini and del Río [54] conducted street interviews to investigate the travel behavior of ride-hailing users, and Shaheen et al. [78] explored motivations for using casual carpooling in the San Francisco Bay Area. Surveys have long been regarded as valuable tools for investigating user-level information. However, the availability of such information is not always guaranteed due to increasing concerns about data privacy. Surveys also have inherent limitations that impact their utility; for example, they can be costly, and ensuring the validity of responses can be challenging [79, 80]. Online surveys, on the other hand, suffer from non-coverage bias as they may not adequately represent the general population, and marginalized groups, including households without internet access and the elderly, are often excluded from such surveys [81]. Moreover, some users may avoid participating in online surveys out of concern for the potential leakage of their private data.

The advances of ICT have brought significant positive changes in the field of data collection, including the incorporation of new sources of information, such as social media, that were not previously accessible for traditional transportation studies [82]. Also, ICT expanded the possibilities of collecting and analyzing large quantities of new data types, commonly referred to as big data [83, 73]. The term "big data" has gained significant attention and has sparked increased efforts from industry and research sectors to explore its potential opportunities. Several factors have contributed to the accumulation of vast amounts of data, including advancements in computational power, decreasing costs of data storage, and the development of smart cities platforms, all of which have fueled the interest in big data [84, 85]. Big data has been extensively examined in various applications within the field of transportation research, such as estimating origin-destination flows in transit networks [86], assessing parking availability through sentiment analysis of location-based social network data [82, 87], enhancing traffic management and planning [88], and analyzing the impact of pricing scheme changes on bikesharing usage [89]. Different entities, particularly operators and city authorities, are openly sharing their data, characterized as big based on its volume, velocity, or variety. The aim is to encourage innovation, develop new methods and ideas to enhance the urban environment, foster integration among various transportation services, and facilitate the regulation and dynamic adjustment of shared mobility services within urban settings [27, 84].

Modeling framework

Two common approaches generally used when modeling different aspects of shared mobility are the target of the research are; i) regression models, and ii) Machine Learning (ML) algorithms. Regression models aim to establish a relationship between a dependent variable and one or more independent variables [90]. The goal is to fit an equation that best describes the relationship between the variables and allows for prediction or inference. Regression models make assumptions about the distribution and linearity of the data and rely on statistical techniques to estimate the model parameters. On the other hand, ML models are a broader class of algorithms that can handle a wide range of tasks. ML models focus on learning patterns and relationships within the data without explicit assumptions about the underlying distribution [91]. These models aim to optimize a specified objective or loss function by adjusting the model parameters based on the training data [22]. ML models can capture complex patterns and non-linear relationships, making them suitable for classification, clustering, and prediction tasks. While regression models focus on understanding and quantifying relationships between variables, ML models emphasize pattern recognition and prediction and often have more flexibility. They can handle large and complex data but may require more computational resources and have less interpretability than traditional regression models [92].

Numerous shared mobility studies examined factors that influence the adoption of shared mobility or the transition from using different modes to utilizing shared mobility. In such cases, the modeling process involves estimating factors that affect the choice between two or more mutually exclusive options. Binary and multinomial probit and logit models are commonly employed in these scenarios. For instance, the introduction of Uber and Lyft in California was investigated using a binary logit model [81]; also, a multinomial logit model was utilized to explore the factors that influenced the shift to ride-hailing from various modes in Boston, USA [30]. In certain studies, the factors under investigation are characterized by an ordered nature, such as responses on an ordered scale, the ordered frequency of use, or satisfaction with specific services. This requires using models that account for the ordered nature of these factors. Ordered logit and probit models (OLM) are commonly employed in such cases. Other modeling techniques such as generalized additive mixed models, multiple regression, structural equation, and partial least squares structural equation models (PLS-SEM) were used to investigate carsharing and ridesharing use and motivation to use [93, 94, 95, 77, 96].

ML use was also evident in studies related to SMS; for instance, Yang et al. [97] proposed a spatiotemporal mobility model for bike-sharing and developed a prediction mechanism for origin-destination (OD) demand using historical bike-sharing and meteorological data. They employed a probabilistic model for check-in demand and introduced a random forest (RF) model for check-out demand. Factors such as time of day, day of the week, holidays, and weather conditions were found to be significant in predicting demand. Gammelli et al. [98] involved a general method for modeling censorship-aware demand, accounting for supply restrictions in simulating realistic scenarios. They devised a censored likelihood function within a Gaussian Process model to address the issue of biased demand prediction when supply restrictions are not explicitly considered. This approach was validated using bike-sharing demand data, highlighting the impact of supply limitations on transport demand for shared mobility services. Saum et al. [99] combined Box-Cox transformation, seasonal autoregressive moving average (SARIMA), and the generalized autoregressive conditional heteroskedasticity (GARCH) models to predict hourly demand and volatility for scooter sharing at Thammasat University in Thailand. Deep learning models are also gaining popularity in the field of transport research, e.g., Gao et al. [100] proposed a moment-based model that combined a fuzzy C-means (FCM)-based genetic algorithm (GA) with a back–propagation–network (BPN) to predict bike-sharing rentals. Xu et al. [101] developed a long short-term memory (LSTM) model incorporating various data types, including trip, weather, air quality, and land use data, to predict bike-sharing trip generation and attraction at different time intervals. These studies demonstrate the growing prominence of ML techniques, including RF, Gaussian Process, LSTM, and other popular ML models, in enhancing the prediction and understanding of shared mobility patterns and demand.

2.2 Data

This section summarizes the data that were used in the next chapters of this dissertation, showing the data collection and processing stages.

Table 2.1: Summary for data used in this dissertation

Data	Chapter
Open source data	
Shared E–scooter trips	3, 4, 7, 8
Census Sociodemographic	3, 4, 5,8
Meteorological data	3, 4
Land use	3, 7 ,8
POI	3, 8
Infrastructure	3, 4
GTFS files	3, 7, 8
Survey Data	
Carsharing vs. shared E-scooter Survey	5
Carsharing payment scheme choice survey	6
Munich carsharing trip data	5, 6

2.2.1 Open source data

Scooter trip data

Chapters 3, 4, 7, and 8 used shared E–scooter (scooters) trip data retrieved from four cities located in the USA (Austin; TX, Chicago; IL, Louisville; KY, Minneapolis; MN), and one city in Canada (Calgary; AB) [102, 103, 104, 105, 106]. These cities made their scooter trip data publicly and openly available. Three of these cities' data was based on pilot projects; Minneapolis and Chicago had three months of pilot projects. Calgary ran a 16-month pilot project, with three-month-mid-pilot data published for public evaluation. The main target of the pilot projects was to preliminary evaluate the potential impacts of scooters and public acceptance before the full deployment of the service. Also, scooter fleet characteristics and operation schemes in these cities differ regarding the number of operators and the fleet size. Some cities have imposed limitations on the number of operators (Louisville, Minneapolis, Calgary, and Chicago), while Austin does, having eight different operators in July 2019, which increased to ten by 2020 [64]. Regarding fleet size limitations, each city has imposed cap limitations as a function of the number of operators and ridership rates. For operational hours to use the scooter, Chicago was the only city that imposed time restrictions between 10 p.m. and 5 a.m.

Scooters trips data description

The five datasets have almost standard structures with slight variations between the sets targeting protecting user privacy. All the datasets are in long format, where each row represents a trip observation. Each observation contains the trip's identification code (ID) for each trip, vehicle type (scooter, bike, e-bike), trip, start and end date, as well as trip duration, speed, and trip distance based on providers' route data. Additional information, such as the start and end community number, is provided in the case of Chicago. Different procedures are implemented to protect the user's anonymity in all the datasets. Trip start and end locations in Austin and Chicago are assigned to the corresponding census tract. In Minneapolis, trips are assigned to the nearest street's center line. In Calgary and Louisville, trips are aggregated to a grid, which in the former is based on hexagons with an area of 30,000 square meters and the latter on the block level. The trip starting time is also aggregated to the nearest 15 minutes in Austin [102] and Louisville [103], to the nearest hour in Chicago [104] and Calgary [105], and the nearest 30 minutes in Minneapolis [106].

Trip data cleaning process

Following an exploratory data analysis approach, outliers and false records were removed by setting a lower and upper bound for all trip characteristics, distance, duration, and speed based on previous studies and the standard vehicle's criteria. For a standard vehicle, one charge can power a scooter for two hours or approximately 50km. Therefore, we set the upper bound for the trip's distance to 50 km and the duration to two hours. The minimum trip distance was set to 100 meters for the lower bound, while for the duration, it was set to one minute, and the upper bound for 120 minutes following previous research methods used by [107, 108, 109]. The upper-speed bound was set to (15 mile/hr = 25 km/hr) as per the maximum allowable speed limit in the four cities in the USA. Although the speed limit in Austin is 20 mile/hr, there are several areas where the maximum speed was set to 8 mile/hr, and the number of trips faster than 15 mile/hr when examined was very limited; therefore, we opted to remove these trips to have consistent criteria across all cities. The trip's start and end coordinates were examined in all the cities, and trips with either false start or end coordinates were removed.

Population sociodemographic characteristics

Population sociodemographic characteristics in the scooter operation zones in the four cities in the USA were obtained from the American census database retrieved from the American Census Bureau (`census.gov`) utilizing their Application Programming Interface service (API) through the statistical computing software R [110], and the processing package tidy-census [111]. The data contains population characteristics aggregated to each of the census tracts. The aspect considered in our analysis obtained from this data set is; age, income level, education level, race, employment, car ownership, and modes used to work. The obtained population attributes were aggregated geographically by census tract. This dataset did not need any cleaning, but it was processed by converting all the aforementioned variables into percentages of the total population within each census block, which we used for further analysis and modeling when required. This data was used in the following research articles [32, 38, 36] summarized in Chapter 3, 4, and 8. In the German case studies, Chapter 5, the German Census data was obtained from the German federal statistical bureau (`statistikportal.de`). The data is available in (1km x 1km) resolution raster format and contains the average demographics distribution per zone, such as percentage of population, percentage of females, age distribution, and household size.

Meteorological data

Meteorological data is the dataset that records weather-related information; such data is of significant impact on SMS use [32, 38, 40], especially in the case of micromobility services. This dataset contains the hourly temperature, wind speed, precipitation conditions, snow depth, humidity, and dew point. For the USA data used in Chapters 3 and 4, we obtained the data from (`visualcrossing.com`), and in the case of Germany, we obtained the data from the German weather service online archive (`dwd.de`).

Land use data

These data were retrieved from the cities of Austin; TX, Chicago; IL, Louisville; KY, and Minneapolis; MN online portals [102, 103, 104, 105, 106], the different land uses were collected, and it was assigned to the census tract and blocks, which were the units of spatial analysis and modeling. These data sets were in geographical information systems (GIS) data format. The only cleaning procedure for this dataset applied when a census tract block had more than one land use; the percentage of each land use was calculated based on their area compared to the overall track area. This data set was used in Chapters 3, 7, and 8.

Point of interest data

Points of interest (POI) are the geographical location of points of activities such as: leisure, shopping, educational, health, and different services. POIs were grouped into six main groups, and each of them had different activities as follows:

- **Education:**
  - Kindergarten
  - Library
  - School
  - University
- **Food:**
  - Bakery
  - Bar

- Beverages
- Cafe
- Fast food
- Food court
- Greengrocer
- Pub
- Restaurant
- Supermarket

- **Health:**
  - Clinic
  - Dentist
  - Doctors
  - Hospital
  - Optician
  - Pharmacy
  - Veterinary
- **Leisure:**
  - Art centre
  - Cinema
  - Community centre
  - Nightclub
  - Park
  - Picnic site
  - Playground
  - Sports centre
  - Stadium
  - Swimming pool
  - Theatre
  - Zoo
  - Artwork
  - Attraction
  - Guesthouse
  - Hotel
  - Memorial
  - Monument
  - Museum
- **Service:**
  - ATM machine
  - Bank
  - Beauty Shop
  - Fire Station
  - Hairdresser
  - Laundry
  - Police station
  - Post office
- **Shopping:**
  - Bicycle shop
  - Bookshop
  - Clothes
  - Computer shop
  - Convenience store
  - Department store
  - DIY store
  - Furniture shop
  - Gift shop
  - Jeweller
  - Mall
  - Market place
  - Mobile phone shop
  - Shoe shop
  - Sports shop
  - Stationery
  - Toys shop

POI data was processed as the summation of the different points of interest within the spatial aggregation unit, in this case, the census block. This data was used in Chapter 8.

Infrastructure data

Infrastructure data, in terms of the different elements inside the road right of way, such as the length of sidewalks within the spatial aggregation unit, and the lengths of different types of lanes, such as the lengths of the bike lanes within the spatial aggregation unit. Infrastructure data and POI were obtained from (`openstreetmap.org`) in GIS data format. This data was mainly processed as the summation of the lengths of the different elements within the spatial aggregation zones, mostly census blocks. This data was used in Chapters 3, 4, and 7.

General Transit Feed Specification Files

General Transit Feed Specification Files (GTFS) are structured data files that describe public transportation schedules and routes, and it contains information regarding stops locations, timetables for the different routes, calendar dates, fares, and rules that apply to the fairs, and operating agency information. This specification was developed by Google[1] to facilitate the exchange of transit information

[1](`developers.google.com/transit/gtfs`), accessed 10/06/2023

between different applications. The data was retrieved from (transitfeeds.com) for the four US cities. GTFS is a rich source of information as it helps understand the operational schemes of the transit operation in the study area and is available in text format. We used this data in Chapters 3, 7, and 8.

2.2.2 Survey data

Choice between carsharing and shared E-scooter

Chapter 5 main objective was to understand user's preferences for E–scooters compared to carsharing. A stated preference survey was designed and conducted in Munich, Germany, and it was shared online for two months starting December 2019 using Limesurvey Pro (limesurvey.org). It was distributed through digital channels of communication, such as Facebook and Instagram, as well as mailing lists adopting a snowball data collection method. The target population was young individuals from 18 to 34 years old, as they are most likely the potential users of scooter–sharing systems [112, 113]. Moreover, by focusing on the target group that will most probably join scooter–sharing, sampling, and coverage errors were reduced, as suggested by Efthymiou et al. [114].
The survey contained 31 questions and was structured in four parts.

- The first part included travel behavior questions, such as the main mode of transport, the ownership of a driver's license, the access to a car, and the overall satisfaction with the existing public transport system.

- The second part was a stated preference experiment that introduced carsharing and scooter–sharing as possible alternatives for a fictitious trip of 4km between two points A and B. Here, nine choice scenarios were given, and respondents had to choose for each one among: "Certainly carsharing," "Probably carsharing," "Indifferent," "Probably scooter–sharing," "Certainly scooter–sharing," or "none"; the 'none' option aimed to cover other modes, and therefore the bias of not including them in the stated preference study. The SP part was designed with 11 blocks and 9 scenarios/block, using a random design, as previous literature did not find strong evidence that efficient design outperforms random design [115]. The attributes and levels used are summarized in Table 2.2. Figure 2.3 illustrates an example of one scenario of the SP experiment.

- The third part of the survey, questions pertained (but were not limited) to social media use, comfort with online services, willingness to share a ride, enjoyment of driving a car, environmental perceptions, and previous involvement in a car crash (with different levels of intensity).

- The fourth and last part entailed sociodemographics such as age, gender, income, household size, higher level of education achieved, and main occupation.

In this part of the survey, you are given 9 scenarios designed to determine how your transportation choices would change if the attributes of the modes were altered.
You will be asked to choose from two available modes (car-sharing and electric scooter: e-scooter), given a set of attributes. Please base your evaluation only on the following attributes:

- **Travel time**: The time spent in the vehicle to go from A to B.
- **Access & Egress time**: The total amount of time spent in access to the mode (at the beginning of the trip in reaching your car/scooter) and egress from mode (at the end, from where you park it to your destination); this is mostly walking time spent outside the vehicle.
- **Trip cost**: The amount of money you spend on this trip.
- **Safety level**: The likelihood of having an incident in an e-scooter compared to a car-sharing vehicle (which is at least as safe as e-scooters).

The travel process is, therefore, as follows: Access to mode (**access time**), Travel in-vehicle (**travel time**), Egress from mode (**egress time**).

We are aware that the options may be different from the ones that you would like to be offered, but we would like to know which option you would choose only if the mentioned choices were available.

If you would not choose either of the options, you can choose neither.

The given modes are illustrated below: a car-sharing scheme (such as DriveNow), or an electric scooter (such as Circ, Lime, etc.)


Scenario 1	Car-sharing (A)	E-scooter (B)
Travel time (min)	11	8
Access and Egress Time (min)	1	1
Travel cost (€)	2.5	3.7
Chance of having an incident (compared to car-sharing)	Reference level	2 x more likely of having an incident

Certainly **A** | Probably **A** | **Indifferent** | Certainly **B** | Probably **B** | **None**

Figure 2.3: Scenario details and block example

Table 2.2: Attributes and levels used in the survey's SP part

Variable	Unit	Levels
Travel time of scooter–sharing	min	[8, 11, 14]
Travel time of carsharing	min	[5, 8, 11]
Access time of scooter–sharing	min	[1, 3, 5]
Access time of carsharing	min	[1, 3, 5]
Cost of scooter–sharing	€	[2.5, 3.1, 3.7]
Cost of carsharing	€	[2.5, 3.5, 4.5]
Scooter accident risk compared to carsharing	-	[1, 2, 4] * higher
Rain	-	[Yes, No]

Table 2.3: Sample sociodemographic summary

Variable	Subgroup	n (Pct %)	Munich Census (2011)
Gender	Female	161 (32.0%)	48.3%
	Male	337 (67.0%)	51.7%
	Other	1 (0.2%)	-
Age	18-24	208 (41.3%)	8.1%
	25-34	295 (58.7%)	18%
Household size	1	182 (36.2%)	50%
	2	80 (15.9%)	29%
	3	65 (12.9%)	11%
	4	85 (16.9%)	7%
	5+	58 (11.5%)	3%
	I prefer not to answer	33 (6.6%)	-
Education	High school	34 (6.8%)	34.1%
	Apprenticeship	3 (0.6%)	40.7%
	Bachelor	271 (53.9%)	Bachelor/MS: 22.7%
	Masters	179 (35.6%)	
	PhD	7 (1.4%)	2.5%
	No answer	6 (1.2%)	-
Employment	Full-time employment	175 (34.8%)	Full/Part-time: 87.1%
	Part-time employment	52 (10.3%)	
	Student	240 (47.7%)	2.9%
	Self-employed	10 (2.0%)	7.8%
	Unemployed	14 (2.8%)	2.2%
	Other	7 (1.4%)	-
	I prefer not to answer	5 (1.0%)	-
Income	Up to 500 €	87 (17.3%)	Avg: 4220 €/household [116]
	500 to less than 1000 €	121 (24.1%)	
	1000 to less than 2000 €	69 (13.7%)	
	2000 to less than 3000 €	35 (7.0%)	
	3000 to less than 4000 €	29 (5.8%)	
	4000 € or more	45 (9.0%)	
	I prefer not to answer	117 (23.3%)	

$N = 503$

Carsharing adoption

Chapter 6 main goal was to investigate the roles of personality traits and attitudes on the carsharing users in terms of service adoption, shifting from other modes, the choice between the different payment schemes, and knowledge about the service. A four parts survey was designed, implemented online platform (Limesurvey.com), and deployed to different population groups in Munich, Germany, from 20 January to 25 March 2022. We opted to deploy the survey online as it was deployed during the COVID-19 pandemic, and we wanted to eliminate the chances of infection during the data collection process. The targeted group was young users as they are most likely users of carsharing services as concluded in many studies in different locations, e.g., Munich and Madrid [60], and Vancouver, Canada [117]. We collected 1170 completed responses; the average survey completion time was 12 minutes. The survey consisted of four main parts;

- The first part investigated respondent's general travel behavior; respondents were asked to specify the different use frequencies for the different urban modes of transport, availability of public transportation (PT) subscription ticket, ownership of the bike, e-bike, and private car, and the ownership of driving license in Germany.

- The second part investigated respondent's familiarity with carsharing services and their service usage; we asked regarding the use of carsharing in terms of frequency, willingness to walk to a vehicle pickup location, usual trip purposes for carsharing use, the modes they would have used if they did not use carsharing in their last carsharing trip, the familiarity of the carsharing services, users evaluation for the different aspects of carsharing services such as; mobile-application rating on the digital store, application ease of use, the provider service availability in different cities, service availability in EV, service availability in the airport, service availability in different size vehicles (SUV, trucks, etc), and the availability of offers bundles (discounts, e.g., for all-day rental, and long-distance rentals).

- The third part of the survey was the stated preference experiment; refer to Figure 2.4 for an example of one scenario and Table 2.4 for the details of the attributes and levels of the different scenarios. In this experiment, we assumed that the user had to choose one carsharing service to perform an 11-kilometer trip; the choice was between operator A, where the user pays a fixed cost per kilometer. The other choice is operator B, where the trip cost would vary based on actual trip data of carsharing trips collected in Munich, Germany, discussed in detail in Section2.2.3. The trip cost for operator B was calculated on the minute of use basis: the minimum cost based on the fastest speed of the collected trip data, the average cost based on the average speed of the collected trip data, and the maximum cost based on the slowest speed of collected trips data.

Carsharing services are gaining popularity for their ease of use, and their increased availability in our cities, especially among the young population. The service was initially priced by the minute of use, but now there are new schemes of paying a fixed price per kilometer. The main difference between the two schemes is the certainty regarding travel time, as users might encounter delays that would increase the trip cost if users are paying per minute of use and not by kilometer traveled. In the following scenarios, we ask you to choose the most convenient option to use based on your evaluation of the available options based on a hypothetical 11 km long leisure trip in Munich, Germany noting the following:

- ***Travel cost***; fixed if you choose to pay per kilometer and could fluctuate if you pay per minute based on the unknown road conditions and unexpected delays.
    - **Min cost**: The minimum expected cost based on fastest speed of previous trips
    - **Avg cost**: The average expected cost based on the average speed of previous trips
    - **Max cost**: the maximum expected cost based on the slowest speed of previous trips
- ***Access distance in meters***: the distance you will need to walk to pick up the carsharing vehicle
- ***Application rating in store***: the used operator app users' rating on the digital store you use

	Operator A Payment by KM Fixed cost	Operator B Payment by Minute
		cost depends on congestion conditions
Travel cost in €	7.34 €	Min 5.6 € Avg 8.1 € Max 12.1 €
Access distance in meter	150 m	150 m
Application rating on digital stores (stars)	4 Stars	3 Stars
Engine type: Electric	Yes	No

Certainly A | Probably A | Indifferent | Certainly B | Probably B | **None**

Figure 2.4: Scenario details and one block example

- The fourth part of the survey investigated the sociodemographic characteristics of the respondent, where respondents specified their age, gender, education level, occupation, number of people and children in the household, and the average monthly income. Also, in this part, we asked the users to specify their agreement on a five-points-scale (totally disagree, disagree, neutral, agree, totally agree) with 18 personality traits;

1. optimist
2. adventurous
3. like routines
4. spontaneous
5. like being outdoor
6. risk taker
7. like to stay close to home
8. efficient
9. variety seeking
10. punctual
11. like to be alone
12. independent
13. creative
14. calm
15. anxious
16. like being in charge
17. participative
18. lazy.

Table 2.4: Stated preference attributes and levels

Variable	Levels: Operator **A** (payment by Km)	Levels: Operator **B** (payment by Minutes)
Travel cost €	[7.3, 9.8, 12.2]	Minimum cost [5.6, 7.1, 9.2] Average cost [8.1, 10.3, 13.2] Maximum cost[12.1, 15.4, 19.8]
Access distance (Meter)	[50, 100, 150]	[50, 100, 150]
Application rating (star⋆)	[3, 4, 5]	[3, 4, 5]
Engine type: Electric	Yes / No	Yes / No

Table 2.5: Sample sociodemographics summary

Variable	Subgroup	n (pct%)	Munich Census
Age	18-24	415 (35%)	(18-29) 27.2%
	25-30	521 (44%)	
	31-35	108 (9.2%)	(30-39) 16.7%
	36-40	46 (3.9%)	
	41+	81 (6.9%)	(40+) 51.5%
Gender	Female	523 (45%)	51.70%
	Male	648 (55%)	48.30%
Education level	Masters & PhD	386 (33%)	(PhD 2.5%)
	Bachelor	657 (56%)	Bachelor/MS: 22.7%
	High School or less	128 (11%)	66.90%
Monthly income	500€ or Less	140 (12%)	
	500€ - 2000€	580 (50%)	Avg: 4220 AC /household
	2000€ - 4000€	259 (22%)	
	4000€ and more	192 (16%)	
Occupation	Full time	405 (34.6%)	full/part-time 87.1%
	Part-time	165 (14.1%)	
	Self employed	43 (3.7%)	
	Student	510 (43.6%)	4.50%
	Other	48 (4.0%)	8.40%
Children	No	1,019 (87%)	
	Yes	152 (13%)	
Household size	1	441 (38%)	50.30%
	2	296 (25%)	28.80%
	3 and more	434 (37%)	20.90%

N =1,170
*Subscription-based tickets; **Valid in Germany

2.2.3 Carsharing trip data

The carsharing dataset is an hourly carsharing trips dataset from a carsharing operator in Munich, Germany, for the entire year of 2016, and the dataset contained 972,459 trips. Each trip's average distance and duration and the starting and ending zone numbers were provided. A separate shape file containing the geo-information of the parking zones was also received to locate the trip origins in reference to the map of Munich. Figure 2.5 shows the carsharing zoning system compared to the boundaries from the Munich census. Figure 2.6–B, C, and D show carsharing trips' characteristics, including trip distance, duration, and speed, respectively. Also, Figure 2.6-A shows the hourly demand for carsharing for the different weekdays, and Figure 2.7 shows the daily demand for 2016.

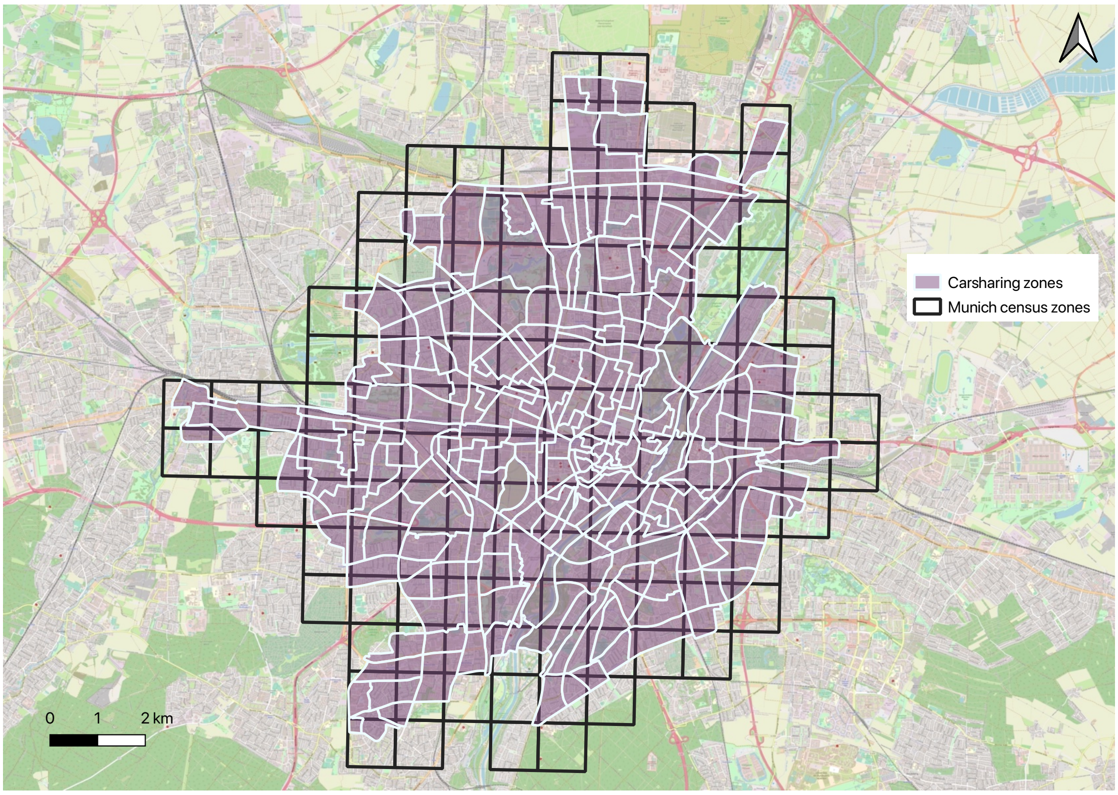


Figure 2.5: Carsharing operator zoning system of, and Munich census blocks

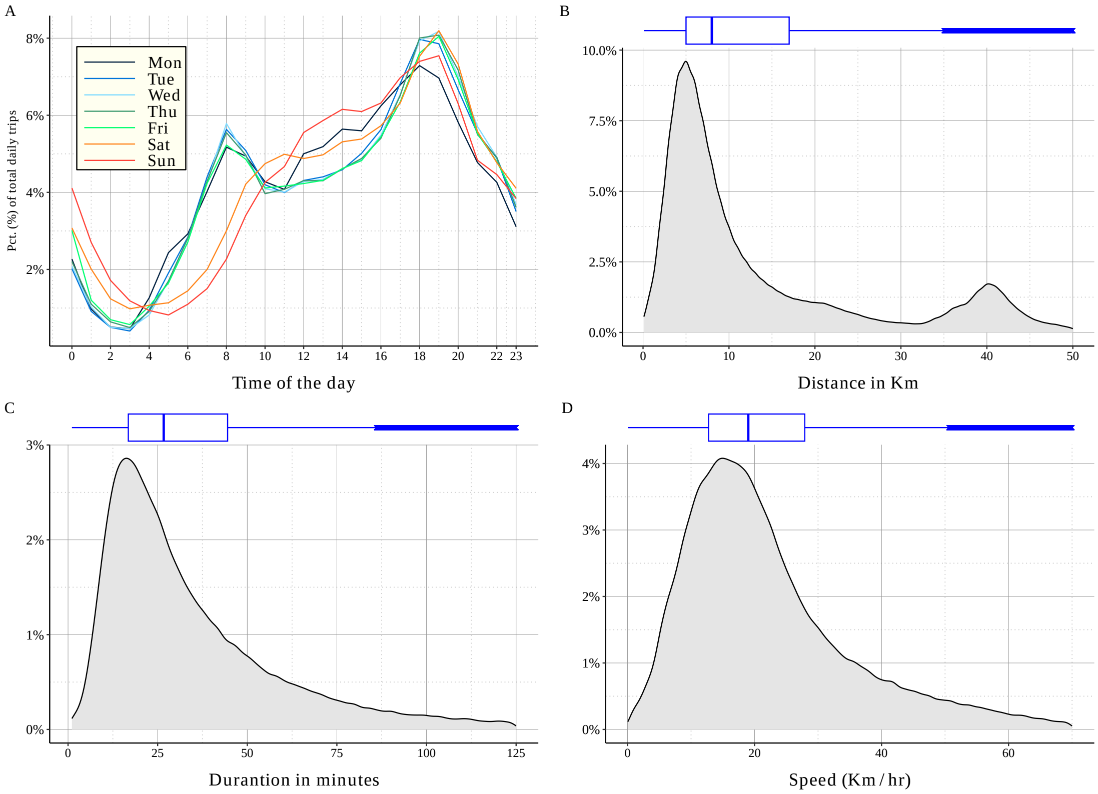


Figure 2.6: Carsharing trips characteristics

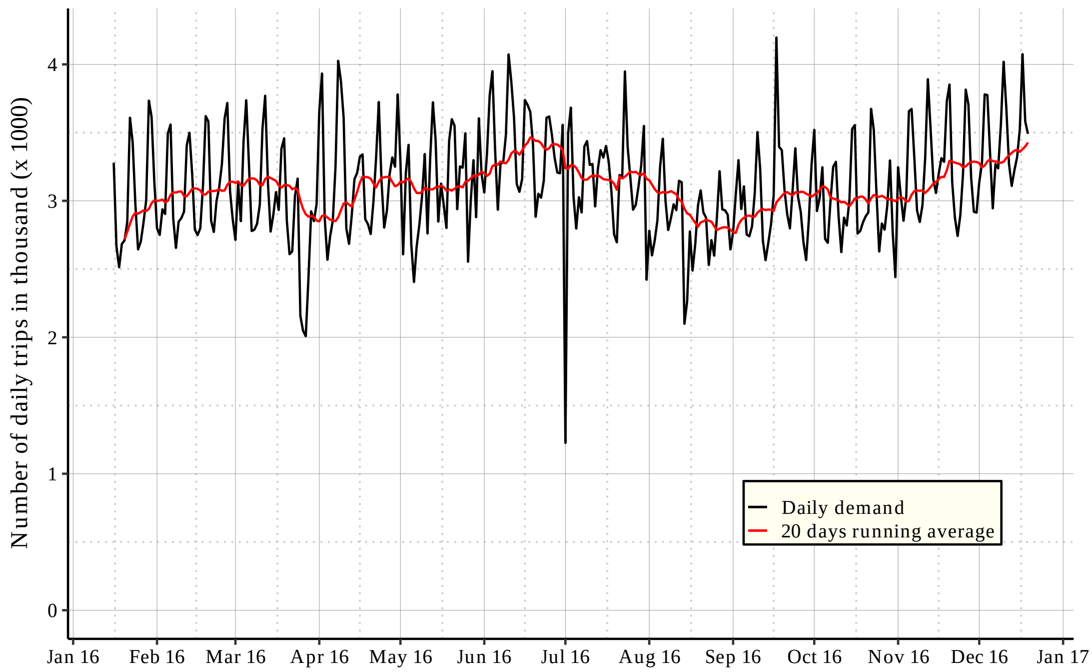


Figure 2.7: Carsharing daily demand

2.3 Methods

This section summarizes all the methods that were used in the next chapters.

Table 2.6: Summary of all used methods

Method	Chapter
Modeling techniques	
Zero-inflated negative binomial model (ZINB)	3
Explanatory Factor Analysis (EFA)	6
Multinomial logit model (MNL)	5
Hybrid Choice model (HCM)	6
Machine learning techniques	
Linear Regression (LR)	4
Support vector machine (SVM)	4
Gradient boosting decision tree (GBDT)	4
Long Short-term Memory Neural Network (LSTM NN)	4
Geographical analysis	
Local index of transport accessibility (LITA)	3, 7
Approximate neighborhood search algorithm (ANN)	7
Potential mobility index	8
Local Indicators of Spatial Association (LISA)	8
Getis-Ord (G_i^*)	8

2.3.1 Modeling techniques

Zero inflated negative binomial model

In Chapter 3, RQ **RQ-3.3** targeted modeling exogenous factors impacting shared E-scooter demand. The dependent variable was set as the daily number of trips per census tract, a count variable exhibiting both high dispersion and a substantial number of zero counts in low-demand areas. Therefore, a zero-inflated negative binomial distribution (ZINB) model was utilized. Unlike the standard negative binomial distribution, the zero-inflated negative binomial distribution does not impose the constraint that the variance must equal the expected mean, thereby allowing for additional overdispersion when the variance exceeds the mean. The underlying hypothesis of zero-inflated negative binomial models (ZINB) is that there are two latent classes of count data: one that consistently yields zero counts and another that produces non-zero counts. These models consist of two parts: the first estimate the probability of encountering zero counts, while the second accounts for the non-zero counts and the absence of zeros [118, 119]. Typically, a logit or probit model is suitable for determining the latent class of the data, Equation 2.1, and (β) represents the parameters vector. The probability of the excess zero (denoted as p_i), and the probability of the other counts is $(1 - p_i)$ follow a negative binomial distribution, with a mean of (μ), and following a Gamma distribution (Γ). Once the data class has been determined and when the probability ($p_i = 0$), the probability mass function for the zero-inflated model is represented by Equation 2.2 [120].

$$\mathrm{logit}(p_i) = x_i^T \beta \tag{2.1}$$

$$P(Y_i = y_{ij}|p_i, \mu_{ij}) = \begin{cases} p_i + (1-p_i)(\frac{\theta}{\mu_i+\theta})^{\theta} & y_i = 0 \\ (1-p_i)\frac{\Gamma(y_i+\theta)}{\Gamma(\theta)y!}\frac{\mu_i^y \theta^{\theta}}{(\mu_i+\theta)^{y+\theta}} & y_i = 1, 2, 3, ... \end{cases} \tag{2.2}$$

The mean of the ZINB distribution $E(y_i) = (i - p_i)\mu_i$, and variance $Var(y - i) = (i - p_i)\mu_i(1 - p_i\mu_i + \mu_i/\Gamma)$. The ZINB distribution is given by equation 2.2; where (θ) is the shape parameter that allows for the overdispersion [121, 122].

Factor Analysis

In Chapter 6, one of the main objectives was to model the impacts of attitudes and personality traits on car-sharing use. A standard method to understand and estimate the underlying latent construction between the different variables is explanatory factor analysis [123]. EFA captures common factors affecting the variables and the influence of the variables on each factor [124, 123]. EFA relies on the covariance between variables, making it well-suited for examining ordinal and ratio data. The process of obtaining factor analysis involves solving a set of linear equations for each variable (x), as illustrated in the equation system provided below, Equation 2.3, where (F_i) are the factors, (ℓ_{im}) is the factor loadings for factor (m) and variable (i), (μ_i) is the population mean and (ϵ_n) is the associated random error. In general, (m), the number of factors is smaller than the original number of variables. Factor loading near to one indicates that the (X_i) is highly influenced by (F_j). On the contrary, if the factor loading is near zero, this indicates the (X_i) is less influenced by (F_j)

$$\begin{aligned} X_1 &= \mu_1 + \ell_{11}F_1 + \ell_{12}F_2 + ... + \ell_{1m}F_m + \epsilon_1 \\ X_2 &= \mu_2 + \ell_{21}F_1 + \ell_{22}F_2 + ... + \ell_{2m}F_m + \epsilon_2 \\ &\vdots \\ X_n &= \mu_n + \ell_{n1}F_1 + \ell_{n2}F_2 + ... + \ell_{nm}F_m + \epsilon_n \end{aligned} \tag{2.3}$$

Five main assumptions are considered while estimating EFA:

- Random error terms have a mean value of zero; E(ϵ_i) = 0 for i =1,2,...,n
- Factors means are zero; E(f_i) = 0 for i =1,2,...,m
- Common factors have a variance equal to one; $\sigma^2(f_i)$ = 1; i =1,2,...,m

- Specific variance is the variance of the error term; $\sigma^2(\epsilon_i) = \Psi$, where Ψ is a diagonal matrix
- No correlation between any of the factors; $Cov(f_i, f_j) = 0 \quad \forall \quad i \neq j$

Discrete outcome models

Definition: discrete outcome models encompass a group of models used to represent situations where an agent selects among a set of alternatives, products, or a sequence of options over time or expresses an ordered response on a scale. These choices possess a discrete nature, indicating that the selection of one option is restricted to that specific option due to its countable and distinct characteristics. Three fundamental properties characterize the discrete nature of these alternatives or choices: i) mutually exclusive options: Selecting one option precludes the selection of any other options; ii) exhaustive options: The choice set includes all possible options; iii) limited and countable number of options: The number of options available is finite and can be counted [125, 126]. The most common forms of these models are binary and multinomial models. These models were used in Chapter 5 to answer **RQ-5.1** .

Ordered discrete responses models: ordered response models are extensions of multinomial logit models that account for ordered outcomes, which are not initially considered in the standard multinomial models [123]. In the case of ordered models, the assumption of independent errors, as in the logit model, does not hold. Instead, each alternative is closely related to values near it and irrelevant to alternatives further away. These models were utilized in Chapter 6 to answer **RQ-6.5** .

Hybrid choice models: the Hybrid Choice Model (HCM), or Integrated Choice and Latent Variables Model (ICLV), is an extension of rational discrete choice models. Initially proposed by MacFadden in 1986 and Train et al. in 1987, the HCM integrates latent variable models into choice models [127]. The main objective of this integration is to enhance the interpretability of the choice process by incorporating the user's cognitive behavior, attitude, and psychological factors into the choice model. Additionally, the integration aims to improve the model's goodness of fit when appropriate. This approach combines observed and unobserved factors to provide a more comprehensive understanding of decision-making processes in various domains [128]. These models were utilized to answer **RQ-6.2** , **RQ-6.3** , **RQ-6.4** , and **RQ-6.5** .

2.3.2 Machine learning techniques

In Chapter 4, we employed the model transfer problem for time series prediction [129] to predict scooters' fleet utilization or the number of trips per vehicle per day. We compared the prediction results using different evaluation matrices for four machine learning techniques; Linear Regression (LR), Support Vector Regression (SVR), Gradient Boosting Decision Tree (GBDT), Long Short-term Memory Neural Network (LSTM–NN). Given the historical demand data in the source city (Austin) alongside the first month of the demand data in the target city, Louisville, a time series model was trained and applied to predict future fleet utilization in the target city. The source city is the city that provides us with the long-term patterns of historical demand and fleet utilization changes. In contrast, the target city only has information on demand changes over a short pilot stage.

The historical data of a city is denoted as $\boldsymbol{D} = \{\boldsymbol{d}_i\}_{i=1}^{Z}$, where (Z) is the number of census tracts (demand aggregation zones). $\boldsymbol{d}_c = \{\boldsymbol{t}_c, \boldsymbol{z}_c\}$ is the data of census tract (c), consisting of both historical time series $(\boldsymbol{t}_c \in \mathbb{R}^L)$ and auxiliary census tract attributes $(\boldsymbol{z}_c \in \mathbb{R}^N)$, where (L) is the length of the time series and (N) is the length of auxiliary attributes. The length of $(\boldsymbol{t}_c)$ depends on the available amount of historical time series data, and $(\boldsymbol{z}_c)$ depends on the other auxiliary variables' length. The data of the source city and the target city can be respectively denoted by $(\boldsymbol{D}_S)$ and $(\boldsymbol{D}_T)$. The two lengths (L) and (N) can be determined based on the richness of data rather than fixed. For example, longer pilot stage duration and more accessible land use attributes allow the choice of larger (L) and (N).

An autoregressive formulation was adopted for the time series prediction problem, transforming it into a supervised ML problem. The raw data was split into two samples for model training and testing. A sample is described by a vector pair $(\boldsymbol{x}_i, y_i)$, where (i) is the index of the sample. The first element $(\boldsymbol{x}_i = \{x_i^j\}_{j=1}^m \in \mathcal{X})$ is an $(m$-dimensional) feature vector, which is comprised of (m) features extracted through feature engineering from the census tract attributes and the time series data of (w) consecutive days in a specific census tract (c), i.e., $(\boldsymbol{t}_c^{(i:i+w)})$. The label $(y_i \in \mathcal{Y})$ is the succeeding time series value in the census tract (c), i.e., $(t_c^{(i+w)})$.

The ordinary time series prediction problem aims at learning an accurate mapping $(f : \mathcal{X} \to \mathcal{Y})$ on future time steps in the same time series as in $(\boldsymbol{D}_S)$. However, the model transfer of the time series prediction problem aims at learning another mapping $(f' : \mathcal{X} \to \mathcal{Y}$ from $\boldsymbol{D}_S)$, but still performs well on the time series of $(\boldsymbol{D}_T)$. The foremost difficulty in model transfer lies in the inconsistency between the distributions of data in $(\boldsymbol{D}_S$ and $\boldsymbol{D}_T)$, also known as the covariate shift. To address this problem, we proposed a simple yet effective approach to align the distributions of time series in two cities and minimize the generalization error of the time series prediction model. Following the standard ML procedures, the four-step pipeline of (*sample construction – feature engineering – model training – inference*) was adopted. Two strategies were used to facilitate the transfer of the time series prediction model: sample normalization and label difference. Note that the proposed framework is compatible with various base ML models, which will be discussed in subsection *Base models*.

Feature engineering

Feature engineering is an essential step in ML model development; raw data were examined and processed before using it in the modeling process. Our model incorporated two categories of features, namely time-series features and auxiliary features. Historical time series characteristics were included in the feature set so that the model could learn the patterns of time series dynamics from them. Trend and seasonality should be removed through differencing before applying classical time series prediction tools like ARIMA [130]. Although ML models do not explicitly assume stationarity for time series prediction, a nonstationary time series is not always suitable for prediction without preprocessing, especially for decision-tree-based models, which is explained in the following section. Therefore, a first-order differencing was applied to the demand data as prediction labels. Apart from time-series features, auxiliary information was proven to help significantly prediction tasks [131]. In the used models, we incorporate four auxiliary features, i) temporal features, ii) meteorological features, iii) built environment features, and iv) sociodemographic features. Temporal and meteorological features vary across different days (dynamic data); built environment and sociodemographic features are static for each census tract, along with the road network and infrastructure attributes.

Base models

This subsection introduces the four ML techniques we applied in Chapter 4. We choose the models based on four different types of ML; linear regression (LR) depends on the assumptions of the linear relationship between the features and the outputs; support vector regression (SVR) uses a kernel method to impose the non-linearity of the data; gradient-boosting decision tree models the data using an ensemble of if-else rule sets based on tree representation. Finally, we used a deep learning technique, long short-term memory neural network (LSTM–NN), to capture the non-linearity of the relationship between the features and the output; the details of each of these models are as follows;

- **Linear Regression (LR)**: is a classical machine learning model that assumes a linear or affine relationship between input features and output labels. The simple linear regression takes the following formulation,

$$f(\boldsymbol{x}_i) = \boldsymbol{w}'\boldsymbol{x}_i + b, \tag{2.4}$$

  where $\boldsymbol{w} \in \mathbb{R}^m$ is the coefficient vector, and $b \in \mathbb{R}$ is the intercept. The residual $y_i - f(\boldsymbol{x}_i)$ is assumed to follow a Gaussian distribution assuming the independence of training samples; the parameters can be estimated through the least squares method, equivalent to maximum likelihood estimation. It aims at minimizing the sum of squared error, formulated as follows,

$$\min_{\boldsymbol{w},b} \sum_i (y_i - f(\boldsymbol{x}_i))^2 . \tag{2.5}$$

- **Support Vector Regression (SVR)**: is an extension of an ordinary support vector machine (SVM) for solving regression problems, originally designed for classification. To make binary classification, SVM adopts a separating hyperplane ($\boldsymbol{w}'\boldsymbol{x} + b = 0$) to split the feature space ($\mathcal{X}$) into two half-spaces. In the regression case, the hyperplane is turned into a real-valued function ($f(\boldsymbol{x}_i) = \boldsymbol{w}'\boldsymbol{x}_i + b$) resemblant to linear regression. Instead of least squares, SVR is trained based on the ϵ-insensitive loss, as formulated:

$$\ell_\epsilon(z_i) = \begin{cases} 0, & \text{if } |z_i| \leq \epsilon, \\ |z_i| - \epsilon, & \text{otherwise,} \end{cases} \tag{2.6}$$

  where ($z_i = y_i - f(\boldsymbol{x}_i)$). Unlike squared loss in the least squares, there is no penalty when the absolute prediction error is not greater than the threshold (ϵ). The complete optimization objective of SVR is given by,

$$\min_{\boldsymbol{w},b} C \sum_i \ell_\epsilon(z_i) + \frac{\|\boldsymbol{w}\|^2}{2}, \tag{2.7}$$

  where $C > 0$ is a trade-off coefficient between the ϵ-insensitive loss and the regularization term [132].

- **Gradient boosting decision tree (GBDT)**: dcision tree (DT) has a superior prediction performance and good interpretability [133]. Each decision rule corresponds to an exclusive path from the root node to a leaf node in the tree, while each leaf node is associated with a group of samples in the training set. The rule set of a DT actually partitions a subspace ($\mathcal{S}$) of the feature space ($\mathcal{X}$) into many sub-regions. For each input feature vector, DT searches for the sub-region to which this vector belongs, and prediction can be made based on the samples associated with the leaf node in the corresponding decision rule. The training process of a DT is a search for a satisfactory set of decision rules, i.e., a partition of ($\mathcal{S}$). It has been proven that finding an optimal rule set for a DT is *NP-Complete* [130]; hence a greedy heuristic algorithm is often used for model training, and the resulting DT is suboptimal. But, concerning a DT for regression problems with a determined feature space partition, the optimal output value of a specific leaf node can be the average labels of all the associated samples [134].

Ensemble learning is combined with DT to improve its generalization ability and reduce the risk of over-fitting, and GBDT is one of the representatives [135]. The principal idea of Boosting is to express the model as a summation of multiple base models. There are several improvements made on GBDT in terms of engineering implementation, including XGBoost [136], CatBoost [137], and LightGBM [138]. In this research, we adopted LightGBM, a highly efficient GBDT framework, which utilizes two specially designed techniques, Gradient-based One-Side Sampling, and Exclusive Feature Bundling, to ease the computational burden of large-scale data involved in model training without sacrificing the prediction accuracy.

- **Long Short-term Memory Neural Network (LSTM–NN)**: LSTM–NN is a recurrent neural network (RNN) model for modeling sequential data. In contrast to most non-recurrent neural networks, RNN allows loop connections in its architecture, which feed the outputs of a layer to itself as its inputs in the following time step [139]. An ordinary RNN layer maintains a hidden state ($\boldsymbol{H}$) for a long time; in each time step (t), it is fed with the current feature vector ($\boldsymbol{x}_t$) and the previous hidden state ($\boldsymbol{H}_{t-1}$). The hidden state of the time step (t) is updated by the non-linear transformations of the two inputs, while another non-linear transformation of the hidden state gives the output. LSTM improves RNN's ability to model long-term relationships by introducing three gated units (i.e., input gate, output gate, and forget gate) and an additional memory state ($\boldsymbol{C}$) in the recurrent layer. The three gated units apply different non-linear transformations on the two inputs, whereby the memory state and the hidden state are also updated,

$$
\begin{aligned}
\boldsymbol{I}_t &= \phi(\boldsymbol{w}_I'\boldsymbol{x}_t + \boldsymbol{v}_I'\boldsymbol{h}_{t-1} + b_I),\\
\boldsymbol{O}_t &= \phi(\boldsymbol{w}_O'\boldsymbol{x}_t + \boldsymbol{v}_O'\boldsymbol{h}_{t-1} + b_O),\\
\boldsymbol{F}_t &= \phi(\boldsymbol{w}_F'\boldsymbol{x}_t + \boldsymbol{v}_F'\boldsymbol{h}_{t-1} + b_F),\\
\boldsymbol{C}_t &= \boldsymbol{F}_t \otimes \boldsymbol{C}_{t-1} + \boldsymbol{I}_t \otimes \varphi(\boldsymbol{w}_C'\boldsymbol{x}_t + \boldsymbol{v}_C'\boldsymbol{h}_{t-1} + b_C),\\
\boldsymbol{H}_t &= \boldsymbol{O}_t \otimes \phi(\boldsymbol{C}_t).
\end{aligned}
\tag{2.8}
$$

  where ($\phi(\cdot)$) and ($\varphi(\cdot)$) are sigmoid and hyperbolic tangent activation functions respectively; ($\boldsymbol{w}$), ($\boldsymbol{v}$) and (b) are parameters; ($\otimes$) is the Hadamard product. The training of LSTM–NN can be realized via back-propagation through time, which unfolds the computation steps along time to allow the use of the chain rule [140].

Model transfer

Time series differencing is used to remove trends from the data (detrend) in response to GBDT's defect in extrapolation. Denote two consecutive time series values as (x_{i-1}) and (x_i), the first-order differencing yields a transformed label (y_i) as follows,

$$y_i = x_i - x_{i-1}. \tag{2.9}$$

However, differencing alone is inadequate regarding the model transfer problem due to the uneven distributions between data in $(\boldsymbol{D}_S)$ and $(\boldsymbol{D}_T)$. Covariate shift happens when the probability distributions between training data and test data differ while the conditional distributions of labels on input data are the same [141]. Nevertheless, an implicit assumption of standard supervised learning models, including GBDT, is that the training and test data follow the same probability [142], refraining from dealing with covariate shift. $(\mathcal{D}_S)$ and $(\mathcal{D}_T)$ denote the distributions of data in $(\boldsymbol{D}_S)$ and $(\boldsymbol{D}_T)$ respectively; denote the actual underlying functions mapping input feature vectors to labels on the two sets of data as (f_S) and (f_T). Then, following [142], we called $\langle \mathcal{D}_S, f_S \rangle$ the *source domain* and $\langle \mathcal{D}_T, f_T \rangle$ the *target domain*. The expected error on the source domain can be obtained by

$$\epsilon_S(g, f_S) = \mathbb{E}_{\boldsymbol{x} \sim \mathcal{D}_S} \left[\ell \left(g(\boldsymbol{x}), f_S(\boldsymbol{x}) \right) \right], \tag{2.10}$$

where $g(\cdot)$ is the model, $\ell(\cdot, \cdot)$ is the loss function. Similarly, the expected error on the target domain can be defined as $\epsilon_T(g, f_T)$.

In general, models are trained to minimize the empirical error on the source domain; nevertheless, in the model transfer problem, we minimize the error on the target domain. One option is transforming the data from $(\boldsymbol{x})$ to $(\boldsymbol{x}')$ such that the corresponding distributions $(\mathcal{D}'_S)$ is similar to $(\mathcal{D}'_T)$. Inspired by the batch normalization strategy in deep learning [143], we proposed the sample normalization strategy to transport the knowledge learned from the source time series to the target time series. We implicitly assumed that time-series dynamics, irrespective of the value scale conditional on given features. For each sample, the input time series segment was normalized to a mean of zero and a variance of one before extracting time series features. Denote the time series segment as $(\boldsymbol{t})$, the normalized segment $(\tilde{\boldsymbol{t}})$ can be obtained by:

$$\tilde{\boldsymbol{t}} = \frac{\boldsymbol{t} - \mathrm{E}\left(\boldsymbol{t}\right)}{\mathrm{D}\left(\boldsymbol{t}\right)}, \tag{2.11}$$

where $\mathrm{E}\left(\boldsymbol{t}\right)$ and $\mathrm{D}\left(\boldsymbol{t}\right)$ are the mean and the standard deviation of $\boldsymbol{t}$ respectively.

Sample normalization was adopted to reduce the covariate shift for the studied model transfer problem. The feature construction procedure with sample normalization was presented in Algorithm 1. Feature vectors are constructed for data in each census tract following the FeatureConstuction procedure. It should be noted that a complete training sample consists of a feature vector and a label, where the label also needs normalization. Recall that sample normalization takes a time series segment of consecutive (w) days; the label corresponds to the day right after this segment and needs to be normalized using the mean and standard deviation of the previous segment. As the label represents the day the demand is predicted, it should not be combined with the previous segment when calculating the normalization parameters, i.e., the mean and standard deviation.

Algorithm 1 Feature Construction (FeatureConstuction) with Sample Normalization

procedure SampleNorm($\boldsymbol{t}$)
  ▷ *$\boldsymbol{t}$ is a time series segment.*
  $\mu \leftarrow \frac{1}{|\boldsymbol{t}|}\sum_{i=1}^{|\boldsymbol{t}|} t_i$
  $\sigma \leftarrow \left(\frac{1}{|\boldsymbol{t}|}\sum_{i=1}^{|\boldsymbol{t}|}(t_i-\mu)\right)^{1/2}$
  $\tilde{\boldsymbol{t}} \leftarrow (\boldsymbol{t}-\mu)/\sigma$
  return $\tilde{\boldsymbol{t}}$
end procedure
procedure FeatureConstruction($w, \boldsymbol{t}, \boldsymbol{x}_{\mathrm{tm}}, \boldsymbol{x}_{\mathrm{bs}}$)
  ▷ *w is the time window size[2], $\boldsymbol{t}$ is a time series.*
  ▷ *$\boldsymbol{x}_{\mathrm{tm}}$ is the temporal and meteorological information.*
  ▷ *$\boldsymbol{x}_{\mathrm{bs}}$ is the built environment and sociodemographic information.*
  Initiate $\boldsymbol{s} \leftarrow \varnothing$
  for $i \leftarrow 1$ **to** $|\boldsymbol{t}| - w$ **do** ▷ i is the index of day.
    $\tilde{\boldsymbol{t}} \leftarrow$ SampleNorm($\boldsymbol{t}^{(i:i+w)}$) ▷ Normalize the time series segment.
    $\tilde{\boldsymbol{r}} \leftarrow$ FeatureExtraction($\tilde{\boldsymbol{t}}$) ▷ Extract time series features from $\tilde{\boldsymbol{t}}$.
    $\boldsymbol{u} \leftarrow \tilde{\boldsymbol{r}} \cup \boldsymbol{x}_{\mathrm{bs}} \cup \boldsymbol{x}_{\mathrm{tm}}^{(i+w)}$ ▷ $\boldsymbol{u}$ is the feature vector of a sample.
    $\boldsymbol{s} \leftarrow \boldsymbol{s} \cup \{\boldsymbol{u}\}$
  end for
  return $\boldsymbol{s}$
end procedure

2.3.3 Spatial analysis

Local Index of Transport Accessibility (LITA)

In chapter 3 and 7, the relation between SMS and accessibility to PT was under examination. We used the Local Index of Transport Accessibility (LITA) to indicate the accessibility level to PT. LITA calculations consider three aspects of PT service characteristics per the geographical aggregation unit; in this dissertation, the census zone was the unit. The three considered aspects are: i) route coverage score: the number of public transportation stops per zone; ii) frequency: the daily number of buses traveling the zone, and iii) mode capacity: seat–miles per capita. LITA score is calculated as follows:

- The route cover score; the number of bus stops in the geographical zone area calculated in the square mile

[2] The window size used for feature extraction is 28 days. In this research, we assume there is only one month available in the target city; hence the choice of window size is approximately one month.

- The number of buses traveling the geographic zone in a day
- The capacity score is calculated as the total daily seats on the bus line, bus capacity multiplied by the number of buses per day multiplied by the length of the bus route in the zone (in miles), divided by the sum of the total resident and employed population per zone

The average of the three scores is calculated and added to 5.5 to avoid negative numbers resulting in the LITA score [144], for which the higher the value, the better the accessibility per zone.

Approximate Nearest Neighbor (ANN)

In Chapter 7, **RQ-7.1** objective was to evaluate the distance between shared E-scooters and the nearest bus stop. One commonly used algorithm for such a task is the Approximate Nearest Neighbor (ANN) [145]. ANN algorithms efficiently find the approximate closest point in a dataset to a given query point. It uses data structures to guide the search, reducing computational costs in high-dimensional spaces. The algorithms trade off accuracy for speed by returning an approximate solution close to the nearest neighbor, refer to 2.

Algorithm 2 Approximate Nearest Neighbor (ANN)

Require: Query point q, dataset D, number of neighbors k
Ensure: k nearest neighbors of q
Initialize an empty priority queue PQ
for each point p in D **do**
    Compute the distance between q and p
    Insert p into PQ with the distance as the priority
    if the size of PQ exceeds k **then**
        Remove the point with the highest priority from PQ
    end if
end for
return The k points in PQ

Potential mobility index (PMI)

In Chapter 8, Potential Mobility Index (PMI) was used to evaluate the efficiency of the transport network of the different modes of transport. PMI is an aerial speed measure from one location to another location, considering the direct distance between the two locations (d) and the network travel time (T) [146]. PMI was calculated, for each mode, as the average aerial speed of each census block's centroid to all the other census block's centroids within the study area using the different modes.

$$PMI(i) = \frac{1}{N}\sum_{i=1}^{N}\frac{d(i, j...n)}{T(i, j...n)} \tag{2.12}$$

where:

$$\begin{aligned} PMI(i) &= \text{average aerial speed for zone i} \\ d(i, j...n) &= \text{aerial distance between i and j} \\ T(i, j...n) &= \text{network travel time between i and j} \\ N &= \text{total number of zones} \end{aligned} \tag{2.13}$$

Local Indicators of Spatial Association (LISA)

In Chapter 8, we investigated the spatial distribution of the sociodemographic characteristics in the study area. We used the Local Moran I index, or Local indicator of spatial Association (LISA), which is a measure for the spatial autocorrelation, or spatial similarity within the study area of one variable in comparison to the surrounding spatial units, in this case, the surrounding spatial blocks. Local Moran's I generates a spatial autocorrelation map, where each location is classified into four categories based on the mean value of the variable: i) High-High: Locations with high attribute values surrounded by neighboring locations with high values (clustered hotspots); ii)Low-Low: Locations with low attribute values surrounded by neighboring locations with low values (clustered coldspots), iii) High-Low: Locations with high attribute values surrounded by neighboring locations with low values (outliers), and iv) Low-High: Locations with low attribute values surrounded by neighboring locations with high values (outliers). Queen-case Contiguity-based neighbor was used for calculating the spatial weights.

$$I_i = \frac{(x_i - \bar{x})}{\sum_{j=1}^{N}(x_j - \bar{x})^2/(n-1))}\sum_{j=1}^{N} w_{ij}(x_j - \bar{x}) \tag{2.14}$$

where:

$$\begin{aligned} N &= \text{number of blocks} \\ x_i &= \text{tested variable for the tested spatial unit} \\ x_j &= \text{attribute of the neighbour spatial unit} \\ \bar{x} &= \text{mean of x} \\ W &= \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} \end{aligned} \tag{2.15}$$

Getis-Ord (G_i^*)

In Chapter 8 , We used the Gi* analysis to identify the trip's hot spots in reference to the distribution zones and to see the relation between the trips and the different POI hotspots. Getis-Ord, also known as the Getis-Ord Gi* statistic [147], is a spatial statistical method used to measure spatial clustering or spatial autocorrelation of a variable within a geographic area. It helps identify whether values of a particular attribute or phenomenon are clustered, dispersed, or randomly distributed across space. The Getis-Ord statistic calculates a z-score for each location in a given dataset, indicating the extent to which the value at that location is similar to its neighboring values. The z-score measures how many standard deviations the observed value is away from the mean value of its neighbors. Positive z-scores indicate clustering (hotspots) of high or low values, while negative z-scores indicate dispersion (coldspots).
For calculating the local Getis-Ord Gi* statistic:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{ij} \cdot x_j - \bar{x} \cdot \sum_{j=1}^{n} w_{ij}}{s \cdot \sqrt{\frac{\sum_{j=1}^{n} w_{ij}^2 - (\sum_{j=1}^{n} w_{ij})^2/n}{n-1}}}$$

Where:

$$\begin{aligned} x_j &= \text{value of the variable at location j} \\ \bar{x} &= \text{mean value of the variable across all locations} \\ w_{ij} &= \text{spatial weight between locations i and j} \\ s &= \text{standard deviation of the variable} \quad (x) \end{aligned} \tag{2.16}$$

For calculating the z-score:

$$z_i = \frac{G_i^* - \mu_G}{\sigma_G}$$

Where:

$$\begin{aligned} z_i &= \text{Z-score for location i} \\ \mu_G &= \text{mean of the Getis-Ord Gi* statistic across all locations} \\ \sigma_G &= \text{standard deviation of the Gi* statistic} \end{aligned} \tag{2.17}$$

3 Spatiotemporal demand patterns

The full details of this chapter can be found in the following article:

Abouelela, M., Chaniotakis, E., & Antoniou, C. (2023). Understanding the landscape of shared-e-scooters in North America; Spatiotemporal analysis and policy insights. Transportation Research Part A: Policy and Practice, 169, 103602.
Appendix A

3.1 Introduction and research objectives

Lime (www.li.me) launched one of the world's first shared E–scooter systems in Santa Monica, California, in July 2017, signifying the start of a revolutionary era of shared micromobility. The expansion and proliferation of scooters come with opportunities and challenges [65]. Efficient curbside space utilization, energy savings, greenhouse gas (GHG) emissions, and congestion reduction are some scooters' benefits claimed [148]. At the same time, the challenges related to the introduction of scooters cannot be overlooked. Scooters' are significantly raising safety concerns, as half of the reported accidents related to scooter use involved severe injuries, while fatal accidents were reported in the USA [62]. Scooters' deployment can cause other disturbing effects on cities. Scooter deployment problems can be summarized as fleet-size control, fleet capping and organization, permit cost, attracting users from active modes, and increased safety hazards [107, 64, 65].
The diverse range of challenges and the potential benefits of the widespread use of scooters identified in the pertinent literature render the need for further investigating their actual use in different urban contexts. While there is a growing body of literature on the topic, see, for example, [149, 150], most studies conducted evaluate scooter's use characteristics on data for limited periods of time (for example: [108] used three months of data; [107] used four months of data, and [151] who used six months of data), ranging from five weeks to four months or utilizing experiences from just one pilot case, or they do not differentiate or compare between pilot/early-stage use and regular use after service adoption and users constructing service-familiarity [108, 109, 107]. At the same time, most studies focus on using data from just one city, with a few exceptions see, for example, [152]. This omission limits the scope of analysis, preventing the comparison and extraction of conclusions regarding the potential generalization of the findings.

In this research, we leverage scooter trip data from four U.S. cities (Austin, TX; Chicago, IL; Louisville, KY; Minneapolis, MN) and one Canadian city (Calgary, AB) to perform a comparative empirical analysis of the spatial, temporal, and demand characteristics of the services, aiming at devising a thorough and informative investigation of scooter use, demand patterns, and factors impacting the demand. To be able to generalize the methodology of this study, we use open source data sources; Meteorological data, census data, infrastructure-related data, land use data, and general transit feed specification files (GTFS), to come up with an investigation of factors affecting scooters' demand, including the use of Local Index of Transit Availability (LITA) for evaluating the relation between scooter use and accessibility to public transportation. As a result of the previous objectives, this research provides answers to the following pertinent research questions:

RQ-3.1 What are the scooter's demand characteristics, and are there similarities and differences between the temporal and spatial scooter use patterns across and within different cities?

RQ-3.2 What are the similarities and differences between scooter trip characteristics in different cities?

RQ-3.3 Which exogenous factors affect scooter demand?

3.2 Data and methods

3.2.1 Data

Using the combined –with external data sources– trip data, we investigate spatiotemporal demand patterns and the impact of the exogenous factors on the daily generated trip demand. Specifically, to answer the posed research questions, we extract and compare demand patterns to understand the similarities and differences of trip characteristics in different cities. The used datasets are trip data, daily meteorological data, infrastructure data, and GTFS files. Refer to Section 2.2.1 for the details of the used data.

3.2.2 Methods

The overall methodology followed is depicted in Figure 3.1. The methodology consisted of three main stages. In the first stage, trip data was cleaned and aggregated by the different spatial and temporal units to examine the demand pattern. In the second stage, trip data was combined with the other external source of data, and they were aggregated by the day and census tract to be used in the modeling process. Finally, zero-inflated negative binomial (ZINB) models were estimated, showing the factors that impact the demand.

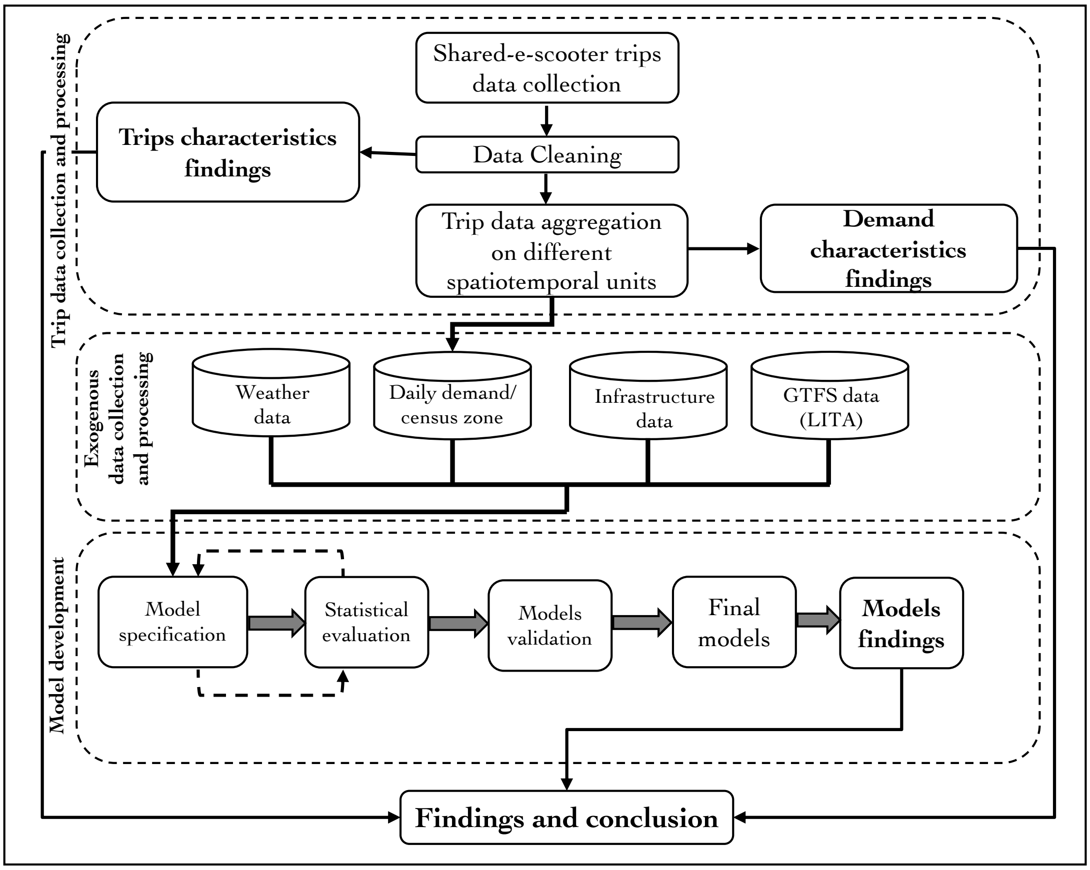


Figure 3.1: Research methodology

3.3 Analysis results

3.3.1 Temporal demand

Seasonal demand

At the beginning of the scooter's deployment, the demand increased rapidly for about two weeks until it reached a steady trend that exhibited seasonal demand patterns. In general, the demand during the pilot projects drops near the end of the project, which is not observed for Austin and Louisville, where scooters continue to operate to date. Minneapolis exhibited a different trend, which has a surge in demand one month before the end of the pilot, where the demand almost doubled in November with no special events observed in the city during this period and despite the cold weather. Also, Chicago had a different demand trend than the other cities, where the demand starts from a high value, and it decreased over time by a steady slope till two weeks before the end of the pilot, where the decreasing slope of the demand is steeper, which we believe was resulted or partially aided by the severe weather conditions during the end of the project period [153].

Hourly and daily demand

We calculated the percentage of the hourly trip in reference to the average daily demand to normalize the impact of the vehicle supply in the different cities and to be able to compare the hourly demand trends between the different cities. It is to be noted that shared mobility demand is a direct impact of the supply [98]. Interestingly, the maximum hourly demand is almost consistent among all the cities, and it ranges between 8% - 12% of the total demand. The only exception to the previous finding was in Minneapolis, where the average maximum hourly demand is high, and it is around 15%. The general hourly demand in the different cities can be described as a bipolar distribution with two different sizes of peaks; one minor morning peak (between 8:00-10:00) in Austin, Chicago, and Calgary during the weekdays, and the prime peak (in general between 16:00 - 18:00). On weekends, scooter demand has one peak during the afternoon and a higher percentage of early morning trips, starting after midnight, compared to the rest of the week. The only exception is Minneapolis, where the weekend and weekday demands are almost identical. Still, these observed patterns in Minneapolis could be because trips' starting times were coarsely aggregated to the nearest half-hour.

3.3.2 Spatial demand

We performed the spatial demand analysis in two steps. In the first step, we aggregated all the trips temporally into weekend and weekday trips; secondly, we aggregated the trips spatially to the census tracts corresponding to their starting locations. We normalized the difference between the weekend and average weekday trips per census tract to compare the examined cities' results. The spatial analysis of scooter demand reveals other exciting findings. In all cities, spatial demand exhibits a very similar pattern: during weekdays, the demand is concentrated outside the downtown area, especially around educational institutes, schools, and universities. During the weekends, demand is concentrated in downtown areas and around specific points of interest POIs, areas known for leisure activities, such as bars and restaurants, recreational areas, parks, and lakes.

3.3.3 Trip characteristics

The overall average trip distance is around 1.7±2 km. Interestingly, the pilot projects presented a longer average trip distance than those observed in later use stages in Austin and Louisville. In the discontinued pilot of Chicago, the average trip distance was longer than in other cities. Similar behavior holds for trip duration and trip speed, where pilots' trips are longer and faster than in the

later use stage. Also, Chicago has the fastest trips on average, and Louisville has a long trip duration. Also, the trips' characteristics in the examined five cities are similar to the trip characteristics of Washington DC analyzed by [154, 109]. It is worth mentioning that the average trip cost in all cities during the data collection period was 1$ for unlocking the vehicle and, on average, 0.33$ per minute; the price in Louisville was slightly lower than the other cities (1$ for unlocking the vehicle + 0.15$ per minute), which could be a reason for observing longer trips in Louisville [151].
We had an initial hypothesis that scooter behavior might be different in terms of trip characteristics at different times of the day. Therefore, we examined the average speed distribution per hour. Figure 3.2 shows the average speed per hour per city. All cities exhibit a similar speed trend during the day, with a noticeable speed increase during the early morning and morning hours between (2:00 - 10:00), except for Minneapolis and Chicago. Minneapolis shows a slightly different hourly speed profile that departs from the average between 10:00 and 16:00. Chicago follows the same trend but with a different speed profile. The speed on average is around 12 km/hr, but still, it exhibits an increase in the early morning and morning hours between (2:00 - 10:00) to approximately 15 km/hr. The rise in the speed during the early morning hours in all the cities might be encouraged by the low traffic volume, which is a factor that might increase injury probability during that time of the day.

3.3.4 Demand modeling

To understand factors impacting the demand, trip generation, we developed ZINB modes, where the dependent variable of the modeling process was the number of daily trips per census tract zone. Rainy days and snowy days reduce the probability of scooter use. On the other hand, warmer days increase the likelihood of scooters' use, except in Chicago, where the average daily temperature coefficient is not statistically significant. Wind speed has a mixed effect. Also, scooter use increased on weekends compared to weekdays in all cities. Zones with higher transit accessibility (higher LITA value) generate more trips than other zones; the increase in the number of shared bike stations and the length of the bike lanes per zone increases the likelihood of scooters' use, except in Minneapolis; the coefficient of bike lanes is not statistically significant. Only in Louisville do the bike lanes have a negative sign coefficient indicating the reverse impact. This can be attributed to the geographic distribution of bike lanes in the northwest and southeast of the scooter operation zones, with fewer trip rates than in the downtown area. Sidewalk length per zone has a mixed impact on the probability of scooter use: in Austin, where it is permitted to ride on sidewalks, the increase in sidewalk length increases the trip generation; in other cities, however, it is not allowed to ride on the sidewalk, it reduced the trip generation rate. Residential land use reduces the probability of generated trips in the area compared to other land uses.

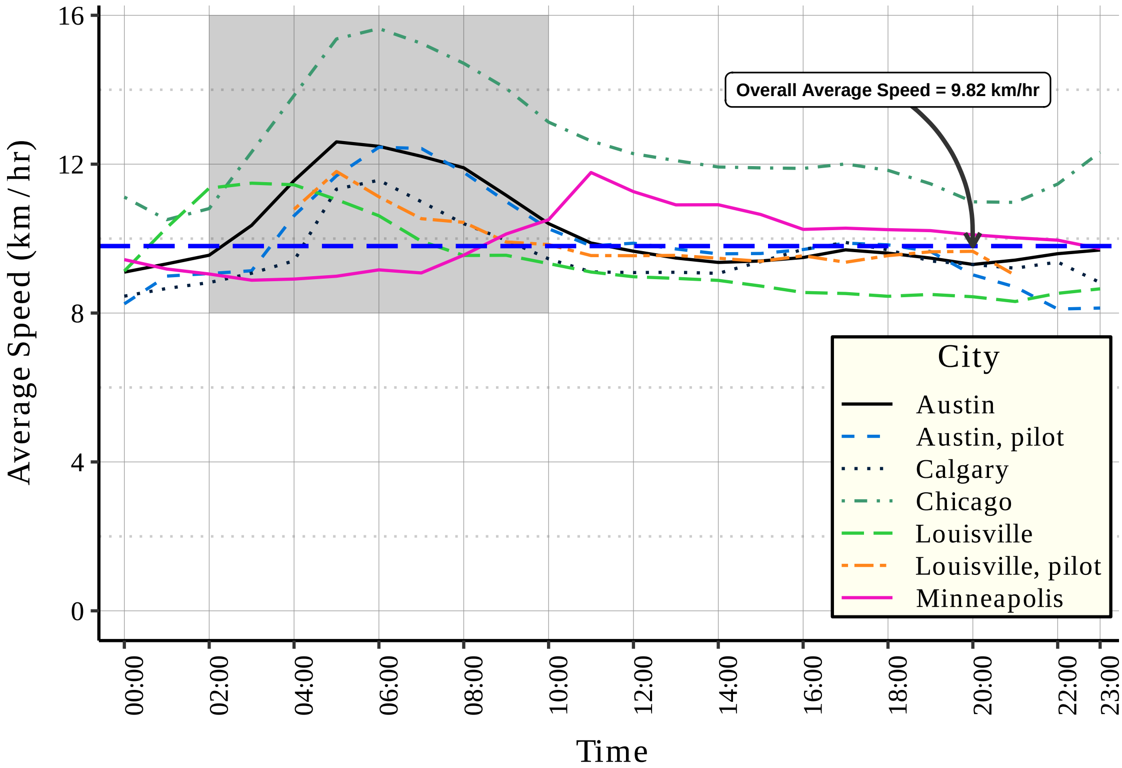


Figure 3.2: Hourly speed profile

3.4 Discussion, study limitations, and conclusion

3.4.1 Discussion

This study used around nine million scooter trips from five North American cities to investigate scooters' demand, trip characteristics, and the factors impacting their use. Several findings suggest the consistency of scooter use in different cities, despite their size and population, urban structure, and general travel demand behavior. The conclusions revealed could help organize the shared–E–scooter service in other cities, or they can be used as guidelines before deploying the service in other cities. The main findings' impacts on operation policies are discussed in the following subsections.

Maintenance and redistribution work should consider spatiotemporal demand patterns, and they should be synchronized with maintenance and vehicle redistribution work to allow the vehicles to be present during peak demand hours. Moreover, the predefined scooter demand patterns would utilize the vehicle redistribution work to minimize the empty VKT. Scooter demand shows several individuals' atypical temporal patterns. For example, in cities that allow late-night operation, late-night use typically increases during the weekends. This increase in late-night/early morning hours scooter demand is an indication that scooters could extend the temporal accessibility for travel options, especially if the vehicles are available in high-demand places during these times. Moreover, scooters' demand increase was found to be associated with the increase in accessibility to PT, as indicated in the estimated regression models, and micromobility has received increased attention as a viable mode for the first/last mile dilemma [39, 152, 155].

Furthermore, seasonal demand trends indicate an increase during warmer months and a demand drop around January. Such patterns could help dynamically adjust the fleet size over the year to optimize operating costs and allow vehicle maintenance during low-demand periods. Scooters' demand is sensitive to special events; in Austin, the daily demand was around four times the average demand during the South by Southwest (SXSW) music festival; similar behavior was also observed in Washington DC during the Cherry Blossom festival [154].

Spatial demand patterns are generally consistent between the examined cities, regardless of their urban structure differences. Spatial demand is concentrated around leisure activities, such as restaurants, bars, and parks, during weekends, while on weekdays, around the downtown area and educational institutes. Also, the demand is more geographically dispersed on the weekends than the more compact and clustered weekday demand. The distribution and maintenance operations should consider these locations as hot spots, while after the weekend, the redistribution process should cover more expansive areas to retrieve the scooters.

Average trip speed, distance, and duration are consistent among the five examined cities. Pilot projects and early use stages exhibited slightly higher speeds and longer trip distances and duration, possibly due to new users' excitement. Considering that accidents are highly correlated with a lesser familiarity with service use [156], which has a higher probability during the scooter introduction period, strict monitoring for vehicle speed should be applied. Furthermore, both cities and operators should provide educational marketing plans to educate the users about how they would use the service adequately and the rules for using the vehicles, identifying the hazards that could arise from improper use.

External factors impacting the demand are almost the same in the different cities; however, their magnitude might differ from one city to another. Meteorological conditions play a significant role in demand generation, with snow and rain being decisive factors. Therefore, seasonal maintenance and fleet size control should be utilized dynamically based on the short and long-term weather forecast to avoid excessive vehicle deployment, which most likely will be occupying public spaces that might impair accessibility. Land use, PT accessibility, and infrastructure are also essential factors impacting the demand, and they are hard to change factors. The previous factors need long-term high capital investment to alter; therefore, scooter deployment should be coordinated to utilize scooter use and decrease disturbance for the other elements of the urban environment. For example, scooter deployment should be reduced in dominantly residential areas. In areas with high PT accessibility, the supply should be increased to encourage scooters' use as a first and last-mile solution. Finally, sociodemographics such as age and income level affect scooter demand; therefore, scooter deployment should consider the population distribution; for example, areas with a younger population might require more vehicles than areas with older population groups. Income-level impact on scooter demand has been observed in different studies [152, 155]

3.4.2 Study limitations

There is no available data reflecting the exact daily number of scooters available in the public right of way; the only available information is the fleet size for each city, reflecting the maximum allowable number of scooters. Therefore, when controlling for the number of vehicles, the exact daily number of scooters was not used, which might affect the actual number of trips per vehicle rate; however, we do not think the overall observed demand trend might have been affected by the lack of the exact number of vehicles. We also did not consider the influence of the re-balancing and redistribution of the vehicle processes that might impact the demand. There was no available information regarding these processes. We assumed that scooters are uniformly distributed through the study area, especially for the datasets where trip Geo-location was aggregated. We believe that the availability of such information should enhance our understanding of the demand pattern. The data used are collected through different periods with no complete overlap, which is expected due to the nature of such data; however, it still represents a limitation.

3.4.3 Conclusion

This research analyzed scooter trips from four US and one Canadian city to answer three main research questions regarding the different demand patterns and the exogenous factors that impact the demand. The answers to the research questions have helped us better understand and provide insights into the current scooter use on different levels. Cities and operators may find these insights helpful in planning the operational schemes for current or future scooter-sharing projects. Based on the demand patterns, both cities, and users are satisfied with scooter use, as expressed by the demand increase and the continuation of the pilot projects in cities like Minneapolis and Chicago. Future research can provide additional insights into this topic, which is only now gaining momentum.

4 Fleet utilization prediction

The full details of this chapter can be found in the following article:

Abouelela, M., Lyu, C., & Antoniou, C. (2023). Exploring the Potentials of Open-Source Big Data and Machine Learning in Shared Mobility Fleet Utilization Prediction. Data Science for Transportation, 5(2), 5.
Appendix B

4.1 Introduction and research objectives

Shared mobility services are an example of the recent innovative solutions that could cater to the growing increase in travel demand. These services provide commuters access to different vehicle types or the ability to share rides based on the user's needs [157]. Shared mobility services have many positive potential impacts on the urban environment, including reducing vehicular traffic [40], reducing energy consumption, and increasing transport system efficiency by achieving saving in travel time and travel costs [158]. Notwithstanding the possible positive effects of shared mobility services, some of them have integration, planning, and policies challenges following their sudden and novel introduction to the urban environment, such as the case of shared-E-scooters, we will refer it as *scooters* in the rest of the article. Scooters face several challenges, such as the increase of related injuries [62], defining the optimal fleet size, vehicles optimal redistribution strategies, speed limits enforcement, and equity regulations [159]. In order to further study these problems and define their causes and factors leading to them, more data is required. The advancement of information and communication technology (ICT) has also opened the horizon for collecting and analyzing new types of data in large quantities, or so-called big data [83, 73]. Different entities, primarily operators and cities' authorities, are currently sharing their data (big based on volume, velocity, or variety) openly to encourage the innovation of new methods and ideas to improve the urban environment, to increase integration between the different transportation services, and to help in regulating and dynamically adjusting the operation of various shared mobility services within the urban environment [160, 84].
In this paper, we use the publicly available scooter trips data from two American cities, Louisville, Kentucky, and Austin, Texas, in combination with other open

data sources, to explore the potential and accuracy of using open source data and Machine Learning (ML) techniques to predict the scooter daily fleet utilization (number of trips per vehicle). The main objective of this research is to create and develop a framework that could help the different stakeholders involved in the operation, organization, and governance of the micromobility services to integrate the service in the urban environment efficiently and to facilitate the policy-making process. The contribution of this work is comprehended by answering the following research questions:

RQ-4.1 Is using open-source data and ML techniques adequate to predict the daily scooter fleet utilization (daily number of trips per vehicle)?

RQ-4.2 Is there any differences between the prediction accuracy for different level complexity ML techniques; Gradient boosting decision tree (GBDT), Linear regression (LR), Support Vector Regression (SVR), and Long Short-Term Memory Neural Network (LSTM-NN) ?

RQ-4.3 Could the proposed methodology predict the demand for long periods, e.g., more extended than one year?

RQ-4.4 Could the proposed methodology be implemented in real-life scooter deployment, organization, and governance processes?

RQ-4.5 Could the proposed methodology be used for other cities?

4.2 Data and methods

4.2.1 Data

Four main sources of data were used in this research; all of them are open-source data that are available publicly. Scooter trip data from the city of Louisville portal [103], Sociodemographic data from the American Census Bureau (`census.gov`), built environment data from (`Osm.org`), and finally weather data from (`visualcrossing.com`) for the details of the collected data and data processing details, refer to Section 2.2.1.

4.2.2 Methods

Figure 4.1 shows the overview of the proposed methodology framework. We employed in this research the model transfer problem for time series prediction to predict scooters' fleet utilization [129]. Given the historical demand data in the source city (Austin) alongside the pilot stage demand data in the target city, Louisville, a time series model was trained and applied to predict future fleet utilization in the target city. We considered the first three months of the service deployed in the source city as a pilot stage, as commuters are generally trying to get familiar with the service, and it is the same period used by other cities to evaluate scooters' deployment, such as Minneapolis, MN [38]. The source city is the city that provides us with the long-term patterns of historical demand and fleet utilization changes, whereas the target city only has information on demand changes over a short period of time. An autoregressive formulation was adopted for the time series prediction problem, such that it was transformed into a supervised ML problem. The raw data was split into two samples for model training and testing.

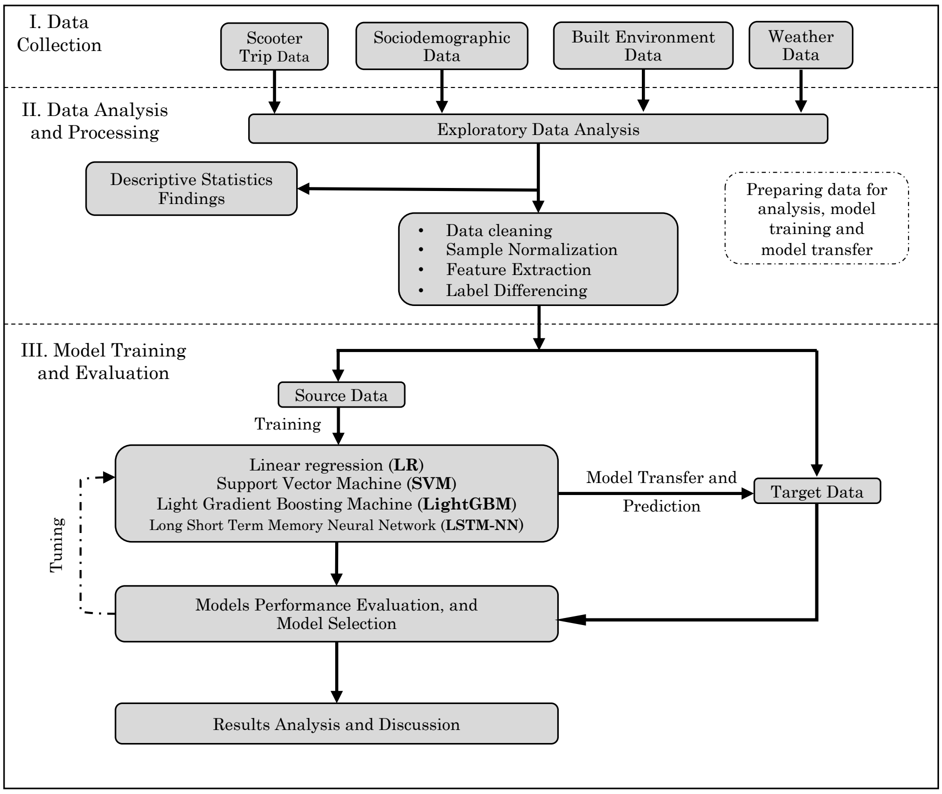


Figure 4.1: The used methodological framework

4.3 Analysis results

4.3.1 Model results

The prediction accuracy was evaluated using two metrics; root mean squared error (RMSE), and mean absolute error (MAE). The proposed framework was applied to the different used ML techniques. We first compare the performance of the models as shown in Table 4.1 upper part, and then we compared the performance of the model after the transfer (label differencing and sample normalization)

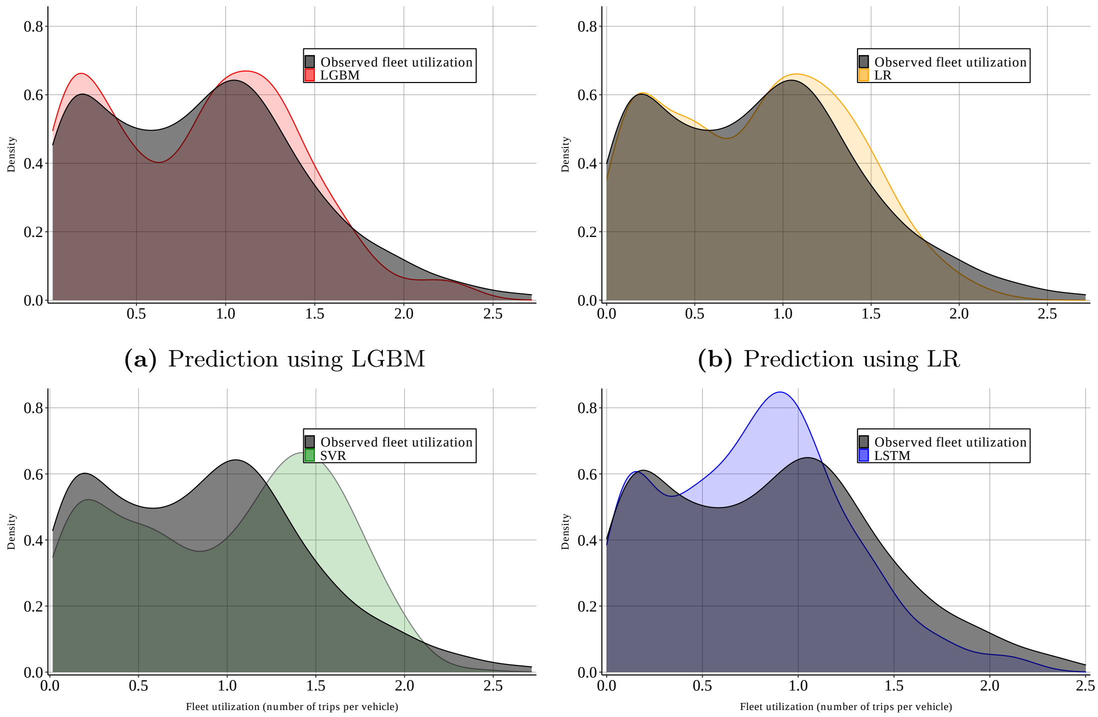
To further improve the transferability of the model, we applied the model transfer strategies to all the models. We applied the different transfer strategies as shown in Table 4.1 lower part, which shows the model's prediction results summary after applying the different transfer strategies. A time series prediction without treatment of the covariate shift issue suffers from low RMSE and MAE on the training set. However, when faced with unseen data in another city, the test set's performance suffers considerably because of distinct time series patterns. Firstly, we applied label differencing, but it did not improve accuracy as the distribution inconsistency in the input space was not addressed; similarly, only applying sample normalization was ineffective. The transfer error was finally reduced when the two strategies were used simultaneously, which is evident in the best-performing model, LightGBM. For LightGBM, The RMSE dropped from 2195.7 to 1845.6, which showed an improvement of the performance by approximately 15.9%. Meanwhile, a drop in accuracy on the training set was also observed, indicating a less severe over-fitting model.
As The LightGBM model was the model with the best prediction performance, we evaluated the importance of factors influencing the prediction using the number of node splits corresponding to each feature in the trained LightGBM model. The more a feature was adopted for a split in the tree, the higher its contribution to the prediction [161]. To quantify the influence of the different factors groups, we categorized the features into five main groups. Time series features accounted for 67.0% node splits in the trees, whereas each category of auxiliary features accounted for approximately 6–10% node splits. Further experiments were performed to see whether removing specific feature groups would significantly reduce prediction accuracy. We found that removing every feature group will more or less negatively impact the model performance. The results are generally consistent with their relative importance; the removal of time series features — the most critical group of features — resulted in a performance drop of around 43% in Test RMSE. Removing auxiliary features did not incur severe impacts, where the accuracy reduction caused by removing built environment features or sociodemographic features was less than 2% per group.

4.3.2 Error analysis

We analyzed the prediction error, its value distribution, temporal distribution, and spatial location considering the test set Louisville's dataset. We observed that all the estimated models captured the overall demand pattern with some shortcomings. The LR model tends to overestimate the utilization rate between (1-1.75) vehicles per trip, and it underestimates the demand when it is higher than 1.75 trips per day; for the rest of the value, it is somehow able to estimate the fleet utilization rate. SVR was consistently unable to predict the utilization rate; for rates below 1.25 vehicle/trip, the model underestimated the results, and for rates over 1.25 vehicle/trip, the model overestimated the utilization rates. Regarding the temporal distribution of the error, SVR was the model with the least prediction capabilities. LSTM could not accurately predict the low utilization rate and tended to overestimate the utilization below 1.2 trips per day and underestimated the demand higher than 1.2; also, the model had some incidents where the estimated utilization rates were significantly higher than the actual rate. The LGBM model had the best performance among the four models. It can be observed that the prediction results of the proposed model capture most of the demand seasonal peaks and troughs dynamics without lag except for the several sudden spikes in the early stage of operation (e.g., the spike in mid-April). However, the model inclines underestimation regarding peak values, possibly an outcome of model regularization, as predictions of large values are more likely to be connected with high errors (error terms are increasingly proportional to the absolute demand value). Potential solutions include increased training data and additional information like special events and fine-grained weather forecasts. The conclusion of the error analysis process, which was done in multiple dimensions, shows that the LGBM model is superior in prediction accuracy compared to the other used ML models, including LSTM.

Table 4.1: Models performance metrics

Label Differencing	Sample Normalization	Performance ($\times 10^{-5}$)				
		Model	Train RMSE	Train MAE	Test RMSE	Test MAE
Models without transfer learning						
—	—	LightGBM	531.6	82.9	2195.7	**382.6**
—	—	LR	1017.2	185.5	2164.1	388.3
—	—	SVR	1064.8	242.9	**2092.5**	440.4
—	—	LSTM	1333.8	360.2	2366.2	484.9
Models after transfer learning						
✓	✗	LightGBM	469.3	97.9	2291.9	394.1
✗	✓	LightGBM	1059.0	174.1	2037.6	390.5
✓	✓	LightGBM	873.9	130.7	**1845.6**	**346.8**
✓	✗	LR	1017.3	185.7	2168.5	389.6
✗	✓	LR	1166.8	178.4	**2034.7**	**378.7**
✓	✓	LR	1263.6	185.4	2054.4	381.2
✓	✗	SVR	1064.0	215.1	2135.6	449.5
✗	✓	SVR	1212.7	181.4	2200.8	381.4
✓	✓	SVR	1296.4	177.8	**2208.3**	**371.3**
✓	✗	LSTM	1274.3	284.6	2647.4	515.8
✗	✓	LSTM	1176.5	182.1	2677.9	480.6
✓	✓	LSTM	1140.6	179.3	**2376.0**	**436.4**



(a) Prediction using LGBM

(b) Prediction using LR

(c) Prediction using SVR

(d) Prediction using LSTM

Figure 4.2: Observed fleet utilization distribution (dark grey) vs. predicted fleet utilization (colored)

4.4 Discussion, study limitation, and conclusion

4.4.1 Discussion

The used framework shows a simplified and effective way to predict the number of trips per vehicle (fleet utilization) for one of the rapidly expanding shared mobility services, shared-E-scooter, depending on open-source data. This framework could be used (after testing) for similar dockless, free-floating micromobility shared systems, which exhibited similar travel behavior, e.g., free-floating bike-sharing services [162, 107]. Moreover, similar data characteristics to the one used in this study should be publicly available for other shared mobility services to implement the used framework; nevertheless, the data need to be anonymized to ensure that users' privacy is not violated. The framework depends on employing the historical demand data combined with open-source data; therefore, different stakeholders could use the framework to predict the daily number of trips per vehicle and deploy the vehicles in the expected locations accordingly. The error analysis section shows that the increase in the number of days used in the prediction process increases the accuracy of the models; therefore, the continuous use of such models would improve the model accuracy over time. It is also to be noticed that we used the ridership (the number of trips per vehicle per day) for the prediction task for two main reasons; firstly, we wanted to control the fleet size in both cities to be able to compare the demand and to normalize the impact of the supply. Secondly, demand is directly tied to supply in the case of shared mobility services, and estimating absolute demand will lead to a biased estimation [98].

4.4.2 Study limitations

While we used a 28 days data window for the target city demand for the transfer learning process, other shorter windows, such as seven days of demand data, should have been investigated to test the absolute minimum amount of data required to use the same framework. However, this limitation can be covered in future work, and it does not affect the integrity of the current research.

4.4.3 Conclusion

The methodology and data show a promising approach that the stakeholders could implement and use to organize scooters and similar shared micromobility vehicle services. However, the model must be tested for the other service to validate user behavior differences. Also, publishing the trip booking data publicly by cities should be further encouraged as it plays a vital role in encouraging researchers from industry and academia to investigate such services use behavior and discover innovative methods to enhance service operations without jeopardizing users' privacy.

5 Synergies within shared mobility services

The full details of this chapter can be found in the following article:

Abouelela, M., Al Haddad, C., & Antoniou, C. (2021). Are young users willing to shift from carsharing to scooter–sharing?. Transportation Research Part D: Transport and Environment, 95, 102821.
Appendix C

5.1 Introduction and research objectives

Micromobility has emerged as an attractive concept for modes with low speed, short–term access, and on–demand trips, including both station–based and dockless or free–floating vehicles such as bikesharing and scooter–sharing; the latter includes both standing electric scooter–sharing and moped–style scooter–sharing [163]. The increasing demand for standing electric scooters has seen considerable growth in various cities, particularly in the US, where the market for scooter–sharing is expected to reach $300B [163]. Interest in micromobility has oriented research and policymakers to investigate its impacts, understand the needs of its users/non–users, but also come up with responsible policy-making and guidelines for its integration to current systems [163]. Few studies, if any, addressed the impacts of scooter–sharing on carsharing, despite quite common characteristics mostly pertaining to shared–mobility. Moreover, to the best of the authors' knowledge, no previous study has conducted a stated preference (SP) experiment including scooter–sharing as a main mode of transport. Other researchers have conducted SP studies in an attempt to understand scooter adoption better [164] or developed scooter choice models, where scooters were introduced as a first–last–mile transportation mode [165].

In this research, the shift from carsharing to scooter–sharing was particularly interesting as we tried to close the gaps in micromobility research. On the one hand, fewer studies have investigated scooter users and demand compared to carsharing, mostly stated preference (SP) studies; on the other hand, studies on micromobility replacement have not looked at the shift from carsharing but rather focused on walking and ride–hailing. This was usually done by asking users about the mode they would have used had scooters not been available for the same trip. This research attempts to close this gap by i) conducting an SP study to estimate a choice model between carsharing and scooter–sharing. ii) Using the estimated model to predict the demand shift from carsharing using a carsharing dataset from a Munich operator. For the SP survey, young individuals (18–34 years old) were targeted, as they are most likely the potential users of scooter–sharing systems [112, 113]. Or, we can state that the main research questions are:

RQ-5.1 Are young users willing to shift from carsharing to shared E–scooters?

RQ-5.2 What is the expected percentage of carsharing trips replaced by shared E–scooters?

5.2 Data and methods

5.2.1 Data

Four main sources of data were used to answer the main research question; survey data, refer to section 2.2.2 for the survey structure and collected data. As the second research question investigated the percentage of carsharing trips replaced by scooters, a whole year of carsharing trips, around one million trips, that took place in Munich for the year 2016 were used, refer Section-2.2.3 to for the details of trips dataset. Finally, open-source data, namely the hourly weather data for 2016 (since the carsharing data was for 2016) and the German Census data. The former was retrieved from the German weather service online archive (`dwd.de`) and contains the hourly temperature and precipitation. The latter was obtained from the German federal statistical bureau (`statistikportal.de`).

5.2.2 Methods

Model estimation

The collected data, the survey, was used to estimate a mode choice model for the different alternatives. Since the aim is to use the model estimate to predict carsharing demand shift, responses were regrouped as follows: varying preferences for carsharing ("Certainly carsharing", "Probably carsharing") were grouped under the carsharing choice and varying preferences for scooter–sharing ("Certainly scooter–sharing", "Probably scooter–sharing") were grouped under the scooter–sharing choice. Moreover, responses with "indifferent" as a choice were removed following [166], as they could not be attributed to either choice; moreover, these amounted to less than 1% of the sample size and are therefore not believed to have an impact on estimation. Accordingly, three alternatives remained and were regrouped (carsharing, scooter–sharing, and none), and a multinomial logit model was estimated using the scenario attributes (time, cost, rain, risk of accidents) and the respondents' demographics.

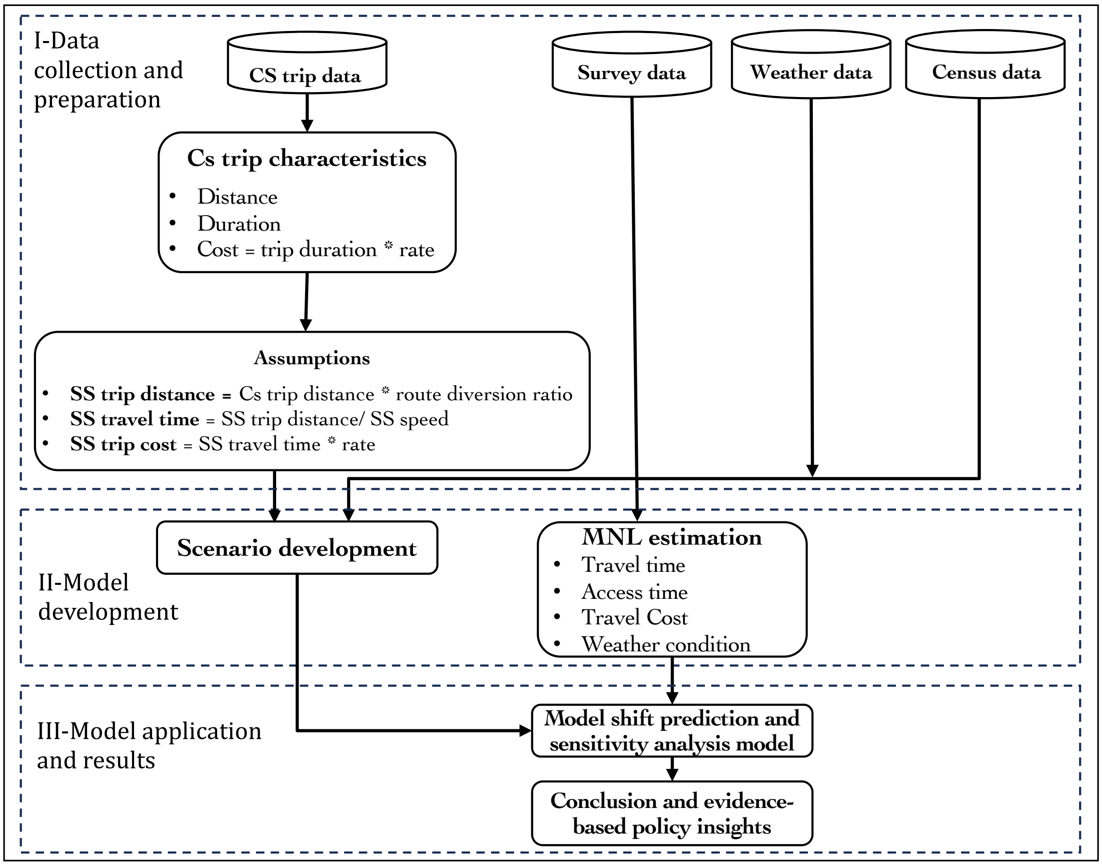


Figure 5.1: Methodology workflow

Model prediction, and sensitivity analysis

To test the attraction of carsharing users to scooters, we developed a number of scenarios based on different assumptions, with the aim of applying the estimate choice model to predict the shift from carsharing to scooters. A comprehensive list of the used assumptions is given below:

- **Carsharing trip cost**: (0.20, 0.28, 0.36) €/min, based on operator ranges from 0.19 to 0.36 €/min (share-now.com).

- **Route diversion or scooter route/carsharing route**: (-30%, -10%, 0%, 10%, 30%).

- **Scooter speed**: (6,14,22,30) km/hr. Based on scooter trip data in five North American cities [38].

- **Scooter trip cost**: (0.15, 0.20, 0.25)+ 1€ unlocking fees. Based on operator rates in Munich: (0.15, 0.19, 0.20)€/min + 1€ (https://www.muenchen.de/freizeit/e-scooter-leihen.html).

- **Percentage of carsharing female members:** 25%, as reported by a carsharing report on users in Munich [167].

- **Carsharing access and egress times:** (1, 3, 5) min., based on the stated preference survey levels.

- **Scooter accident risks compared to carsharing: (1,2,4) times more**, based on the stated preference survey levels.

- **Rain condition** based on the real weather data of the given day.

Based on the above assumptions, a combination of scenarios with the different levels was developed, amounting to 1620 scenarios. These were tested, and a sensitivity analysis was made to understand better the impact of scooter–sharing based on different parameter changes.

5.3 Analysis results

5.3.1 Survey data

The collected data led to 503 valid responses, amounting to 4527 observations (9 choice scenarios per response). The survey responses reflected some limitations in the representativeness compared to Munich. Overall, females are underrepresented (though not drastically), but the notable difference is in the age representativeness, where responses reflect a much higher percentage of a young, highly educated population, mostly students, with a lower income than the average net household income of 4220€.

5.3.2 Choice model results

Survey data was used to estimate a mode choice model for the preferences between carsharing, scooters, and none of them, with the aim to use it later for predicting the modal shift of generated scenarios. Table 5.1 shows the estimated model results; alternative specific variables that were part of the experimental design, such as travel time, travel cost, rainy conditions, and accident risk for scooters, were significant, and only from the demographic characteristics of the population gender was the only significant variable.

Table 5.1: Mode choice model for carsharing and scooter preferences

	Scooter		Carsharing		None	
	Estimate	Rob.t.ratio	Estimate	Rob.t.ratio	Estimate	Rob.t.ratio
ASC	-0.585	-1.44	-	-	-2.52	-9.26
In–vehicle travel time (min)	-0.0297	-1.70				
Total travel time (min)			-0.0161	-1.47		
Travel cost (€)	-0.266	-2.82	-0.123	-2.33		
Rain (no-rain as reference)	-0.977	-7.68	0.159	1.68		
Scooter accident (4*higher)	-0.369	-3.57				
Female (male as reference)	-0.344	-3.55	-0.195	-1.63		
Model summary						
LL(0)	-4973.418					
LL(final)	-3438.472					
Rho-square (0)	0.3086					
Adj.Rho-square (0)	0.3064					
AIC	6898.94					
BIC	6969.54					

Only significant attributes(significance level $\geq$ 90%)are presented in **Bold**.

5.3.3 Sensitivity analysis

The developed scenarios were used to predict carsharing trip percentage by applying the parameters of the estimated mode choice models. After running the 1620 scenarios for each of the dataset trips, an analysis was performed by changing different input parameters, such as trip distance or scooter–sharing accident risk. Figure 5.2 presents the findings on the shift of carsharing trips to scooters–sharing by trip distance and scooter risk. However, as previous literature indicated that for distances above 4km, the share of e–scooters is practically zero [168], only scenarios with trip distances ranging to 4 km were taken into account, as presented in Figure 5.2.

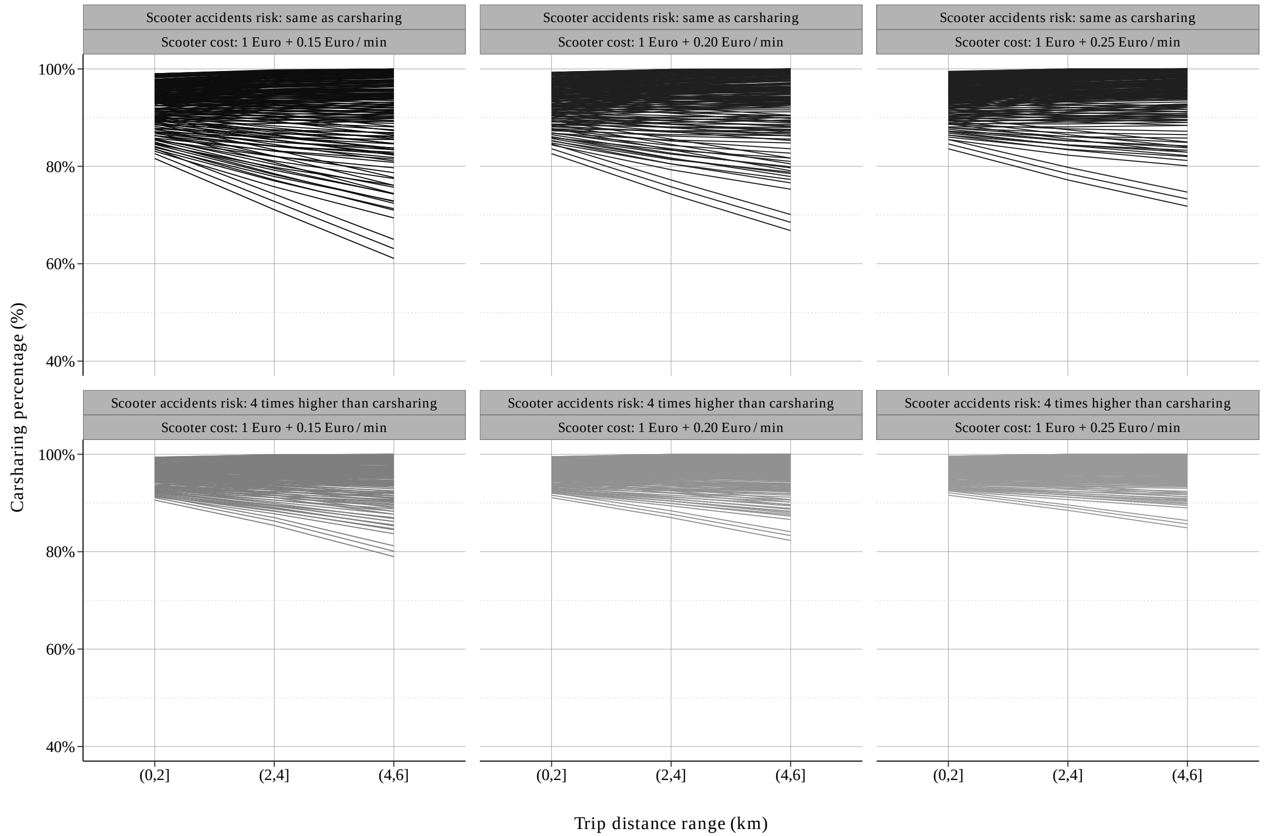


Figure 5.2: Scenarios sensitivity analysis

Sensitivity analysis of scenario prediction of carsharing penetration up to 4 km: by trip distance, scooter price, and scooter accident risk. Multiple curves per subfigure indicate different combinations of scenario parameters: car sharing speed, cost, access and egress times, and scooter speed. *Note: y-axis is truncated to 50% and not all x–axis labels are shown for readability.*

5.4 Discussion, study limitations, and conclusion

5.4.1 Discussion

The estimated choice model for carsharing and scooter preferences revealed findings consistent with prior expectations as well as the literature. The model in Table 5.1 highlighted the significance of travel time, travel cost, rain, scooter accident risk, and gender on the choice between scooter–sharing and carsharing (with different levels of significance, but mostly above 90%. Travel time and travel cost were often cited as significant factors influencing the use of both carsharing and scooter–sharing [169, 113]; for carsharing, travel times also included access and egress times into account as mentioned by [169]. Obtained values of time for scooter–sharing and carsharing (6.7 and 7.9 €/hr) are rather low (possibly due to the high student percentage and the domination of low-income classes); they indicate that carsharing users are willing to pay (1.2 €) more to reduce their travel time in one hour, than scooter-sharing users. It is important; however, to note that a comparison between these values of time is subject to limitations since, in the final model specification, the coefficient estimate for carsharing time is that of the total time (including access and egress), whereas for scooter–sharing, it refers to the in–vehicle travel time.

Rain and accident risk attributes were also highly significant and higher in magnitude for scooters compared to carsharing; again, this makes sense since scooters are more likely to be impacted by bad weather and higher accident risks. These as well are consistent with previous findings pertaining to weather conditions' impact on scooters [151, 113]; accident risks or safety, in general, was often mentioned as a reason for not using scooters [170, 113, 171]. Finally, gender impact, females being less likely to use either scooters or carsharing, was often mentioned in the literature; in this model estimate, the gender attribute has an even higher magnitude for the scooter utility. This is consistent with city reports indicating that the majority of scooter users were males [170, 113, 112].

The model application indicated that scooters have the potential to attract up to 23% of carsharing trips in the best case scenario, for a range between 0 and 4 km; this would drop to about 13% in the worst case scenario; these represent different scooter risks (equal and four times higher than carsharing, respectively). This shift in number of trips and the equivalent distance (in kilometers) inevitably poses the question of the environmental impact this might induce. From a life cycle assessment perspective, a dockless shared scooter system produces more CO_2-equivalent per passenger-kilometer than the modes they replace [66]; in other words, scooters attract users from environmentally friendly modes, such as walking and biking, generate empty vehicle kilometers traveled (redistribution and maintenance). On the other hand, benefits from scooters can be noted every time an e-scooter substitutes for a personal automobile; it thus saves a significant amount of end-use energy. One-kilowatt hour of energy could propel a scooter 100 km compared to 2 km for a passenger vehicle using the same amount of energy[1] [172]. In the case study presented, this would amount to a saving of roughly 57,850 kWh. Of course, this is based on the assumptions made and not taking into account the entire vehicle life cycle.

5.4.2 Study limitations

This study has its own limitations, such as the survey data representativeness of Munich, which led to lower-than-expected values of time and could have impacted the model prediction. Moreover, stated preference studies are subject to biases and might not help capture realistic decision scenarios. For the case study of Munich, a revealed preference study would be highly beneficial to validate and calibrate the estimated models. This could be done by using pilot data similar to what was done in other cities. It is also worth noting that the substitution shares from carsharing to shared E–scooter are only valid under the assumption that travelers can only choose between carsharing and scooter–sharing. Finally, while the study targeted young users as the ones most probably using shared mobility systems, as suggested by previous research [114], it would be interesting for future research to further enrich the findings and policy insights by collecting additional datasets and compare the obtained values of time, but also by extending the current work to take into account age differences [173]. Further approaches considering machine learning methods could also be considered for self–learning systems [174] or even to enhance discrete choice models [175].

5.4.3 Conclusions

The methodology in this paper estimated a choice model for preferences between carsharing and scooter–sharing. The estimated model was applied to the developed scenarios with different parameter inputs to predict the shift from carsharing demand to scooter–sharing. The estimated model findings, on the one hand, revealed the importance of travel time, travel cost, weather, scooter accident risk, and gender. On the other hand, calculated values of time showed a higher willingness to pay for one minute of carsharing compared to scooter–sharing. For the case study in Munich, in the best case scenario, scooter–sharing was found to potentially shift the demand from carsharing by about 23%. This implies a reduction in total kilometers traveled in motorized travel and the corresponding energy consumption and CO_2 emissions.

[1] The comparison is between a VW Golf 1.0 TSI (4.8 L Gasoline per 100 KM), and 0.47 kWh battery Bird scooter

6 Factors impacting carsharing use

The full details of this chapter can be found in the following under-review article:

Abouelela, M., Al Haddad, C., & Antoniou, C. (2023). Personality and Attitude Impacts on Carsharing Use. Under revision.
Appendix D

6.1 Introduction and research objectives

Carsharing is a form of shared mobility that provides easy access to on-demand car use without the burden of car ownership responsibilities, the need to process paperwork such as for car rental services, or even the need to return the vehicle to the pickup points as in free-floating systems or one-way trips [176]. Carsharing services and other shared mobility services are not only changing the landscape of urban mobility, but also the traditional idea of a car manufacturer producing, buying, and selling vehicles. Currently, some leading car manufacturers are promoting themselves as mobility providers, including Daimler, BMW, Volkswagen, Toyota, and General Motors [59]. Therefore, there is an essential need to understand in–depth the different aspects of these services for better operation and integration within the urban environment. Some of the main aspects of shared mobility that are important for the different stakeholders are the sociodemographic characteristics of the users and their general travel behavior to understand their role in deriving the demand and identifying user target groups [177]. While user sociodemographics were well examined and explored in the current literature [178], there is still much more to investigate in terms of other key factors related to psychological behavior and use, such as user attitudes and personality traits [60]. Also, a large number of the carsharing studies have been completed before the services were even launched or during the early operational and adoption stages, during which users might have a different use behavior as they are getting familiar with the service.
The motivation of this research is to contribute to the existing body of research with more timely case studies in which the operation of carsharing services is ongoing at the time the research is done [179]. Moreover, many aspects of carsharing services are not under the focus of the current research, such as the digital-related aspects of the service and service-related features, as well as their impact on service

adoption and use frequency [180]. The digital dimension of the carsharing services includes the mobile application friendliness and ease of use, provider's website landing page, digital marketing of the service, online marketing campaigns, and business–to–business offers [181]. Finally, the impact of the payment schemes (per minute or kilometer as recently introduced by some operators) on user choice of the different services is another crucial consideration to remember. In this research, we contribute to the current literature by answering the following research questions investigating the roles of personal attitudes on the different aspects of carsharing services.

RQ-6.1 What are the differences between carsharing users and non-users?.

RQ-6.2 Which factors impact the adoption of carsharing?

RQ-6.3 Which factors impact the shift from different modes to carsharing?

RQ-6.4 Which factors impact the choice between the different carsharing payment schemes?

RQ-6.5 Which factors impact the users' knowledge regarding carsharing services?

6.2 Data and methods

6.2.1 Data

All the research questions were answered using survey data collected in Munich, Germany. The details of the survey structure and collected sample characteristics are discussed in Section 2.2.2.

6.2.2 Methods

The first question examines the differences between the users and non-users of carsharing in terms of travel behavior and knowledge, which are categorical response questions; therefore, a Pearson's Chi-squared test [182] was performed to verify the significance of the differences between the two groups. Research questions **RQ-6.2** , **RQ-6.3** , **RQ-6.4** , and **RQ-6.5** are mainly concerned with defining the factor impacting the different aspects of carsharing use, and these aspects are discrete in their nature. Also, we aimed to examine the impacts of personal attitudes and personality traits on these aspects; therefore, we used Hybrid Choice Models (HCM), which combine the discrete choice model with the latent variable model, and it is usually used for such situations.

6.3 Analysis results

6.3.1 Sociodemographic and travel behavior

The collected sample (N = 1170) is skewed in comparison to the city population in terms of age, education, occupation, number of children in the household, and income; however, this is a direct result of the sampling strategy targeting young users, as in general, the sociodemographic characteristics of the shared mobility users. In terms of age, 89% of the sample is younger than 36 years old, compared to 40% of the city resident. Also, the users are highly educated, with 85% of the sample having at least a bachelor's degree compared to 26% of the city's residents, and the number of students in the sample is over-representative in comparison to the city, as 43% of the sample respondents are students compared to only 4.5% of the city population. Therefore, the age and occupation of the respondents are reflected in other aspects, such as income being lower than the city. However, the differences between the collected sample and the city's population are justified by the characteristics of the target group being young. As the focus target group of this research are users younger than 35 years old, we only considered them in the following analysis, excluding all the other users (N = 1044). When comparing carsharing users and non-users, the differences are significant in terms of users being males, more educated, higher income, full-time occupation, having access to a car, and owning a driving license that is valid in Germany.

We performed a chi-square test to examine the modes use frequency per gender with no significant difference found. The sample can be described as active PT users, with at least 40% of the sample using PT more than once a week, which is reflected in their ownership of PT subscription tickets. The ownership of a PT subscription ticket reflects various aspects, such as the user's loyalty to the service or the high quality of the PT system. Also, the same observation of the young population being active users of PT compared to the older population, tending to use private cars, was observed in other locations [183]. Also, a considerable percentage of users have access to private car use, reflected in their car usage. Active travel is evident in the sample, mainly in the form of walking and private bike, and not much use for the shared micromobility modes. In terms of gender differences in mode frequency, differences were significant in the case of car use as a passenger and as a driver, shared bike, and taxi. Males were using cars as drivers and using more bike sharing compared to females. In terms of mode use differences between carsharing users and non-users, the differences were more significant; from the eleven compared modes, only three modes did not have significant differences; walking, tram, and the underground metro.

6.3.2 Car sharing usage and familiarity

In this section, we explore user and non-user familiarity with carsharing services. We asked the users to rank their familiarity with the carsharing service on a four-point scale ranging from: "I do not know about them" to " Very familiar, I know almost everything about them." The majority of the users (65%) know about the service, and around one-fifth are very familiar with the service. We asked this question as we hypothesized that service use is directly linked to users' familiarity with them, and we wanted to test the familiarity impact on the different service use aspects. There is no significant difference between genders in terms of knowledge, except that males are very familiar with the service compared to females. In terms of users and non-users, it is obvious that users have a higher level of familiarity with the service compared to non-users; for example, almost 88% are familiar with the service compared to 43% of non-user.
Also, the majority of users use the service as passengers, and they use it mainly less than once per week. The major trip purposes are leisure, visits, work, and shopping. Users were asked about the modes they replaced the last carsharing trip with, and the top five modes are the underground, car as a passenger, suburban train, E-hailing, and car as a driver. These results show potential for negative impacts, as carsharing trips replace mainly PT trips which might increase the vehicle kilometer traveled (VKT) on the roads. We also asked the users to express their willingness to walk to the nearest carsharing vehicle locations, where 75% of the users specified that they would walk up to seven minutes for the pickup location.

6.3.3 Modeling results

Exploratory Factor Analysis (EFA)

In this part, we modeled the latent construct, user's attitudes, for three question groups investigating respondent evaluation of carsharing-related aspects, personality traits, and travel behavior to study the impacts of these attitudes on the different aspects of carsharing use.

Service aspects importance: we asked respondents to rate how important different aspects of carsharing services were to them on a five–point Likert [184] scale that ranges from (1 = not important at all, 2 = not important, 3 = neutral, 4 = important, 5 = very important). The top part in Table 6.1 shows the investigated aspects of carsharing service and the factor analysis results with two main factors representing the main latent constructs and explaining 46% of the total data variability. Factor one can be described as the physical offers, and the second factor as the application-related factors. The results of the EFA for the carsharing service aspects reflect the important dimensions of the service that operators need to focus on to achieve a high level of satisfaction.

Personality traits: respondents were asked to specify their agreement with different personality types on a five–point Likert scale (ranging from "Totally disagree", "Disagree," "Neutral," "Agree," "Totally agree"). Our initial hypothesis for the EFA of personality traits was that we would estimate five factors representing the five major personalities: risk-taking, loner, ambitious, organized, and lazy, similar to what was proposed by [185, 186, 187]. The middle part in Table 6.1 presents the estimated EFA results for the personality–related questions, for which two prominent personalities were extracted, interpreted as "adventurous" and "organized." The two factors explain 39% of the data variability. The results of these factors were further used to estimate the impact of these two types of personalities on carsharing use.

Travel behavior: the final set of questions analyzed using EFA focused on the frequency of use of the different available modes. For this question, we hypothesized three types of users: PT users, private mode users, and finally, shared mobility users. The bottom part in Table 6.1 presents the EFA results for the mode use frequency. Two factors were extracted and found to be significant, one for PT users and the other for shared micromobility users; the two factors explained 51% of the variance of the data, and the initial hypothesis was partially correct.

Factors impacting carsharing adoption

This model investigates the factors impacting carsharing adoption to answer the second research question **RQ-6.2** . A hybrid choice model (HCM) was estimated to investigate the examined factors. The dependent variable was coded as a binary variable considering that responses indicated that they never used carsharing were coded to zero, and the rest of the users were coded to one. The estimated model shows that people familiar with carsharing services, have a driving license, are full-time workers, own bikes, have a high-income level, and have a higher education level are more likely to adopt carsharing compared to other population groups. These significant variables are aligned with the general profile of shared mobility users, who are, in general, wealthier and more educated than the average population. On the other hand, people with access to a car, who live in a small household and have a subscription to PT tickets, are less likely to adopt carsharing service. Two significant latent variables, adventurous personality and frequent users of shared micromobility services, indicated carsharing adoption.

Factors impacting the shift to carsharing

In this model, we investigated the factors that impact the shift from different modes to carsharing as the answer to the third research question **RQ-6.3** . We clustered the modes that were replaced by carsharing into two groups; the first group is the low-capacity vehicles, including cars as a driver, cars as passengers, E-hailing, and Taxis, and the second group was bus, tram, underground, and suburban trains users. These observations were 478, representing 93% of the total number of carsharing users, 515 users. The remaining 37 observations were removed from the sample used to estimate the model. The model's dependent variable was coded as a binary variable with the value of one in the case of a low occupancy vehicle, the first group, and zero otherwise. The estimated model results show that high-income individuals, who are full-time employed, have access to a car, and are willing to walk less than five minutes to carsharing pick-up locations are more likely to shift to carsharing from low occupancy vehicular trips compared to the rest of the population, which are in line with the profile of shared mobility user. Only one latent variable was significant, frequent PT users, and it had a negative sign indicating that these users are less likely to shift from low-capacity vehicle trips to carsharing.

Factors impacting the choice between different operators

This model's main target was to model factors that impact the choice between the two payment schemes, payment per minute or per kilometer, and to answer the third research question **RQ-6.4** . Six choice options were available; indifferent answers, representing 9.3% of the total responses, were removed, and options certainly A and Probably A were aggregated to A, and the same aggregation was done for options B. Option None was kept as the third option following similar procedures to [39, 188]. Finally, the choices of the remaining scenarios were distributed as 53.1% for option A, 33.6% for option B, and 4% for Neither option. Our hypotheses here were that males and people who are adventurous and risk-takers would always opt for operator B for its possibility of cost savings. Also, we believe some users would drive faster for the less responsibility carsharing service provided than car ownership. An HCM multinomial logit model was estimated. The interpretation of the model results considers the Non-choice option as the reference level for comparison with other options. The choice experiment tested the significance of four carsharing-related attributes on the choice between the two operators; cost, access distance, rating of the app, vehicle type, vehicle engine type, electric or not. All the variables were significant except the access distance. Interestingly app rating on the app store was the variable with the highest coefficient for this group of variables. The cost coefficient for option B (pay-per-minute option) is based on the average cost shown in the experiment. The cost coefficient shows that users value the cost of paying per minute to be cheaper than per km;

we believe this is most likely since there is a chance to pay a lower price when choosing to pay per minute. Other factors show that app rating is more effective in choosing option A than option B. Finally, the coefficient of the vehicle being electric or not is generic for both options. Six user sociodemographic characteristics were significant, showing that users with high-income levels, familiarity with carsharing services, valid driving licenses, and who have used carsharing before are more likely to adopt carsharing than other population groups. On the other hand, people who live in small households and own bikes are less likely to choose carsharing compared to other groups. Finally, the two latent variables were only significant for option (B), and they indicate that shared micromobility users are more likely to choose option (B), and people who value the importance of the app are more likely to choose option B. We believe the main reason is that shared micromobility trips are paid per minute of use. Also, they are people who value the importance of the app in the service users are more likely to be used to the scheme of paying per minute, which was the original offer for all the shared vehicle services.

Factors impacting the knowledge about carsharing

This model answers the last research question **RQ-6.5** investigates factors impacting carsharing knowledge. The answer to the question investigating the knowledge about carsharing was set as the dependent variable, which is ordered in nature, and an HCM model was estimated. Four variables and two latent variables were significant and are associated with a higher likelihood regarding more knowledge about carsharing services: previous use of carsharing, ownership of a driving license, full-time workers, people who live in small households, adventurous persons, and frequent PT users. The thresholds between the different knowledge levels are significant, showing that people understand the difference between the different levels.

6.4 Discussion, study limitations, and conclusion

6.4.1 Discussion

In this research, we collected data regarding the different aspects of carsharing use, with an aim to understand the impact of personality traits, attitudes, and travel behavior on the different service aspects, such as the adoption, the shift from other modes, the choice between different payment schemes, and the knowledge about carsharing services. The research was applied to a case study in Munich, Germany, focusing on young users. The collected data shows that carsharing users are young, highly educated males with high-income levels, full-time jobs, living in small size households, and with a valid driving license, which is aligned with the general profile of shared mobility services and specifically carsharing users

[189, 117]. Obviously, the characteristics of carsharing users show the potential for inequitable use problems, wherein population groups, such as low-income and low-education groups, are not frequent carsharing users, which was evident in the collected sample, and revealed by the analysis process and the estimated models.

The collected data analysis showed that users and non-users have distinguished travel behavior with significant differences, which indicates the need for further investigation into how to adjust carsharing service operations to cater to the different travel behaviors and to attract non-users, if possible. Moreover, users reported mostly (40%) replacing PT (underground, suburban train) and small occupancy vehicles (35%) (cars as passengers or drivers, and E-hailing), showing that there is a potential that carsharing might increase the VKT, as it replaces large occupancy vehicles (PT). On the other hand, replacing car and e-hailing trips might have positive impacts such as reducing the number of vehicles, reducing energy consumption and CO_2 emissions, and requiring parking spaces [190, 191].

The EFA was conducted on the three main question groups (service aspect rating, personality traits, and travel behavior), and each of these groups showed two factors. The first question group related to the carsharing service's important aspects showed two factors: I) the app-related attributes and II) physical offers. These estimated factors show the importance of the app-related attributes, which were not examined in previous research, up to the best of our knowledge, and which need more investigation to reach the recommended design by users, as it has a role in impacting service use, as shown in the estimated models. App-related attributes were significant in the preference of paying per minute; however, physical attributes were not significant in any of the estimated models, confirming the importance of the app-related aspects of the service. The second question group is the personality trait group, which showed two distinctive personality traits, III) an adventurous personality and IV) an organized personality. Our hypothesis was that an adventurous personality would be more likely to use carsharing services compared to other types of personality due to the higher levels of mobility and independence provided by carsharing, which fits the characteristics of the adventurous personality [187].

The estimated models showed that sociodemographics attributes, knowledge about carsharing, and personal attitudes and personality traits play significant roles in carsharing use. The first estimated model, answering the second research question, showed that the attributes that increase the probability of carsharing service adoption are: high familiarity with carsharing service, having a valid driving license, full-time employment, a high education level, high-income level, owning a bike, having an adventurous personality, and being a frequent micromobility user. The results of this model are in line with the general profile of shared mobility users [192, 193]. It is to be noted that the variable with the highest estimated coefficient is familiarity with carsharing services, followed by the availability of a driving license and the (high) level of education. It is clear that knowledge about the service is very important in impacting its adoption, which highlights the role of marketing in service use.

Again, sociodemographic characteristics and attitudes play a significant factor in the shift from different modes to carsharing, where high-income people who are full-time employed, willing to walk for a short period (less than 5 minutes) and have access to a car have a higher likelihood to shift from low occupancy vehicles to carsharing, while PT frequent users are less likely to do so. This model also shows the significance of sociodemographics and travel behavior in replacing different modes with carsharing services. It also aligns with the profile of shared mobility users.

The fourth research question was answered by estimating the model to examine the factors deciding the use of the different payment schemes, which showed that trip cost, rating on the app store, and availability of electric vehicles are significant factors in choosing between the different operators. App rating was the coefficient with the highest reported value, showing its importance in the choice between different payment schemes. Also, people perceive the payment per minute as cheaper than the payment per km, which is an interesting result showing the preference of users for the payment scheme per minute (the oldest, more common scheme for carsharing payment) over the payment per km with all the other factors being constant. Also, sociodemographics are crucial in choosing between operators, such as high income, driving license, familiarity, and previous use of carsharing services.

The answer to the final research question regarding the knowledge about carsharing services emphasized again the importance of sociodemographics and attitudes on the level of knowledge; in particular, previous use of carsharing, availability of a driving license, living in small size households, and full-time employees were more likely to have a higher level of knowledge regarding carsharing service. Service adoption and knowledge about the service were found to be significant in increasing the probability of each other, showing the need to advertise the service to attract more users and to focus on the different social groups that do not have enough knowledge regarding the service and subsequently who do not adopt it.

6.4.2 Study limitations

This research tries to update the current knowledge regarding carsharing using a stated preference experiment, but it faced some limitations that would not impact the overall research integrity. The main objectives of appraising the limitations are to have a transparent outcome and for similar studies to avoid or consider them in the future. The collected sample is balanced regarding users vs. non-users of carsharing and gender but biased for other sociodemographic characteristics such as income level and education level; however, shared mobility users are likely to be young and highly educated compared to the average population. Moreover, the sample is not representing the city's population, so the findings should not be directly interpolated or carried out on other social groups. Different attitudes were examined, and their impacts on the various aspects of carsharing use were examined; However, attitude and personality traits are hard to quantify and measure, they are essential to understand user preference for the different aspects of shared mobility use, and they might be more significant and influential in deciding travel behavior in general and shared mobility use. The used stated preference experience examined a few numbers of attitudes, travel cost, app rating, electrification of the vehicle, and access distance to the nearest vehicle; other attributes could have been used. However, this was done purposefully not to distract the respondent's attention and to have a more straightforward experience. The SP experiment assumed that the payment by KM is a fixed cost. However, this can slightly change in reality, as in case of congestion, users could alternate from the original route, the shortest path, causing extra travel distance that would increase the trip cost. However, the variation of the travel cost ($\pm 25\%$) around the average trip value would cover this possibility. The survey was deployed online, which can create a responding bias, as groups with no access to the Internet and older populations might not be represented in the sample. However, as shown in previous studies, shared mobility users generally are young, highly educated individuals with access to the Internet. The hybrid choice or ICLV models are not the only way to implement attitudes into discrete models. However, we believe that in this research, they fit the required methodology to answer the main research questions.

6.4.3 Conclusion

This research investigated the impacts of personality traits and attitudes on the different aspects of carsharing use; adoption, the shift from other modes, the choice between different operators, and finally, the knowledge about the carsharing services. A large sample ($N = 1044$) of the young user's data was used in the analysis collected from Munich, Germany. The results continue highlighting the importance of the user's sociodemographic characteristics in impacting service use and raising questions regarding inequitable service use and adoption. The findings of the estimated econometric models also show the significance of personality traits, travel behavior, and digital service aspects such as app ease of use and rating on the app store on using carsharing. These findings also stress the importance of designing user-friendly apps and maintaining good ratings, which attract more users. Also, results show that frequent shared mobility users adopt shared mobility in different service forms, showing the potential of MaaS in increasing shared mobility use and the possibility of multimodality. Finally, the estimated model could be used as a part of broader travel demand models that estimate the adoption of carsharing. It might also quantify the operators' share based on their payment methods.

Table 6.1: Factor analysis models

I–Service aspects rating	Physical offers	Application
App ease of use		0.92
App rating		0.60
Availability in airport	0.71	
Availability of different size vehicles	0.62	
Service offers bundles	0.56	
Availability in other cities	0.53	
Availability of EV	0.51	
Model diagnostics		
Factor loadings	1.82	1.38
Proportion variance	0.26	0.20
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.80		
Cronbach's alpha = 0.73		
II–Personality traits	Adventurous	Organized
Adventurous	0.82	
Being outdoor	0.51	
Spontaneous	0.61	
Risk taker	0.58	
Variety seeking	0.50	
Efficient		0.70
Punctual		0.46
Model diagnostics		
Factor loadings	1.93	0.76
Proportion variance	0.28	0.11
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.75		
Cronbach's alpha = 0.6		
III–Travel behavior	PT	Shared micromobility
Bikesharing		0.75
Shared E-scooter		0.70
Tram	0.68	
Underground	0.85	
Suburban Train	0.73	
Bus	0.69	
Model diagnostics		
Factor loadings	2.43	1.10
Proportion variance	0.35	0.16
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.78		
Cronbach's alpha = 0.72		

7 Synergies between public transport and shared mobility services

The full details of this chapter can be found in the following article:

Abouelela, M., Al Haddad, C., & Antoniou, C. (2021). Are e-Scooters Parked Near Bus Stops? Findings from Louisville, Kentucky. Findings.
Appendix E

7.1 Introduction and research objectives

Scooters could arguably replace motorized trips [40], or at least reduce their negative impacts, especially if they are well integrated with existing public transportation. This integration can solve the first–last–mile dilemma [194], increasing accessibility to public transportation [195], but also leading to more sustainable transportation models [196]. One of the most important but not yet studied aspects of scooter integration with public transportation is the distance between the stops and the scooters, as walking distance willingness could be a significant factor affecting or determining the use of different transportation services. In this study, we assessed the distances between bus stops and parked scooters temporally and spatially. The temporal analysis considered different hours and days of the week, while the spatial analysis looked at different land uses, distances from the city center, and accessibility to public transportation (bus). This assessment aimed to answer the following research questions:

RQ-7.1 What is the average distance between scooter trip starting points (origins) and the nearest public transportation stops, in this case, bus stops?

RQ-7.2 How do different temporal and spatial factors influence the distance between parked scooters and the nearest bus stops?

7.2 Data and methods

7.2.1 Data

Scooter trip data from Louisville, KY [103], and general transit feed specification (GTFS) files from (transitfeeds.com) were used in the analysis; the details of the data collection and processing are explained in detail under Section 2.2.1

7.2.2 Methods

To answer the first research question, we used the Approximate Nearest Neighbor (ANN) searching algorithm library [197] available in the statistical software package R [198] in order to calculate the Euclidean distance between trips' starting points and the nearest bus stops. To answer the second research question, the distance was calculated and aggregated for different temporal features, meaning different hours of the day and different days of the week. For assessing the impact of spatial features, three metrics were considered: land use (considering the land use of the trip starting point), distance from the city center, and LITA (for the different census zones).

7.3 Analysis results

7.3.1 Parking distance

Table 7.1 shows the summary results for the scooter parking distance per the different variables; time of the day, day of the week, land use, LITA ranges, and finally, the different distances from the downtown. It is to be noted that the parking distance did not have any distinguished pattern when disaggregated per the different categories of the different variables, except in one case, or one-time interval, between 2 and 3 a.m., where parking distances were statistically different from the rest of the day and tend to be longer, meaning that scooters tend to be further from bus stops.

7.4 Discussion, study limitations, and conclusion

7.4.1 Discussion

The obtained mean parking distance was ($\mu = 115$, with a standard deviation $\sigma = 134m$), which answers the first research question. Findings show that for 50% of the trips, scooters were parked within 70 meters from the nearest bus station, and for 85% of the trips, the parking distance was less than 200 meters. The hourly distribution of the distances for the different days (Figure 7.1) shows that the parking distance has a similar pattern throughout the day, except between 2 and 3 a.m. Parking distances between 2 and 3 a.m. are statistically different from the rest of the day and tend to be longer, meaning that scooters tend to be further from bus stops. One possible reason could be the small share of trips originating between 2 and 3 a.m. (about 0.6 % of the total daily trips). To investigate whether this was due to rebalancing and redistribution, distances were calculated between trip starting and ending points and the nearest bus stops, and their distribution was compared. Yet, as no statistical difference was found between both, there was no evidence of the rebalancing and redistribution effect. Longer distances might indicate that people use scooters from bus stops to travel further distances during early day hours (between 2 and a.m.), which have no bus temporal coverage; in Louisville, the service hours for the buses are between 5:30 am and 10:30[1]. Also, early morning distances tend to be longer during the weekend compared to weekdays, which could be attributed to an increase in recreational activity during weekends.

Analyzing the distances according to varying land uses did not reveal any significant differences; however, the trip percentages showed that half of the trips started in commercial and public, and semi-public land uses; this might indicate that scooters were used for recreational trips (although there is no evidence for this), as was observed in Washington, D.C. [107]. The distance to the nearest station per each category of LITA values showed no significant differences or relation between the distances and the zonal bus accessibility. However, 40% of the scooters were parked in highly bus–accessible areas, which could indicate that scooters complement the use of buses or extend bus accessibility. Also, the distance between scooters and the nearest bus stop was not affected by the scooter's locations away from the city center.

7.4.2 Study limitations

It is to be noted that the trips' geo-locations (latitude and longitude) were rounded to the nearest three decimal numbers for privacy reasons, which on average, could affect the scooter location by 30 meters. While this approximation could have affected the distance calculations, the methodology used in this research could be generalized for other datasets with more accurate coordinates.

7.4.3 Conclusion

The findings of this research indicated that scooters could be used to extend the temporal accessibility of the bus service. On the contrary, there was insufficient evidence that distance is impacted by any tested spatial features, including LITA and land use. The methodology presented in this paper could be replicated in other cities in order to understand scooter parking patterns better, and the results

[1] https://moovitapp.com/index/en/public_transit-lines-Louisville_KY-1442-11408, accessed 1/7/2021

obtained in Louisville would be comparable in other cities in the US and the rest of the world. The methodology could be used to give insight to service providers on how to integrate scooters with existing public transportation systems better.

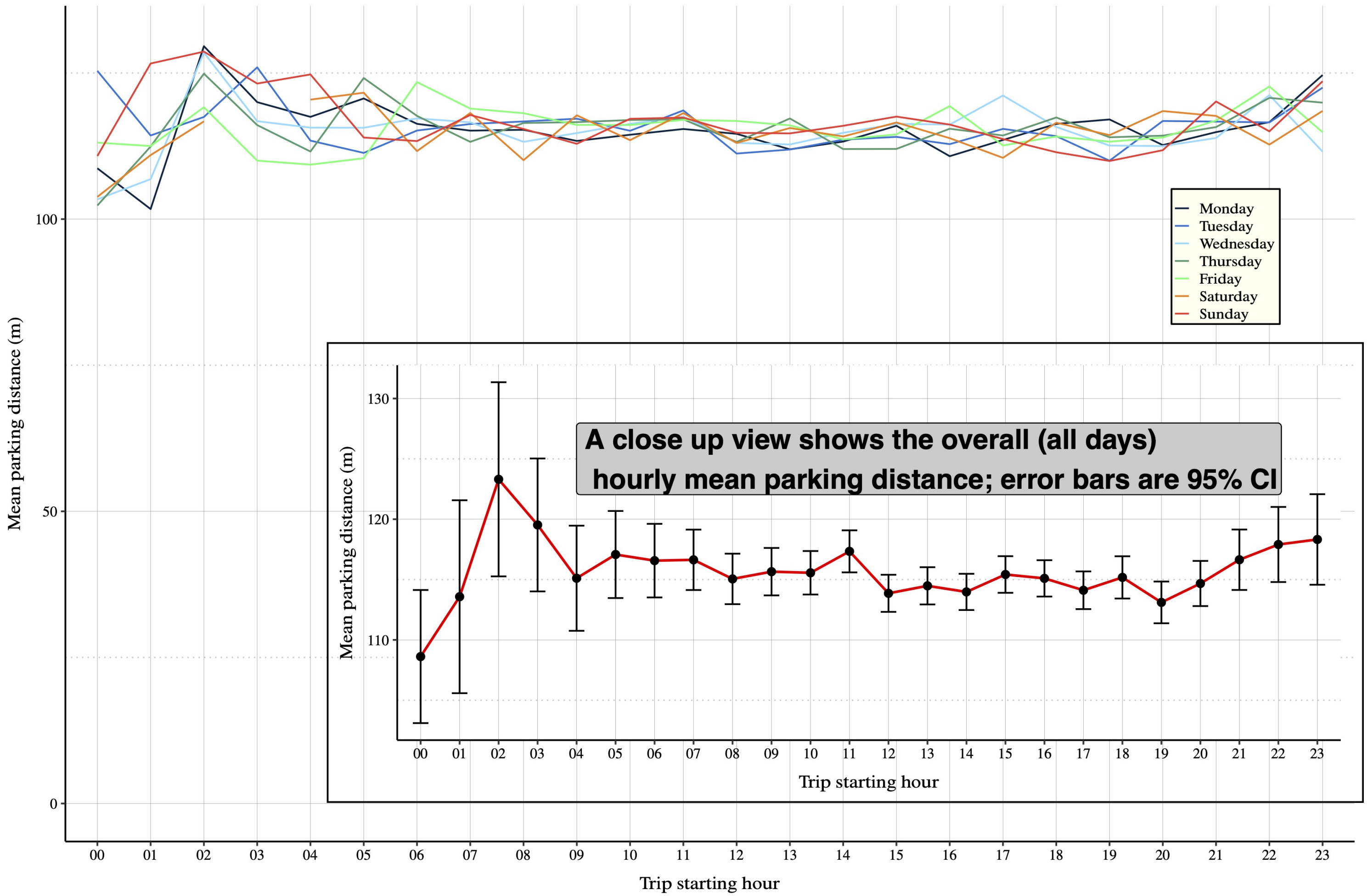


Figure 7.1: Average hourly distance distribution; error bars in the zoomed view show the hourly standard deviation

Table 7.1: Parking distance to the nearest bus station summary per different temporal and spatial categories in meter

Variables	Min	$1^{st}Q$	mean	Median	$3^{rd}Q$	Max	Std	Trips (N)	Pct (%)
All trips	1	42	115	70	132	2948	134	379,308	100%
Time of the day									
Morning (00:00-06:00)	1	71	116	71	136	1622	135	23,548	6.2%
Before noon (07:00-12:00)	1	70	116	70	133	1731	134	119,665	31.6%
After noon (13:00-18:00)	1	70	115	70	132	2948	133	171,137	45.1%
Night (19:00-23:00)	1	70	115	70	133	2004	133	64,958	17.1%
Day									
Weekdays	1	70	115	70	132	2483	133	256,382	67.6%
Weekend	1	70	115	70	132	2948	134	122,926	32.4%
Land–use									
Right-of-way	1	70	115	70	132	2192	133	112,501	29.7%
Commercial	1	70	115	70	132	1733	133	91,257	24.1%
Public and semi-public	1	71	116	71	135	2004	133	89,925	23.7%
Residential	1	70	115	70	132	2948	136	52,314	13.8%
Industrial	1	70	114	70	132	1323	132	19,586	5.16%
Parks and open space	1	71	117	71	136	1924	138	11,018	2.9%
Vacant	1	71	115	71	136	1013	130	2,707	0.71%
LITA									
4-5	1	72	117	72	135	1193	134	9,256	2.4%
5-6	1	70	115	70	133	2948	134	149,826	39.5%
6-7	1	70	114	70	132	1223	133	27,280	7.2%
7-8	1	70	113	70	132	1731	131	35,006	9.2%
10-11	1	70	115	70	132	2192	134	157,933	41.6%
Distance from downtown (km)									
Less than 0.5km	1	70	115	70	132	2192	133	85,119	22.4%
0.5km - 1.0km	1	70	116	70	132	1731	135	58,130	15.3%
1.0km - 1.5km	1	70	114	70	132	1290	132	39,476	10.4%
1.5km - 2.0km	1	70	114	70	132	1731	131	18,808	5.0%
2.0km - 2.5km	1	70	115	70	132	1223	133	13,304	3.5%
2.5km - 3.0km	1	70	114	70	131	1193	134	12,048	3.2%
3.0km - 3.5km	1	70	115	70	132	2004	134	23,053	6.0%
3.5km - 4.0km	1	70	116	70	135	2483	136	51,009	13.4%
More than 4.0km	1	70	115	70	132	2948	133	78,361	20.7%

Land–use description, retrieved from American Planning Association (planning.org)

Commercial	Retail and whole sales, business offices
Public and semi-public	Public and private schools, municipal buildings, public property rather than parks, hospital, churches, and golf courses
Residential	Residential uses
Industrial	Light and heavy industrial uses
Parks and open spaces	All public parks, playgrounds, swimming pools, athletic fields
Vacant	Includes undeveloped land

8 Equity-based evaluation for shared mobility

The full details of this chapter can be found in the following under-revision article:

> **Abouelela, M.**, Durán-Rodas, D., & Antoniou, C. (2023). Do we all need scooters? An accessibility–centered spatial equity evaluation approach. Transportation Research Part A: Policy and Practice, 181, 103985.
> **Appendix** F

8.1 Introduction and research objectives

Urban transportation has undergone significant changes in the past decade, thanks to advancements in technology, the emergence of eco-friendly options, and the introduction of shared mobility services (SMS) [199]. Shared mobility can be succinctly described as a pay-per-use system, where users are charged based on the time or distance they utilize them.[157]. These services are commonly provided through digital platforms and mobile phone applications and are usually paid using digital banking services [200]. Several reasons have encouraged the use of SMS; in principle, SMS are more sustainable transportation options compared to the private passenger car, as they have the potential to reduce the vehicle idle time, reduce energy consumption, have a milder impact on the environment, travel cost saving, and utilize more compact urban space [22, 23, 201, 202].
One main challenge of SMS is their equitable use, which might not always be achieved and can lead to social exclusion for specific user groups [70]. The inequitable use of SMS is widely expected from its unique setup as users, in general, should have digital skills, a smartphone, and digital banking access; otherwise, they will be excluded from using the service by default [71]. Also, SMS might not be affordable to all population groups, and the spatial coverage of SMS might be limited to areas with high demand, primarily near the downtown, and ignoring areas located in the city's suburbs [72]. While there are efforts in the literature to identify factors behind the inequitable use of SMS, these efforts, especially in the cases of micromobility and specifically scooters, have focused on the user's profile, socioeconomic and demographic characteristics, or availability and proximity of vehicles to the users as the main reasons causing the inequitable use [203, 204].

We believe that the issue of inequitable use is not limited to the user's characteristics or the availability of the vehicles but is extended to the urban forms in terms of land use, neighborhood design, and the availability of opportunities, points of interest (POIs), within an acceptable travel distance and travel cost [205, 206]. Therefore, we hypothesize that the observed inequitable use of scooters in terms of trip density might have resulted from the fact that the scooters' introduction did not add significantly to the population's accessibility to different opportunities (POIs), especially for the transportation–disadvantaged population groups. This research contribution comes from verifying the below hypothesis:

> ***The introduction of shared E-scooters does not increase or poorly increases the accessibility to different opportunities compared to the available modes of transportation, especially for the disadvantaged population groups.***

Which can be rephrased as a research question stating:

RQ-8.1 Does Shared E-scooter increase population accessibility to opportunities?

The proposed methodological framework to assess the equitable use of SMS, specifically shared E-scooters, referred to hereafter as scooters, to the best of our knowledge, has not been used or evaluated so far.

8.2 Data and methods

8.2.1 Data

The proposed methodology was based on open-source data to grant transparency for the different stakeholders and its reproducibility for further use. The research hypothesis and methodology depended on assessing the added accessibility to the population after the introduction of scooters, with a close focus on the disadvantaged population groups' gains in comparison to the rest of the population; therefore, we used five primary sources of data: Sociodemographic data from the American Census Bureau (`census.gov`), scooter trip Data from Louisville city open data portal (`data.louisvilleky.gov`), POIs data from Open Street Maps (OSM, `openstreetmap.org`), road and local street network (OSM), and finally General Transit feed specifications, GTFS from (`transitfeeds.com`), which were used to calculate the accessibility from the different available modes of transportation to the different opportunities using an online routing engine (`conveyal.com`), for more details regarding the collected data refer to Section 2.2.1.

8.2.2 Methods

Sociodemographic spatial analysis

The main target of this step was to understand the spatial distribution of the different sociodemographics, especially the variables that are most likely to be attributed to the transport-disadvantaged population in reference to the city structure and in reference to each other. Seven variables were considered in this analysis: low-income, households with zero cars, population older than 45 years old, less than a university degree, non-white population, unemployed, and PT-dependent users. Also, we wanted to examine the impacts of the historical segregation policies and land use policies on the city's population distribution. The first measure applied to examine the spatial distribution patterns of the sociodemographic characteristics in the scooter distribution zones is the Local Moran I index or Local Indicator of Spatial Association (LISA) [207].
The next step in the analysis of the sociodemographic characteristics analysis was to define clusters of the disadvantaged population groups. Disadvantaged groups or poor communities are generally defined by their income level. National guidelines define the household's income thresholds; households below them are considered poor. This step used two criteria: i) household income level, which is a common practice to define the poor population, and ii) car ownership per household, as the main focus of this study was related to travel behavior and one of the most decisive factors of mode choice and daily travel behavior is car ownership [208]. These criteria were calculated as a percentage of the number of households per census block. The US census bureau defines low-income communities as the community (census block group) with 30% or more of its population with household income less than 30,000$ per year; according to the US national equity atlas (`nationalequityatlas.org`), on average, only 9% of the US households do not have access to cars. Therefore, census blocks were clustered into four quarters using a two-dimensional coordinate system. The horizontal axis represents the percentage of households with income less than 30,000$ per annum per census block, and the vertical axis is the percentage of households with zero-car per census block. This technique was used to identify the communities with a high probability of being transport-disadvantaged and those with a high probability of forced car ownership [209]. These two population groups should be the prime target for the policy intervention, and they should be served by SMS in general and scooters, as in our case study.

Trips and POI hotspots

The next step was to identify scooter trip patterns spatially and temporally, then the trips and POI significant hot spot using Getis-Ord (G_i^*) [147]. The analysis was based on the number of trips and the number of POI concentration spatial zones. G_i^* statistical significance is evaluated using Z-score. Only spots with Z-scores equal to or more than 90% were kept; we used this analysis step to identify the trip's hot spots in reference to the distribution zones and to inspect the relation between the trips and the different POI hots-pots. This step targeted quantifying the relationship between trips and POI to understand the impact of POI on trip generation.

Accessibility and PMI calculation

The primary step in this proposed methodology was to compute the accessibility to the different opportunities using the different available modes of transportation: walking, private bikes, PT, and Transport Network Companies TNC (E-hailing), then compare it to the accessibility to the same opportunities using scooters. Accessibility was measured to all the available opportunities combined as people have different preference and subsequently different potential to interact with the different opportunities; measuring accessibility to different opportunities address the multi-dimension nature of accessibility. Also, it is hard to define which activities are more critical and relevant for the different population groups [210]. A two-dimensions coordinate system represents the accessibility of the census blocks to the different number of opportunities, and the other axis is the Potential Mobility Index (PMI) was used to identify the census blocks with critical, below-average accessibility and PMI compared to the rest of scooters' operation area, refer to Figure 8.2.

Sensitivity analysis

There was uncertainty regarding the exact relationship of the modes substituted by scooter; therefore, in order to cover the range of all possible trips substituted by scooter, a sensitivity analysis was considered to cover all the possible combinations of trip duration and trip speeds for the different modes, to ensure that all the possible shifted trips from walking, biking, PT, car, and TNC trips to scooter are captured in this analysis. Table 8.1 shows the assumptions were used to build the different scenarios and calculate the accessibility of the different modes, and perform the sensitivity analysis:

After calculating the accessibility and PMI for all census blocks in the study area using the different modes, 974 main scenarios were obtained. Four accessibility thresholds, similar to [211, chapter 8] and [212, chapter 3] were calculated for each scenario: the average accessibility of all blocks, 10%, 30%, and 50% of the average accessibility, were defined for each of the 974 scenarios, Figure 8.2. The reason to test the impact of scooters on several accessibility thresholds is that there is no definition for the sufficiency level of accessibility, or a person might have low accessibility to the rest of the community and might still be satisfied with this level. For each scenario, the impact of the scooter replacing the current mode on

Table 8.1: Scenarios summary

Mode	Speed (Km/hr)	Trip Duration (minutes)	
		Min	Max
Walking	4.4, 4.82	5	15
PT	Based on GTFS	5	30
Private Bike	12,14,16	5	15
Car	Based on traffic conditions	5	15
TNC*	Based on traffic conditions	5	15
Scooter	6,9,12	5	15

* 5 and 10 minutes waiting times were considered for TNC

the level of accessibility and the accessibility threshold is evaluated. Each of these scenarios was evaluated as follows:

- The census block accessibility using the original mode (walk, PT, bike, TNC, car) is evaluated, and if it is under one of the four thresholds, it is identified as problematic.
- For the problematic situations, the scooter accessibility for the same scenario and the same threshold is evaluated, and if it increases the accessibility of the block to cross over the problematic threshold, it is considering enhancing the accessibility, or it has a positive impact.
- If the evaluated scenario scooter accessibility and the original mode accessibility are both below or over a threshold, it is considered to have no impact.
- Finally, if the accessibility of the scooter is lower than a specific threshold and the original mode accessibility is over the same threshold, the scooter is considered as decreasing the accessibility of the block

Case study setup

The data used in this study was obtained from Louisville, KY, a mid-size city on the Ohio River with a population of approximately six hundred thousand. The city has a long historical problem with racial discrimination and population segregation based on the residents' race [213]. Shared E-scooter was introduced to the city in August 2018 and is still operating; operators follow the city's guidelines for managing and controlling the service within the nine operation zones defined by the municipality, Figure 8.1. We focus hereafter on the regulation related to equity. Operators should deploy a percentage of their fleet in the zones east of the city (1,8, and 9) depending on the operator's fleet size. These zones are identified by the authorities as poor communities areas.

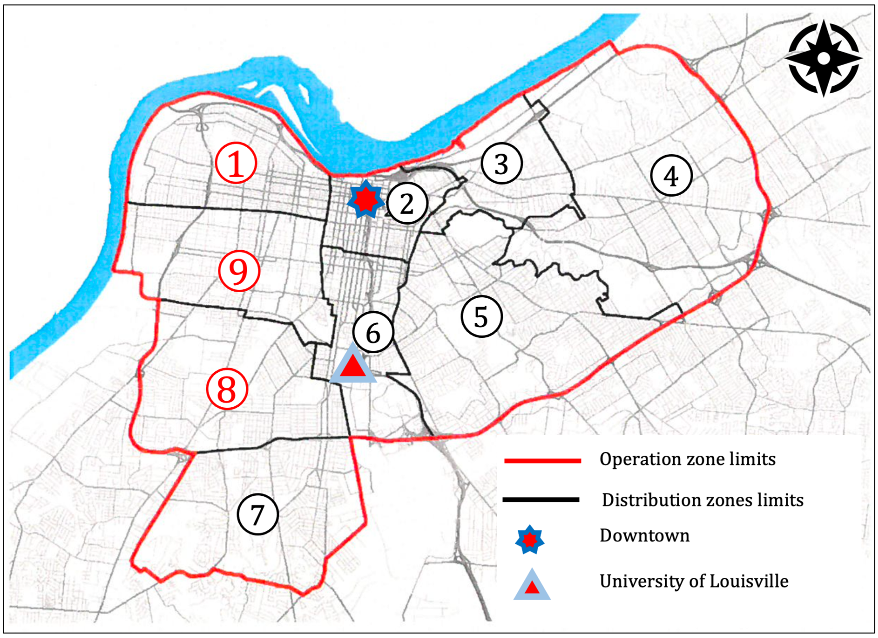


Figure 8.1: Study area

8.3 Analysis results

8.3.1 Sociodemographic spatial distribution

Scooter's distribution zones consist of 252 census blocks that we used for the sociodemographic analysis. We checked the spatial distribution patterns for the population's sociodemographic characteristics that are more likely to impact the inequitable use of scooters. Seven variables were considered in this analysis: low-income (households with income less than $30,000 per year), households with zero cars, population older than 45 years old, less than a university degree, non-white population, unemployed, and PT-dependent users. All the examined variables were significantly clustered except for the old population variable, which showed a random pattern. The spatial analysis results show a clear segregation between the wealthy population and the low-income population group; however, this has been evident historically from the city planning discriminatory practices[1].

A two-dimension coordinate system was used to define disadvantaged groups and to cluster them in a more straightforward way that helps to communicate the results easier. Hereafter we will refer to them as quarters. The population was split into four main quarters, where quarter (Q3), 120 census block (47.6%), represents the severely disadvantaged blocks with low-income and zero car ownership, and (Q4), 24 census bloc (9.5%), represents the forced car ownership group, or low-

[1] storymaps.arcgis.com/stories/8cd986b3c5ab4f1c8bedba85f195662f, accessed on 01/06/2023

income population with a burden to own a car, mainly for the absence of adequate transportation options.

8.3.2 Trips and POI

Trips significant hot-spots analysis, considering spots at least 90% significant level, shows distinctive patterns for weekend and weekday trips. Trips spatial patterns can be described as trips concentrated in three prominent locations, the downtown area (zone 2), the north of the distribution zones, the southeast of the downtown (zone 5), or the Baxter Avenue area, where there is a high concentration of leisure activities (restaurants, and bars). The third trip concentration area is in the city's south (zone 6), around the University of Louisville. These patterns stand when comparing weekday trips with weekend trips, but with different magnitudes, where the leisure area (zone 5) and downtown have more weekend trips than weekdays. Also, the university area (zone 6) has more demand during weekdays compared to weekends.
POIs are concentrated in four locations, the downtown area (zone 2), where there is a diversity of activities; the University of Louisville area (zone 6), Baxter Avenue (zone 5), and Frankfort Avenue (zone 3); both Baxter avenue and Frankfort avenue are areas with a high concentration of leisure activities. Other smaller hot-spots areas are found in zones 8 and 4. It is clear that there is a correlation between the trips hot spots and the POI hot spots, which strongly indicates the importance of POI existence on demand generation. We calculated the coefficient of correlation between the number of trips in each significant hot spot and the number of POI within the same hot spot; Pearson's correlation coefficient was around 0.55 with a 99% significant level, indicating the correlation between the number of POIs and the generated trips.

8.3.3 Accessibility sensitivity analysis

The last part of the analysis is the central part of the research, where the impact of scooter introduction on the accessibility gains for the different population census blocks compared to the existing modes of transportation was examined. Figure 8.2 shows one example of the evaluated scenarios. Each scenario was evaluated on four accessibility thresholds; the average accessibility of the mode and the subsequent 10%, 30%, and 50% of the average accessibility of the original census block accessibility as compared to the scooter accessibility on the different thresholds. A total number of (972 scenarios x 4 thresholds x 252 census block = 981,792) scenarios were analyzed comparing the difference in accessibility between the different modes and scooters; from these scenarios, only 9% indicated enhancement of the accessibility of the blocks when replacing one of (walking, PT, bike, car, and TNC) trips with scooter trip, and in 22% of the scenarios, scooters had less accessibility to the different opportunities than the existing modes. For the rest, there was no impact, or the scooter did not change the level of the accessibility of the block compared to other modes; in other words, if the scooter and the other mode were below the threshold or both of the modes were over the evaluated threshold, we consider it as a no-impact case.

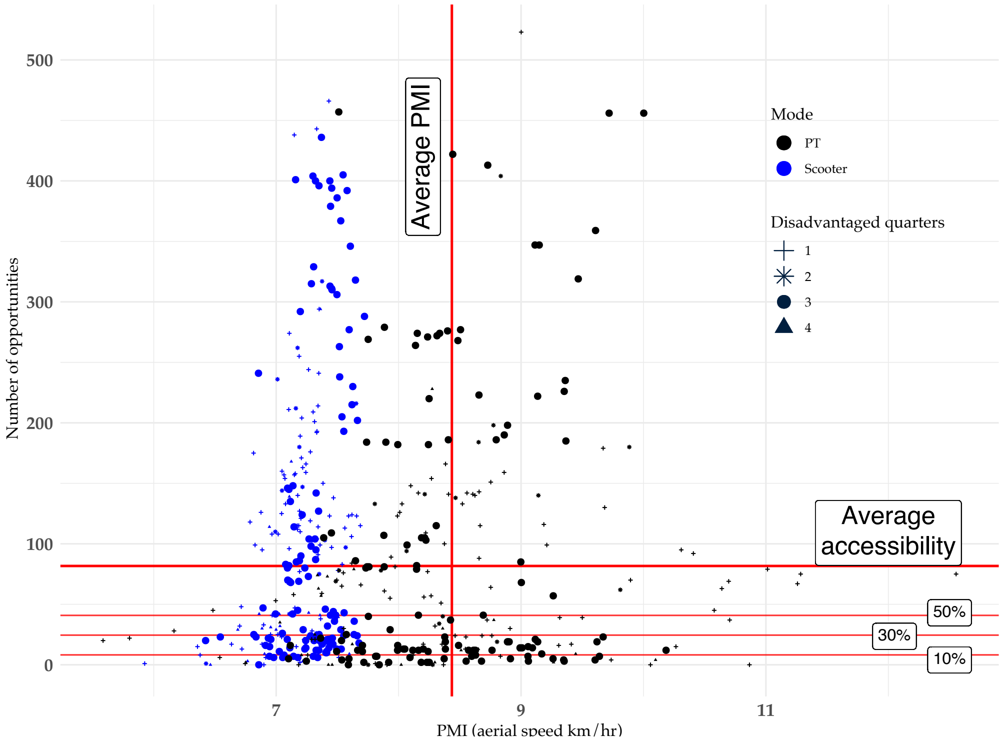


Figure 8.2: Example of accessibility and PMI comparison between PT and scooters

8.4 Discussion, study limitations, and conclusion

8.4.1 Discussion

In this research, we analyzed the changes in accessibility that might occur when shared E–scooter replaces existing modes of transportation, walking, biking, PT, private cars, and TNC, focusing on the impact of scooters on the transport-disadvantaged population groups. In the first step of the analysis, we tried to understand the population distribution in the city by examining the spatial distribution of the disadvantaged groups. This analysis showed a significant pattern that can be described as disadvantaged groups residing in the areas west of the city and the other wealthy population concentrated in the east. The concentration areas of disadvantaged groups west of the city exhibit low to no opportunities. Therefore, regardless of the scooter use, these areas, in general, are relatively excluding the disadvantaged population from participating in activities compared to

the rest of the population, which is mainly a problem of the urban forms in terms of diversity of land use and proximity to opportunities.
We analyzed 972 scenarios, and from them, only 9% had shown enhanced accessibility; when disaggregated by mode, their majority, 53%, materialized when the scooter replaced walking, followed by PT by 26%, and bike by 16%. These analysis results are supported by a similar percentage of the modes displaced by scooters that were stated by users in several surveys [214]; this gives rise to various concerns related to public health and environmental impacts. When disaggregating the scenarios by population per each of the replaced modes, on average, 18% of the population enhanced their current level of accessibility; this 18%, when filtered by age, physical ability, financial ability, and knowledge to use the service, might drop to less than 1% of the overall population showing the small portion of the population that can benefit from the introduction of scooters. Also, we disaggregated the evaluated scenarios by population quarter, and there was no significant difference between the four quarters. There is no doubt that the introduction of scooters would increase accessibility as the number of available modes of transportation will increase; however, this increase in accessibility occurs under specific conditions and for specific scenarios. The analysis purposefully ignored structural barriers to using scooters, such as affordability and the ability to use the service. This was done to support our hypothesis that the problem of equitable use is inherited from the urban forms in terms of the building environment. Even if the cost is not the primary barrier to using the service, scooter use is limited in enhancing accessibility under strict conditions.
Open-source datasets were used to encourage their use for a transparent decision process, especially for transport and city planning policies, which generally have political involvements that the public might need help understanding. We checked the problem of inequitable use of scooters. However, the city has current policies that were issued for the service providers, and the results indicated that the current policies did not allow the service intended equitable use. The policies used in Louisville are similar to most of the programs in the USA, showing that there should be a more profound understanding of the city's urban structure before generalizing the operation policies for SMS, specifically scooters. The performed analysis opens the door for investigating the need for SMS before its deployment, and it raises the question of would extending PT service might be more beneficial for the disadvantaged population groups rather than the new SMS.

8.4.2 Study limitations

This study examined the replacement of scooters for other modes without considering multimodality or using scooters as a first and last-mile solution, which could be the case in some situations. Also, the temporal accessibility to the different services (working hours) was considered fixed, or all the opportunities would be available all the time; moreover, people's ability was considered the same for the whole census block, which is not the case in reality. The used accessibility measure, the cumulative number of opportunities, is a simple measure, and it is clear that there are other more sophisticated methods to measure accessibility. However, simple measures are easy to communicate to other stakeholders, and they perform similar to other sophisticated gravity based models [215]

8.4.3 Conclusion

The proposed methodology and the subsequent analysis focused on the chances of equitable accessibility of all members of the society to the different activities, which are more likely to be missed in transport planning processes [211]. The analysis was based on the enhancement of accessibility level, which is the core of transport planning; however, we did not find any significant gains that might lead to sustainable results, but scooters needed to replace sustainable modes to have a positive impact on accessibility, and definitely, such behavior would not reduce CO_2 emissions, especially for the disadvantaged population groups. Even so, scooter introduction might lead to a lower life quality for disadvantaged groups. We attribute the no-gains of scooter accessibility to the urban forms, represented by the less diverse land uses in poor areas and the limited opportunities. We are not opposing the deployment of the scooters in this research, but we are highlighting the need to consider their direct and indirect impacts before the deployment process.

9 Discussion, future research, limitations, and conclusion

Shared mobility services (SMS) represent an effective solution to several urban transportation problems, such as reducing motorized traffic externalities, reducing travel costs, and increasing the utilization of urban space. These services are gaining popularity as reflected by their abrupt increase in demand and their expansion and availability almost worldwide. However, the sudden introduction of SMS without adequate planning and experience in service deployment and operation created several challenges that, if not treated, might nullify the positive potential of SMS or even make them a burden on the urban environment.

In this dissertation, several aspects of SMS were explored, mainly focusing on understanding the relationship and interactions between SMS and other elements of the urban environment: i) meteorological conditions, ii) built environment characteristics, iii) population's sociodemographic attributes, iv) available modes of transportation , v) SMS characteristics and interaction within the SMS. This dissertation's findings increase the current knowledge regarding free-floating SMS and, subsequently, the optimum way to deploy them efficiently, maximizing the benefits of the different stakeholders involved in the process. This research focused on free-floating SMS, shared E-scooters, and carsharing. However, the findings could also be extended (after testing) to free-floating bike-sharing systems, which showed similar travel behavior to shared E–scooters [162, 107].

This chapter will discuss the findings, the proposed framework, recommendations for future research, limitations, and the conclusion of the different studies performed.

9.1 Discussion

9.1.1 Main findings

Demand patterns

Exploring spatiotemporal demand patterns of free-floating carsharing and shared E-scooters (scooters) highlighted similarities between the two services, especially for the hourly and daily temporal demand, despite using data from different cities having different urban structures. These findings reinforce the proposed idea of synchronizing the maintenance and redistribution of the SMS fleet with the

demand patterns targeting reducing the Vehicle Kilometer traveled (VKT) that might result from the maintenance and redistribution [40, 38].
Seasonal demand showed fluctuation; however, it was not the same for carsharing and scooters, as scooter demand drops significantly during winter months [38], which is intuitive as scooters are not all-weather vehicles. It also shows the significance of the meteorological conditions on demand. Carsharing seasonal demand also exhibits fluctuation, but to a lesser degree than scooters, Figure 2.7. Similar impacts for weather were estimated through a stated preference experience, where the presence of rainy conditions was the most significant factor in the choice process between carsharing and scooters, increasing the probability of choosing carsharing [40]. These findings define the likely relationship between SMS and meteorological conditions. Accordingly, fleet management and control should consider seasonal demand fluctuation, where the number of vehicles on the streets should not be fixed all year long, as is in the current case. Adopting seasonal fleet capping would, therefore, potentially enhance urban space management.
The comparison of the early use stage, pilot projects, demand patterns, and the later use stages demand showed distinctive differences [38], indicating that while pilot projects are a good indicator of how SMS are going to be used, but with expected changes when the service is ultimately deployed. Understanding the demand patterns and factors impacting it covers research objectives O-1.1, O-1.3, and partially O-4.

Trip characteristics

Scooter trip characteristics were examined as the average trip speed, distance, and duration were consistent in the five examined cities [38]. Pilot projects and early use stages exhibited slightly higher speeds and longer trip distances and duration, possibly due to new user excitement to use the service. Since accidents are highly correlated with a lower familiarity with service use [156], which is more likely to happen during the scooter introduction period, strict speed limit enforcement should be in place and continuously monitored. Furthermore, both cities and operators should provide educational marketing plans to educate users on how they would use the service adequately, in addition to the rules for using the vehicles and for identifying the hazards that could arise from improper use. These findings and recommendations cover the research objective O-1.2.

Demand prediction

Demand patterns significantly impact service operation and organization; therefore, predicting the demand for a long horizon is critical for an efficient service operation. The developed demand prediction framework [32] is helpful for service fleet management as it can be used to deploy the adequate number of vehicles, i.e., scooters in the used case study [32], that cater to the expected demand. The deployment of an adequate number of vehicles will benefit the different stakeholders as follows: operators would not deploy an excess number of vehicles, so they have less maintenance and redistribution work, and subsequently, the expected VKT should be lower than the usual cases, increasing the saving of the overall system VKT; however, this is under strict conditions of replacing motorized modes trips, and not attracting users from other sustainable modes such as active mobility. Also, in this case, authorities will have more urban space, and curb-side management operations would be efficiently organized. This framework was targeted through research objective O-2.

Interaction with public transportation

Demand patterns analysis showed that in the cities where late night and early morning hours operation were allowed, there was an indication that scooters were used to expand the temporal accessibility of public transportation [38]. This finding was further investigated using a different approach, where the distance between scooters and the nearest PT station was examined, showing a similar indication that scooters were used to extend PT accessibility during the early hours of the day when PT services are not available [39]. Another positive indicator for the integration of PT with scooters was found through modeling factors impacting scooter demand, where the increase of the demand was associated with areas with increased PT accessibility, which could indicate the potential of scooters as a first/last mile solution [38]. These findings define some of the possible interactions between SMS and PT and contribute to research objective O-1.4.

Population characteristics

Sociodemographic characteristics were found to significantly impact SMS use, as revealed using different approaches and data. When examined, the exogenous factors impacting the scooter demand in North America, areas with high median income were associated with higher demand, and areas with more male residents were associated with higher demand [38]. The former approach depended on aggregated data on the census block level. When stated preference experiences were used, which gives user-level information on the factors impacting choice between SMS, [40], or the general use of carsharing [37], sociodemographic factors such as gender, income, and education level, were significant. These findings emphasize the role of sociodemographics impacts on SMS use. Also, it shows that SMS use is not equitably possible for all society members. Therefore, equitable use of SMS should be included in the early stages of service planning and monitored in the different project stages to ensure equitable service use.

Population attitudes and personality impacts on SMS, specifically carsharing use, were examined and significantly impacted carsharing use. Also, there were significant differences in travel behavior between carsharing users and non-users. On average, carsharing users were more active travelers than non– users. They were more likely to adopt and use other SMS, such as shared micromobility. This opens the door for more investigation of such behavioral impact on adopting Mobility as a Service (Maas) platforms and how it might increase the potential of multimodality if well planned. These findings show the impacts of the population's characteristics on SMS use, and they contribute to research objectives O-3.1, O-3.2, and O-3.3.

Synergies between shared mobility services

Currently, SMS free–floating fleet size permits issued by authorities to providers are considered on a stand-alone service basis or without considering other SMS within the operation area. For example, suppose a city is issuing new licenses to operate shared E–scooters. In that case, the fact that carsharing or bike-sharing is available within the same operational area does not impact the fleet size of the new scooter service. Such an approach ignores the fact that there are synergies between the different SMS, in the form of modal substitution as proven by the stated preference experience conducted in this dissertation to quantify the magnitude of the shift that might happen from carsharing to scooter after the introduction of scooters [40]. Scooters were found to attract up to 23% of carsharing trips that are shorter than four kilometers, which shows the potential of saving around 45,000 trips and their equivalent to 118,000 VKT and saving of roughly 57,850 kWh, ignoring scooter additional VKT resulting from maintenance and redistribution work [40]. This shift from carsharing to scooters might also help reduce the fleet size of carsharing, which utilizes more curbside space than scooters. Therefore, the licensing and planning for the different SMS should consider the availability and the characteristics of other SMS.

The synergies within the same shared service were also examined when the factor impacting the choice between the different carsharing payment schemes (pay per minute or pay per kilometer) of use were investigated [37]. Significant factors impacting the choice can be grouped into two main groups; the first group is related to the service providers: trip cost, rating of the provider on the app store, and availability of electric vehicles. The second group of variables is sociodemographic-related, such as high income, driving license, familiarity, and previous use of carsharing services. These findings show that even within the same service, people do have different preferences for different payment schemes, and other service attributes such as app rating and available vehicle types within the fleet impact the choice highlighting the fact that not all service providers should have the same fleet size, which is the current case. Also, these findings show the service aspects that providers should consider to attract more users.

These findings show some expected interactions and synergies between SMS and how they would enhance the operation and management process, covering research objectives O-3.3, and O-4.

Service marketing

One aspect that was not evident in the literature on SMS is service marketing and its impact on service uses. The familiarity with carsharing services in terms of knowledge about the service use was found to positively and significantly impact the adoption, the choice between operators, and the shift from other modes [37]. Therefore, service marketing in terms of informing prospective users regarding how to use the service and different offers and options positively impacts service use. That could be done by incorporating outreach plans in the planning process for the different services, targeting the different user groups. These findings contribute to research objective O-5.

Equitable use evaluation

Equitable distribution of resources, in this dissertation, access to SMS is essential to all members of society to ensure equitable access to opportunity and development. While SMS faces serious equity use challenges, as by its definition, several perquisites are required, such as digital banking access, smartphone access, and digital skills, other problems, such as affordability and availability of the SMS within reach, do exist. Inequitable use of SMS, evident in this dissertation, was highlighted on several occasions using different methodological approaches showing the persistence of the problem, indicated mainly by the impacts of the population's sociodemographic characteristics on SMS use. Therefore, a framework to evaluate the equitable use of SMS shared E-scooter was developed and centered around the concept of accessibility to investigate if SMS would increase the population's accessibility to different opportunities or not, as compared to available modes of transportation [36].

The findings of this framework suggest that to increase the current level of accessibility, most of the trips that would be replaced would be active mobility trips, walking and bike trips, and PT trips. Also, there are no notable gains for disadvantaged populations, areas with low-income levels, and low access to the private car by the deployment of SMS. Moreover, the framework shows that the problem of inequitable use of SMS is most likely to be inherited from the urban form, which expands the possibility of the sources of the inequitable use problem of SMS, as the current research attributed the problem of SMS inequitable use to user sociodemographic characteristics, and vehicle availability and affordability [36]. The impacts of the urban forms in terms of land use and available infrastructure on SMS use were also evident when the exogenous factors impacting shared scooter demand were examined and were found to be significant [38]. These findings outline the relationship between SMS and urban forms. These findings also imply the need for different measures to fight the inequitable use of SMS. The case study used to validate the proposed equity evaluation framework showed that current measures adopted by operators, such as vehicle deployment in low-income areas, could not help achieve the needed equity; similar measures are implemented in most of the cities, showing that there is a need for alternative measures to achieve the equitable use of SMS. This evaluation framework covers research objective O-6.

9.1.2 Proposed deployment framework

The findings of the research papers, and dissertation objectives are consolidated, and the following framework, shown in Figure 9.1, is proposed for free-floating SMS deployment. The framework consists of five main stages that are explained in detail as follows:

Mobility need assessment (Stage I)

The framework developed to evaluate the equitable use of SMS, scooters, showed three main highlights, among others, SMS might not be the best mobility solution for all population groups, also mobility need assessment are not a common practice in SMS planning, and equitable use outcomes of the projects are not always considered in the planning stage of the project [36]. Therefore, the initial stage of proposing the deployment of one of the free-floating SMS into a specific area should be performing mobility needs assessment. Afterward, the assessment results should be evaluated in terms of their alignment with SMS characteristics and the added value of SMS to all the members of the society regardless of their economic situation and residence locations. The following steps of this stage are proposed :

- The proposal for SMS deployment should be aligned with the overall shared mobility promises of sustainable transportation systems with environmental, economic, and social benefits. SMS should also be allocated equitably to all society's members without discriminating against specific groups based on race, gender, or economic abilities. Mobility needs assessment is an often–overlooked step in the SMS planning process, but it should be mandatory as it targets empowering communities by increasing citizen involvement in the process, as it maximizes societal benefits and minimizes the current burdens of transportation systems.
- Target area characteristics understanding
  - Definition of the operation zone, the sociodemographic characteristics of the residents, the available modes of transportation, the characteristics of the land use, and the availability of point of interest (POI) and opportunities. These factors are significantly impacting the demand [38].
  - Identification of barriers to using SMS for the different population groups in the different geographical locations [36].

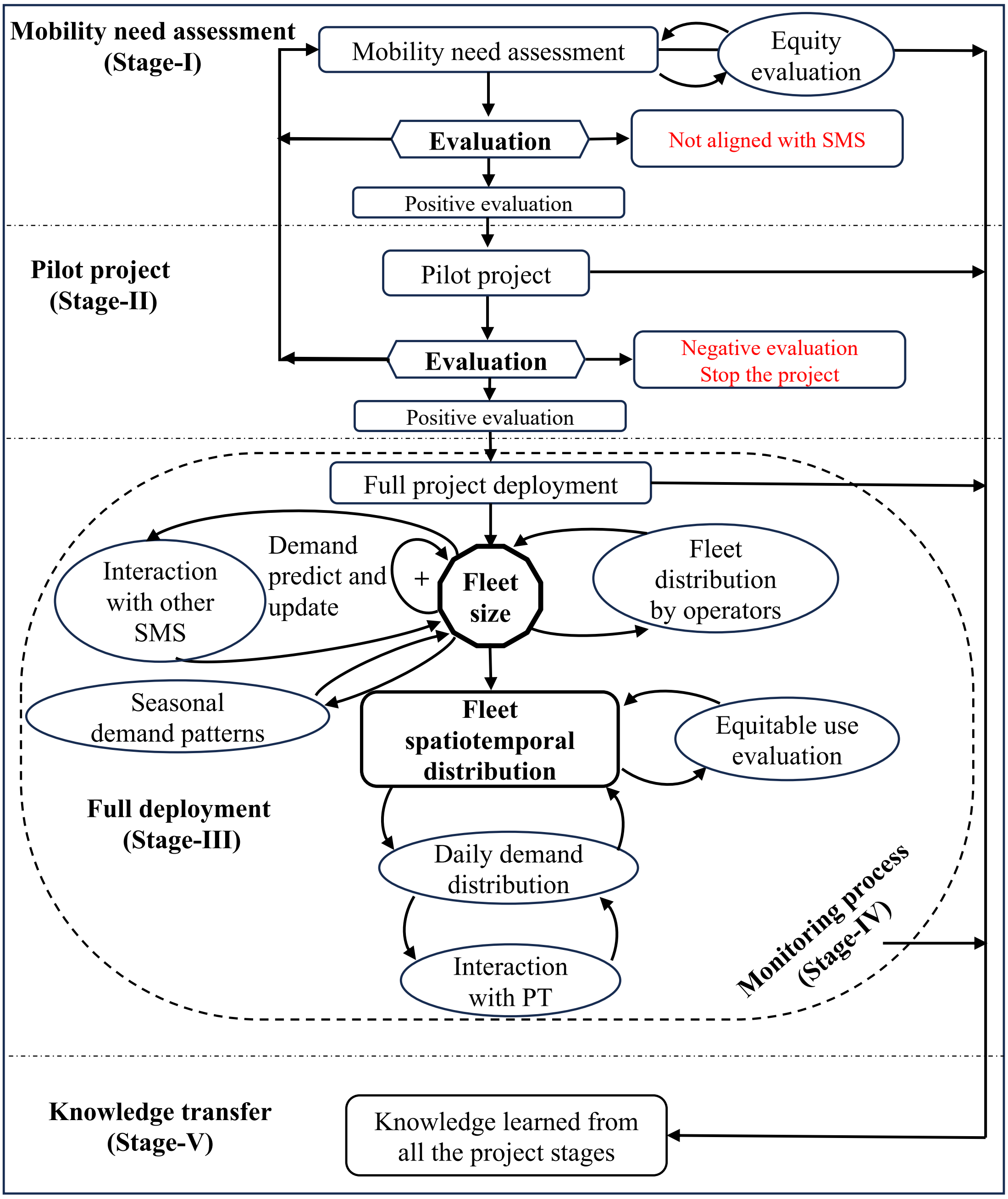


Figure 9.1: SMS deployment framework

- Definition of disadvantaged population groups within the study area to identify their mobility needs, monitor their future use for the proposed services, and remove the structural barriers that might stop them from using the service [36].

  - Investigation of the proposed service affordability for the different population groups to ensure the proposed service does not result in extra burden on low-income groups and other disadvantaged groups [36].
  - Understanding the gaps in the current transportation system to use SMS to bridge these gaps.
  - Understanding the modes of transport that would be replaced by SMS and impact assessment that should be performed to assess the expected sustainability outcomes [36].

- Consultation with different stakeholders [36]
  - Focus groups with the different representatives of community regarding their familiarity with the different SMS options.
  - Focus groups with the concerned stakeholders regarding their targeted and expected benefits and how they would measure the success of the measures in terms of key performance indicators (KPI).
  - Focus groups on the convenience factors that might increase SMS use, such as the willingness to walk, the number of the vehicles in square kilometer, and operation hours [37, 39, 38].
  - The equitable use of the proposed service in terms of additional provided accessibility by the new SMS to the different population groups in the different geographical locations should be evaluated, and it should be the center of the planning process. Accessibility is the center of just transportation systems.
  - Based on the understanding of the project's area characteristics, the mobility needs of the residents, and the targeted benefits from the different stakeholders, a second round of consultation with all the stakeholders should be done in order to conclude the mobility need assessment and final decide if SMS are suitable for the study or not, and other transport alternatives to be considered.
  - Evaluation for the alignment of mobility needs and SMS. The evaluation should consider the different aspects of sustainability, social, economical, and environmental benefits [36].
  - If the final decision is to go forward, the next step should be preparing outreach plans followed by a limited period pilot project [38, 37]. Moreover, if the proposed SMS service expected outcomes are not aligned with the mobility need assessment, there would be two options; the first is to cancel the project, and the second option is to redo the mobility needs assessment study considering the evaluation outcomes, but this should be decided on a case by case basis.

- Outreach plans
  - Development of outreach plans by operators, targeting disadvantaged population groups, to increase their knowledge regarding SMS. Authorities need to monitor such plans to grant their effectiveness [37].
  - Outreach plans should be prepared in different languages to insure inclusivity for all the members of the society, especially in areas with high number of immigrants [36].
  - Disadvantaged population groups generally suffer from lack of internet access, which hinders their possibility to access information regarding using SMS; therefore, alternative options to digital outreach plans should be prepared, such as printed maps showing the proposed locations for SMS, as well as other related information [37].

Pilot project (Stage II)

The second stage is the pilot project and its evaluation stage.

- A pilot project of a limited period should be adopted before the full deployment. The project would aim to measure the popularity and the acceptance of the SMS by evaluating the demand and fleet utilization rate, the impact of the project on user levels of accessibility, the equitable use outcomes of the service, the reasons for using (or not) the service, and finally the received complaints if any. The comparison between the pilot projects and full deployment revealed that pilot projects represent the full deployment well; however, differences in demand and use patterns were observed [38]. Therefore, pilot projects are recommended to be conducted before the full SMS deployment, and the following steps are to be considered:

- Operation rule definitions: clear operation rules and regulations such as but not limited to operation zone limits, locations to use the vehicle such as allowing the use of sidewalks and roadways, and a definition of parking rules speed limit, fleet size, operation hours need to be communicated to the different stakeholders through different educational means, to reach the different population groups within the operation area, to increase the resident familiarity and knowledge about the service, which subsequently might lead to better service usage [37, 38].

- Pilot project monitoring: in order to be able to efficiently and effectively evaluate the pilot project, the following points need to be monitored:
  - Number of trips per vehicle to be monitored by the authorities during the pilot phase [32].
  - Feedback from residents should be collected and further analyzed.

  - Complaints received during the pilot project period need to be evaluated within the pilot project evaluation process; mitigating those complaints would also be recommended by taking the necessary actions during the pilot phase.
  - Areas with high conflict incidence with pedestrians need to be defined, and suitable countermeasures to be adopted, such as but not limited to excluding such locations from the operation zones or are defined as low-speed areas [60].
  - Vehicle parking hot-spots location to be identified, especially areas with wrong parking location, which might block sidewalks in case of shared micromobility.

- Pilot project evaluation
  - Authorities should conduct a user satisfaction survey targeting users and non-users of the different operated services, investigating their feedback regarding the service at the end of the pilot project. Also, reasons for not using the service should be investigated [37].
  - Analysis for the violation to be conducted, and to be discussed with the different stakeholders in order to adopt mitigation measures in the next operation stages.

- Non adoption should be assessed based on the different barriers expected [216, 72]:
  - Spatial barriers: vehicles are not available within a convenient reachable distance; there are no opportunities that are nearby to be accessed through a convenient trip distance, especially for shared micromobility services.
  - Temporal barriers: the case of limited operation hours, congested roads.
  - Economical barriers: travel costs, and indirect costs such as smart phone, internet subscription, and digital banking options.
  - Physiological barriers: perceived safety for some modes, especially shared e-scooter, for old population groups.
  - Social barriers: language barriers, crime rates, poor outreach and educational plans.

- The pilot project evaluation should be based on the three main concepts of sustainable equitable transportation system that have social, environmental, and economic benefits.

If the pilot project evaluation results are positive, the next phase should be the full deployment of the service. Moreover, if there is negative feedback from the pilot project, there would be two options; the first is to terminate the project entirely, and the second option is to redo the mobility needs assessment study; however, this to be decided on a case by case basis.

Full deployment (Stage III)

The third stage of the SMS project is the full SMS deployment. This stage is the most dynamic and complex stage of the project, as it is expected to be a long-duration stage until the project's end, and the previously identified five main interactions between SMS and other elements of the urban environment should be considered. The deployment process has two main interconnected variables: the fleet size and the spatiotemporal distribution patterns, which are directly linked to the exogenous factors impacting demand and service use.

- Fleet size
  - It is essential to highlight that the current practice of issuing permits of fixed fleet size per operator for the whole project's period is not to be adopted. Fleet size should be dynamic, as temporal demand fluctuation has been observed in different services in different locations [40, 38].
  - If a new SMS is introduced during the full deployment phase, the interaction with the current services should be evaluated. These services might replace each other, and the fleet size should consider such interaction and be updated accordingly [40].
  - Fleet size to be predicted using the pilot project's demand data. The importance of this step comes from predicting the exact required number of vehicles to avoid clattered and idle vehicles and unnecessary occupation for the right of way [32].
  - Currently, SMS fleets are distributed equally between the different operators; however, as shown in the case studies, users might prefer one of the operators more than the others. Also, operator evaluation by users impacts their usage; therefore, licensing should consider user preferences and the operator evaluation by the user to increase the operator efficiency [37].
- Fleet spatiotemporal distribution
  - Demand of different SMS has shown distinctive spatiotemporal patterns that are closely tied to the urban forms, especially on a daily and hourly basis; therefore, such patterns should be monitored, and fleet distribution should consider it to minimize the redistribution process and subsequently the empty VKT that might result from redistribution work [40, 38].

- The different SMS and public transportation (PT) interactions should constantly be monitored. SMS could play a role as a complimentary service for the PT that would extend its spatiotemporal accessibility and could also be a solution for the first/last mile dilemma. The presence of the SMS vehicles within acceptable reachable distance from PT station might increase the likelihood of using SMS as a first/last mile solution, increase multimodality, and subsequently increase the efficiency of the overall transport system [39, 38].
- The equitable use of SMS should be checked against demand spatiotemporal distribution; such a process might impact the access to the service, especially in suburban and disadvantaged population areas. Authorities need to monitor SMS vehicle availability among those groups and areas. Also, operators must submit periodic reports regarding service use in disadvantaged areas [36].

Monitoring process (Stage IV)

The fourth stage of the project, the monitoring stage, runs in parallel with the full deployment stage. The main purpose of this stage is to monitor the service and operator performance and the user's feedback to maintain an efficient service. Several items need to be monitored closely:

- Performance reports must be submitted by the operator detailing their fleet utilization rates and the equity measure outcomes.
- Any changes in the land use within the project area needs to be evaluated; for example, if a major attraction such as a new shopping mall is opened in the operation area, its impact on SMS use and deployment should be considered.
- Safety reports and detailed accident reports need to be submitted by the operator for the authority evaluation.
- All the reporting should be done periodically.

Knowledge transfer (Stage V)

Finally, after the project's end, a final report covering all the project stages conveying all the lessons learned from the project to the stakeholders should be issued. Such a report should include all the negative and positive outcomes of the project to avoid adverse outcomes in the planning of similar projects and to strengthen all the positive outcomes.

Data characteristics and requirements

Finally, adequate data should be collected to examine, monitor and generalize the previous findings and discussion. It is recommended to be publicly available for a transparent decision-making process. The following requirements were based on the data used for the different case studies, and Brown et al. recommendations [72].

- User-related data is to be provided from operators to authorities while protecting user identities (i.e., anonymizing the data) so that data can be publicly available. If such data can jeopardize user privacy, it is recommended not to publish it publicly.
  - Number of users for the different operators
  - Use frequency per user
  - Number of enrolled users from disadvantaged groups
  - Periodic user survey data controlled
- Trip data can be publicly available, but adequate anonymization to protect users and operators should be followed. Examples of such practices are the scooter use data provided by the cities of Louisville, KY [103] and Austin, [102].
  - Trip star and end geographic coordinates
  - Trip characteristics: speed, distance, and duration
  - Number of trips per disadvantaged group
  - Device unique identification to estimate the number of trips per device, device life cycle, and vehicle idle time
  - Trip data provided on a daily basis
- Vehicles related data
  - Fleet size, including spare vehicles, and daily number of available vehicles
  - Reports of stolen, broken and misused devices
  - Maintenance plans
- Public interaction
  - Customers complaints in detail and responses to them
  - Equity plan outcomes, and follow–up reports
  - Work done to promote outreach and education plans
- Accident reports in detail, including time, location, and severity, and the corresponding hospital reports if applicable.

9.2 Future research

The findings and discussion of this dissertation highlight the need to answer several additional research questions that should be covered in future research to enhance the process of SMS deployment and their efficient integration into the urban environment.

SMS fleet control: as highlighted before, the fleet size definition process for the different free-floating SMS only considers each service separately, without consideration of the existence of other services. Therefore, the fleet sizing for the different free–floating shared vehicles SMS, carsharing, bike-sharing, and shared E-scooter should be holistically evaluated and estimated to reach an overall fleet considering the interactions between such services.

Dynamic fleet sizing policies: examining demand patterns for scooters showed a significant variation in the demand on an hourly, daily, and seasonal basis, which suggests the possibility of using dynamic supply. Such consideration would reduce the empty VKT, the cost of fleet maintenance, and the number of unnecessary vehicles in the right of way. However, this approach for free-floating SMS has not been investigated before; therefore, further investigation is needed to develop this fleet control methodology and define the optimum time unit to consider for the dynamic fleet supply.

Optimum pricing: travel cost is one of the significant detriments of mode choice, and it can be used as a pull and push measure from the different modes of transport, including SMS. Moreover, SMS are priced separately or individually without considering the existence of other services; therefore, there is a need to study the optimum pricing that would increase the likelihood of multimodality and most efficient trips, including SMS, in terms of minimizing the expected traffic externalities. Also, the pricing scheme should consider other extra constraints, such as the equitable use of SMS.

Impact of travel behaviour: travel behavior is one of the significant factors in user decision to adopt SMS. However, this is often overlooked in SMS, despite being fundamental for developing the service in new directions, such as integrating all SMS in one digital platform or developing Mobility as a Service (Maas) platforms. While SMS users have shown a distinctive travel behavior, SMS should also consider the current non–user travel behavior so they are attracted to the service and achieve equitable use for the service without excluding groups based on their current travel behavior.

Factors impact the choice between the different operators: one of the most overlooked aspects of SMS are factors impacting the choice between the different operators for the same service. While we discussed the potential differences, in the case of carsharing service, the factors impacting the choices between the different operators for other services, such as scooters and bikesharing, are still vague. Such factors would help the operators enhance their services to attract more people and help the authorities issue permits considering such differences.

9.3 Limitations

The limitations of each case study and framework were discussed in detail in the corresponding chapter and Appendix. However, it is essential to highlight that some of the case studies were not applied to the three main free-floating shared modes (car, bike, and E-scooter) due to many constraints, such as the unavailability of the data for the three modes or even the unavailability of the modes themselves in all the locations where data was collected. Moreover, for the survey-based studies, Chapter 5 and 6, designing a survey for each of the three modes was not an option, as survey data collection was both time- and cost-consuming. Finally, the surveys presented in Chapter 5 and 6 were collected in Germany, while the open scooter trip data that the rest of the case studies analyzed were collected from North America. Undoubtedly, it would be ideal if the surveys were collected in the exact location from which the scooter datasets were extracted; however, this was impossible. However, we believe that based on the literature review, users of SMS have a similar profile globally. Other factors might impact SMS use, such as but not limited to the city's urban form, the availability of other modes of transport, and the accessibility to different opportunities. Therefore, to generalize the findings and the conclusion of this dissertation in different locations, the external factors that interact with free-floating SMS should be verified against the findings of this dissertation.

9.4 Conclusion

This dissertation consolidates the work done by Abouelela et al.[32, 36, 37, 38, 39, 40], where several aspects related to SMS were explored to better understand SMS and their integration potential within the urban environment. This was done by answering several research questions fulfilling six main objectives to understand the interaction between free–floating SMS and different elements of the urban environment, leading to the development of a framework for the efficient deployment of free–floating SMS.

Shared mobility planning is a complex multi-dimensional process that should consider the interaction with the different elements of the urban environment, such as meteorological conditions, built environment characteristics, population sociodemographic attributes, available modes of transportation, SMS characteristics, and interaction within the SMS. These interactions were investigated throughout six research papers. The findings of these papers were consolidated into practical framework for the dynamic deployment of SMS.

It is essential to note that this dissertation does not advocate for or against SMS, but highlights the need to consider their direct and indirect interactions within the urban environment for better service integration. SMS is not a one–size–fits–all mobility solution. Some cases might call for different measures, such as higher investments in public transport or even changes in land use, resulting in possibly more plausible mobility solutions.

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Understanding the landscape of shared-e-scooters in North America; Spatiotemporal analysis and policy insights

Mohamed Abouelela [a], Emmanouil Chaniotakis [b,*], Constantinos Antoniou [a]

[a] Chair of Transportation System Engineering, Technical University of Munich, Munich, Germany
[b] MaaSLab, Energy Institute, University College London, London, UK

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ABSTRACT

Shared-e-scooters are being introduced in cities worldwide, with their introduction often being distant from the actual service characteristics understanding, potential benefits, and threats realization. This research explores scooter use by examining approximately nine million scooter trips from five North American cities (Austin; TX, Calgary; AB, Chicago; IL, Louisville; KY, Minneapolis; MN). By investigating the spatiotemporal hourly and daily use, we found that demand patterns tend to be similar in the different cities. Trip characteristics (speed, duration, and distance) are almost empirically consistent across the five cities; however, there is evidence that trip characteristics change over time in the same city. We also examined the impact of exogenous factors on scooter demand, and found that weather (temperature, wind speed, precipitation, and snow), day of the week, infrastructure (bike lanes, sidewalks, and shared bike stations), sociodemographics (gender, age, and income), land use, and accessibility to transit significantly impact demand. Findings highlight the need for evidence-based examination of shared-e-scooters and regulatory processes to guide policy decisions by the different stakeholders.

1. Introduction

Micromobility is commonly defined as the set of small vehicles weighting less than 350 kilograms with a maximum speed of 45 km/h (Santacreu et al., 2020), with the shared version of it refering to the shared use of such vehicles on a pay-as-needed basis (Shaheen and Cohen, 2019). This group of vehicles encompasses –private or shared– bicycles, e-bikes, skates, self-balancing unicycles, segways, and scooters (Santacreu et al., 2020; Turoń and Czech, 2019). Shared standing (kick) e-scooters (for matters of brevity, hereon referred to as scooters) are one of the latest members of the shared-micromobility modes. Lime (www.li.me) launched the world's first shared scooter system in Santa Monica, California, in July 2017, signifying the start of a revolutionary era of shared micromobility. By the end of 2018, an astounding number of 38.5 million trips were completed using scooters in the USA, representing 45.8% of the total trips completed by micromobility in that year, while in 2019, scooters were available in 109 cities in the USA. The number of scooter trips in 2019 raised to 88.5 million achieving around 130% increase in scooter trip number compared to 2018, showing the exponential increase in scooter use before the pandemic (NACTO, 2020). Scooters quickly gaining a share of micromobility trips shows the magnitude of its success, especially when compared to bike-sharing systems, which were introduced at least eight years earlier than scooters (NACTO, 2020). At the same time, the use of scooters has also grown globally with the deployment of new systems in Asia, Europe, and Australia (Santacreu et al., 2020; Heineke et al., 2019; Møller and Simlett, 2020); the total micromobility market is expected to keep growing to reach between 330$ - 500$ billion by 2030 (Heineke et al., 2019).

* Corresponding author.
E-mail address: M.chaniotakis@ucl.ac.uk (E. Chaniotakis).

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The expansion and proliferation of scooters come with opportunities and challenges (Gössling, 2020). Curbside space utilization, energy savings, greenhouse gas (GHG) emissions, and congestion reduction are some of claimed benefits of scooter (Allem and Majmundar, 2019). To give a few examples, scooters occupy 0.3–0.6 m^2 for parking space versus 20 m^2 for cars (NYC Board of Standards and Appeals, 2021); one-kilowatt hour of energy could propel a scooter 100 km compared to two km for a passenger vehicle[1] (Agora Verkehrswende, 2019); some operators claim a net-zero emission over e-scooters life-cycle (VOI)[2] (Møller and Simlett, 2020); and scooter's trip distance on average is around one mile (Schellong et al., 2019; NACTO, 2020), approximately the distance of 10% of the entire daily car trips in the USA, indicating the potential of scooters to replace a significant amount of car trips, and their potential to reduce VKT (FHWA, 2014).

At the same time, the challenges related to the introduction of scooters cannot be overlooked. Scooters are significantly raising safety concerns, as half of the reported accidents related to scooter use involved severe injuries, while fatal accidents were reported in the USA (Yang et al., 2020; Schlaff et al., 2019; Stephens, 2019; Trivedi et al., 2019; Vernon et al., 2020). Scooters deployment can cause disturbing effects on cities. McKenzie (2019), Janssen et al. (2020), Gössling (2020) summarized scooter deployment problems as fleet-size control, capping and organization, permit cost, attracting users from active modes, and increased safety hazards. A commonly met issue is that users commonly abandon them in the middle of the sidewalk, obstructing pedestrians, while there exist various reports of vandalism (e.g., scooters thrown in rivers) (Turoń and Czech, 2019). Regarding emissions, Moreau et al. (2020) performed a life cycle assessment for a dockless shared scooter system and showed that over their entire life cycle, scooters produce more CO_2-equivalent per passenger-kilometer than the modes they replace. At the same time, they are also found to attract users from environmentally friendly modes (NACTO, 2020), such as walking and biking, generating empty vehicle kilometers traveled (VKT) during redistribution and maintenance processes (Møller and Simlett, 2020).

The diverse range of challenges and the potential benefits of widespread use of scooters identified in the pertinent literature render the need for further investigating their actual use in different urban contexts. While there is a growing body of literature on the topic, see for example (Nigro et al., 2022; Kachousangi et al., 2022; Ziedan et al., 2021; Abouelela et al., 2021a; Luo et al., 2021; Reck and Axhausen, 2021; Nikiforiadis et al., 2021), most studies conducted evaluate scooter's use characteristics for limited periods of time (for example: Liu et al., 2019 used three months of data; McKenzie, 2019 used four months of data, and Noland 2019 who used six months of data), ranging from five weeks to four months or utilizing experiences from just one pilot case, or they do not differentiate or compare between pilot/early-stage use and regular use after service adoption and users constructing service-familiarity (Liu et al., 2019; Zou et al., 2020; McKenzie, 2019). At the same time, most studies focus on the use of data from just one city, with a few exceptions (see for example Bai and Jiao, 2020). This omission limits the scope of analysis, preventing the comparison and extraction of conclusions regarding the potential generalization of the findings. In addition, demand analysis in most cases is limited. Bai and Jiao (2020), Noland (2019) examined the factors affecting demand for scooters; however, they used the average daily trip counts as the dependent variable, which does not reflect the variation in daily trip count. Also, Jiao and Bai (2020) modeled the total number of trips per each zone (hexagon), and Reck et al. (2021) modeled the total number of trips per census tract, Hosseinzadeh et al. (2021) used the scooter trip number density per zone; however, these are not capturing the zero count area. Finally, while the pertinent literature emphasizes the potential of scooters to increase accessibility as a first- and last-mile solution (Zuniga-Garcia et al., 2022; Yan et al., 2021), very few studies discussed the relation between scooter use and accessibility (Aman et al., 2021).

In this paper, we leverage scooter trip data from four U.S. cities (Austin, TX; Chicago, IL; Louisville, KY; Minneapolis, MN) and one Canadian city (Calgary, AB) to perform a comparative empirical analysis of the spatial, temporal, and demand characteristics of the services, aiming at devising a thorough and informative investigation of scooter use, demand patterns, and factors impacting the demand. To be able to generalize the methodology of this study, we use open source data sources (meteorological data, census data, infrastructure-related data, land use data, and general transit feed specification files (GTFS)) to come up with an investigation of factors affecting scooters' demand, including the use of Local Index of Transit Availability for evaluating the relation between scooter use and accessibility to public transportation (PT). As such, the contributions of this study are summarized into (i) assessing and comparing the scooter trips' spatiotemporal characteristics in these five cities, (ii) distinguishing among pilot projects, early use stage, and later use stage, and (iii) investigating the exogenous factors that impact scooter's demand, using open-access data, and zero-inflated negative binomial regression models (ZINB). ZINB models have not been previously used in shared micromobility demand prediction to deal with the issue of excess zeros data, as discussed in detail in Section 5. As a result, this research provides answers to the following pertinent research questions:

- (RQ1) What are the scooter demand characteristics and are there similarities and differences in the temporal and spatial scooter use patterns across and within different cities?
- (RQ2) What are the similarities and differences between scooter trip characteristics in different cities?
- (RQ3) Which exogenous factors affect scooter demand?

The remainder of this article is structured as follows. The user data and the methodology utilized for the cleaning, analysis, and modeling processes follow in Sections 3 and 4 respectively. Section 5 explores the exogenous factors impacting trip generation, while in Section 6, study limitations, conclusions, and an overall discussion of this research are presented. In the upcoming section, a literature review is presented in Section 2 to identify the different factors affecting scooter use and the use of shared micromobility in general.

[1] The comparison is between a VW Golf 1.0 TSI (4.8 L Gasoline per 100 KM), and 0.47 kWh battery Bird scooter (Agora Verkehrswende, 2019)

[2] www.voiscooters.com, accessed 11 March, 2022

2. Literature review

The popularity and exponential growth of scooter use and the service's introduction to different cities globally have encouraged researchers to explore the service from different perspectives to integrate the service into the urban environment. Scooter-related research can be grouped into four main areas; (i) safety hazards, (ii) scooter use patterns and comparison with other micromobility services, (iii) potential to replace other modes, and (iv) demand characteristics, demand prediction, and factors impacting scooter's demand.

The first area of research covers the growing safety hazards concerns related to the widespread use of scooters; for example, in the USA, the growth of scooter-related injuries is significant. In 2018, the number of injuries increased by 140%, compared to 2016, before introducing the first shared scooter system (Namiri et al., 2020). Studies in other locations, such as Europe, Israel, Canada, New Zealand, and Singapore, tried to identify the demographics of the users involved in crashes (accidents), as well as crash severity variability, using crash reports, hospital diagnostic reports, or even media news reports' mining techniques, concluding that novice young male users are more prone to injuries compared to other user groups (Puzio et al., 2020; Dhillon et al., 2020; Zagorskas and Burinskienė, 2020; Störmann et al., 2020; Lin et al., 2020; Uluk et al., 2020; Bekhit et al., 2020; Nisson et al., 2020; Liew et al., 2020; Basky, 2020; Ishmael et al., 2020; Bauer et al., 2020).

The second research focus area is to extract and analyze the scooter's demand patterns and compare the defined scooters patterns with other micromobility services (e.g., bike-sharing) use patterns. In these studies, researchers used distribution techniques to perform temporal and spatial pattern analysis and geo-statistical methods, such as Moran index, and G^* (Younes et al., 2020; McKenzie, 2019; Moran, 1950; Cliff and Ord, 1969; Fotheringham, 2009). McKenzie (2019) and Younes et al. (2020) compared scooter use and bikesharing use in Washington D.C. to find that casual bikesharing user used the system temporally quite similarly to scooter users. On the spatial level, the use pattern of the two systems was different. Both systems' trips started and ended from different land use areas showing different purposes of using the two systems. When comparing regular bikesharing member use patterns to scooter use patterns, the spatial and temporal use patterns differed.

The potential of scooters to replace other travel modes was also examined in the literature. Two studies in Chicago, Il, and New York used the cities' current modal split and introduced scooters as a new mode to find that, in Chicago, scooters could replace 47%–75% of private car trips between 0.5 and 2 miles, while in New York, scooters could replace up to 1% of all taxi trips (Lee et al., 2021; Smith and Schwieterman, 2018). Abouelela et al. (2021b) conducted a stated preference survey in Munich, Germany, among young users (18–34 years old) that showed that scooters could replace up to 14% of carsharing trips. Several cities conducted user surveys to investigate which modes are replaced by scooters. Walking, biking and PT are the top replaced modes; with the percentage of replaced walking trips up to 55% as in Calgary, Canada (ADOPT, 2019), 15% of bike trips as in Brussels, Belgium, and 30% of PT trips in France (Lyon, Marseilles, Paris) (6-t, 2019). In Arizona, e-scooters are replacing bike and walking short trips for all trip purposes (Sanders et al., 2020).

Factors impacting scooter demand are another topic of concern to the research, and different statistical modeling techniques were used to predict the demand. Jiao and Bai (2020), Bai and Jiao (2020) used negative binomial regression to examine factors impacting trip generation in Austin, Tx, and Minneapolis, Mn. Spatial regression techniques were also applied for the same purpose in Austin, Tx, where Caspi et al. (2020) used spatial lag and spatial Durbin log–log models to examine the factors impacting scooters' trip generation. Noland (2019) used ordinary least square regression to predict the average number of trips, average distance, and average speed per day. Factors impacting scooter demand could be summarized as, but not limited to, distance to downtown, intersection density, land use diversity, population density, access to PT (Bai and Jiao, 2020; Jiao and Bai, 2020), bike infrastructure availability (Caspi et al., 2020), temperature, snow, precipitation, and wind speed (Noland, 2019).

In the trip generation and attraction studies, only areas with consistent trip rates were considered in the modeling process. Areas with low trip generation rates were excluded; in other words, factors impacting low trip rates areas were not examined; in this study, we apply zero-inflated models to model the low trip demand areas as discussed in detail in Section 5. Other research areas, such as scooter use policies and recommendations, as well as parking regulation (Gössling, 2020; Janssen et al., 2020; Turoń and Czech, 2019; Shaheen and Cohen, 2019; Fang et al., 2018), charging and maintenance stations location optimization (Chen et al., 2018), and customer segments identification (Degele et al., 2018) were also addressed in the literature.

3. Methods

3.1. Data

For our analysis, we used data from five cities. Four of them are located in the USA (Austin; TX, Chicago; IL, Louisville; KY, Minneapolis; MN), and one in Canada (Calgary; AB). The cities are different in size and population, as shown in Table 1, as well as the mode split of work trips — Chicago and Calgary have larger transit trip share (28%–16%) compared to the other cities' transit trips share (2.5% Austin, 4% Louisville, and 8% Minneapolis). The examined cities have all made their shared-e-scooter trips data publicly and openly available, with their scooters' operation schemes and setups to differ (see Table 1). Moreover, the collected trip data was obtained from continuous use operations or pilot projects executed to preliminary evaluate the potential impacts of scooters and the public acceptance before the full deployment of the service. For example, Minneapolis and Chicago had limited-time pilot projects of around three months. Calgary runs a 16-month project, with three-month-mid-pilot data published for public evaluation. Louisville and Austin have scooters regularly. The operation is also different regarding the number of operators and fleet size. Some cities have imposed limitations on the number of operators (Louisville, Minneapolis, Calgary, and Chicago), while Austin does, having eight different operators in July 2019, increased to ten by 2020 (Janssen et al., 2020). Regarding fleet size limitations, each city has imposed cap limitations as a function of the number of operators and ridership rates. When it comes to times to use the scooter, Chicago was the only city that has imposed time restrictions for scooter use between 10 p.m. and 5 a.m.

Table 1
Summary of city characteristics, scooter regulations and policies.

City	Pop. in Millions	Operators	Number of vehicles	Speed limit (mph)	Helmet regulation	Permitted use	Ref.*
Austin, USA	0.95	10	15000	20	Advised; mandatory for under 18	Bike lanes and sidewalk	**1**
Calgary, CA	1.34	3	1500	12.4	Advised	Bike lanes and sidewalk	**2**
Chicago, USA	2.71	10	2500	15	Advised	Bike lane	**3**
Louisville, USA	0.62	4	1200; increased to 1050/operator	15	Mandatory	Roadways, and in bike lanes or paths	**4**
Minneapolis, USA	3.63	4	2000	15	Advised	Bike lanes	**5**

Reference* **1** = Austin Shared Mobility Services (2022), **2** = Calgary Open Data Portal (2022)
3 = Chicago Department of Transportation (2022), **4** = Louisville Open Data (2022)
5 = Minneapolis Public Works (2022)

Trips data description

The available datasets from the five cities have a standard structure with slight variations between the sets targeting protecting user privacy. The datasets' format is longitudinal, with each row represents a trip observation, and each observation contains the trip's identification code (ID) for each trip, vehicle identification (scooter, bike, e-bike), trip, start and end date, as well as trip duration, speed, and trip distance based on companies route data. Additional information, such as the start and end community area number, is provided in the case of Chicago. Different procedures are implemented to protect the users' anonymity in all the datasets. Trip start and end locations in Austin and Chicago are assigned to the corresponding census tract. In Minneapolis, trips are assigned to the nearest streets' center-line. In Calgary and Louisville, trips are aggregated to a grid, which in the former is based on hexagons with an area of 30,000 square meters and in the latter on the block level. The trip starting time is also aggregated to the nearest 15 min in Austin (Austin Shared Mobility Services, 2022) and Louisville[3] (Louisville Open Data, 2022), to the nearest hour in Chicago (Chicago Department of Transportation, 2022) and Calgary (Calgary Open Data Portal, 2022), and the nearest 30 min in Minneapolis (Minneapolis Public Works, 2022). If there are few trips in the exact aggregated location in Louisville, the points are moved 0.5 km randomly without specifying which points were moved.

Other data sources description

To augment the above-described datasets, we collected data from other sources. Specifically, we use (a) *meteorological data*, obtained from visualcrossing.com, containing the hourly temperature, wind speed, the precipitation conditions, snow depth, humidity, and dew point, (b) *sociodemographic data* from the American census database retrieved from census.gov containing population characteristics, aggregated to each of the census tracts. The aspects considered in our analysis obtained from this dataset is; the percentage of the different; age groups, gender, median income, transportation mode used to work, and population of each tract, (c) *infrastructure data* obtained from openstreetmap.org containing characteristics such as the length of bike lanes, the length of sidewalks, and the number of shared bike stations, (d) *Land use data* (from the cities' online portals), the different land uses were collected, and it was assigned to the census tract. If a census tract has more than one land use, the percentage of each land use was calculated based on their area compared to the overall track area, (e) *General Transit Feed Specification Files* (GTFS) from transitfeeds.com, we downloaded the GTFS for the four US cities, and the local index of transit availability (LITA) was calculated to study the relation between scooter demand and accessibility to public transport.

3.2. Methods

The above-described datasets are used as the basis for the analysis performed. Using the combined –with the external data sources– trip data, we investigate the impact of the exogenous factors on the daily generated trip demand. Specifically, to answer research questions, we extract and compare demand patterns to understand the similarities and differences of trip characteristics in different cities. The process followed (Fig. 1) includes data cleaning procedures collating the datasets, models' estimation, and findings and conclusion.

Trip data cleaning process

Following an exploratory data analysis, outliers and false records were removed by setting a lower and upper bound for all trip characteristics, distance, duration, and speed, based on previous studies and the standard vehicles' criteria. One charge can power a scooter for two hours or approximately 50 km. Therefore, we set the upper bound for the trip distance to 50 km and trip duration to two hours. The minimum trip distance was set to 100 meters for the lower bound, while for the duration, it was set to one minute, and the upper bound for 120 min following previous research methods used (McKenzie, 2019; Liu et al., 2019; Zou et al., 2020). The upper-speed bound was set to 15 mph (25 km/hr) as per the maximum allowable speed limit in four of the subject cities for the

[3] The data format can be checked from this link data.louisvilleky.gov/dataset/dockless-vehicles/resource/fd252fa3-a829-4d20-9879-c5b4f8b39f7f

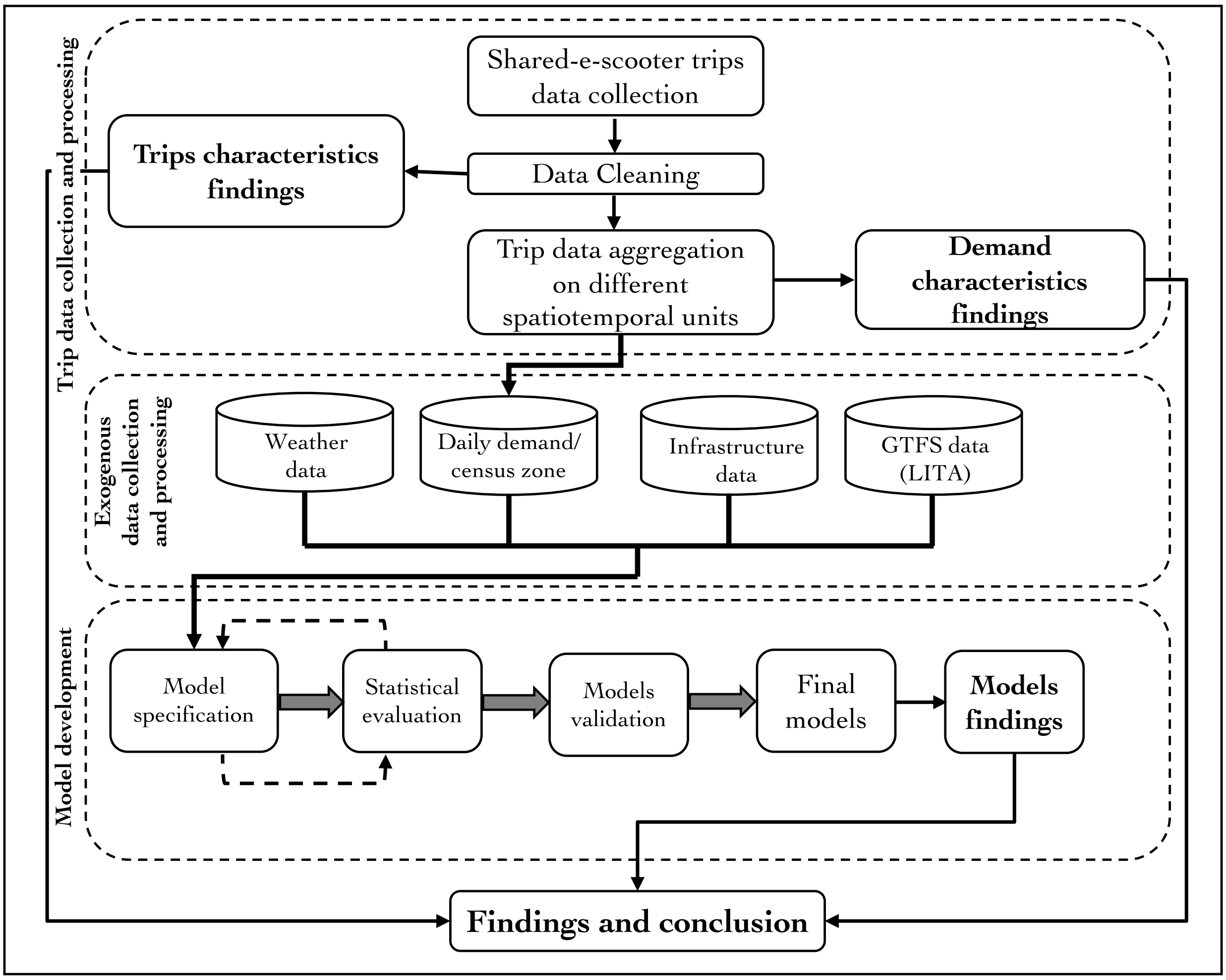


Fig. 1. Research methodology.

trip speed. Although the speed limit in Austin is 20 mph, there are several areas where the maximum speed was set to 8 mph, and the number of trips faster than 15 mph when examined was limited; therefore, we opted to remove these trips to have consistent criteria across all cities. The trip's start and end coordinates were examined in all the cities, and trips with either false start or end coordinates were removed.

To test the difference between the early use stage –or what can be named the service adoption period–, and the later use stage –where users establish familiarity with the service–, we split the dataset of Austin and Louisville into two parts. The first part is the first three months of use, resampling the adoption period (referred to from hereon as the pilot period), and the rest of the use period, as the other part of the dataset (referred to by the city name). The main reason for choosing three months of the data to test as an adoption period is that the other three datasets, Chicago, Calgary,[4] and Minneapolis, were around a three-month-long pilot project. The primary purpose for splitting the data was to investigate if there is a change in travel behavior between the early service use and adoption stage when people are getting familiar with the service and the later, regular-use stage.

Data aggregation and preparation for modeling

The dependent variable was set to the number of daily trips per census tract. We used the census tract as the spatial aggregation unit for two reasons. First, the delineation rules for all the census tracts are homogeneous for the same country, the USA. Second, the sociodemographic data for the population are provided from the American census database (census.gov) are provided on the census tract level.

As explained hereunder, the collected data sources were aggregated and combined temporally or spatially, and in some cases, both temporally and spatially. Also, it is to be noticed that all the external sources of information can be grouped into two main categories; (i) time-dependent or time-varying data, such as meteorological and demand data, and (ii) time-independent variables, such as sociodemographic information, infrastructure information, land use, and GTFS files. The following points summarize the aggregation and preparation process for the used sources of information;

[4] In Calgary the total pilot project period is 16 months; however, only the first three months trips records were published for public evaluation for the project

- Trips data were aggregated temporally per day of the data collection period and spatially per census tract. So for each tract, the number of daily trips per day along the data collection period was calculated.
- Meteorological data included the average daily temperature, average daily wind speed, and the presence of precipitation and snow in our analysis. The meteorological data were the same for the same day and all the tracts of the city. We considered precipitation as a binary variable, where it was set equal to one if it was a rainy day and zeroed otherwise. Like precipitation, we considered the snow conditions, where we considered it a binary factor, where snowy days were set equal to one and zero otherwise. No aggregation was done for the meteorological data.
- Sociodemographic information was collected per census tract. Intuitively, the sociodemographic information is the same throughout the data collection period.
- Infrastructure information, such as the sidewalk lengths, the bike lanes lengths, and the number of shared bike stations, was aggregated spatially to each census tract by calculating the lengths or counting the numbers by each census tract.
- Land use information was assigned to each census tract as a proportion of its area to the total area of the census tract. For example, when a tract had one land use, this land use was assigned as 100% of the tract, and when a census tract had two land uses, the percentage of each land use was calculated as the proportion of each area to the total area of the tract.
- GFTS data was used to calculate the Local Index of Transit Availability (LITA) to examine the relation and interaction between PT use and scooter use; therefore, we used the accessibility to the public transit as a proxy for testing this relation. The main reason to use LITA as a measure of accessibility was that it considers different aspects of the PT service or namely, spatial availability, headways (temporal availability), and service capacity (Fu and Xin, 2007). LITA is calculated as the bus capacity (the number of seats per bus) multiplied by the daily number of buses that passes through the tract (the number of buses per day) multiplied by the bus route length inside the tract and finally divided by the summation of the total population and employed people within the same tract (Chen, 2018).

Demand models

The dependent variable of interest used was the number of daily trips per census tract zone, a count variable with high dispersion and high number of zero counts resulted from the low demand areas. Zero-inflated negative binomial distribution allows additional probability to detect extra zero counts compared to the standard negative binomial distribution. Contrarily to the negative binomial distribution, the zero-inflated negative binomial distribution does not have the restriction of the variance to be equal to the expected mean value, which allows for extra overdispersion, which is the case when variance is larger than the mean. The zero-inflated negative binomial models' hypothesis that there are two latent classes of count data one that is always zero, and the other class, which is not always zero. These models consist of two parts the first part predicts the probability of the excess zero, and the second part account for the non-zero count and the not excess zeros as well (Pew et al., 2020; Loeys et al., 2012). Naturally, the best model to determine the latent class of the data is a logit or probit model. After determining data class, and when ($p_i = 0$), the probability mass function for the zero inflated model is represented in Eq. (2) (Washington et al., 2020).

$$\text{logit}(p_i) = x_i^T \beta \tag{1}$$

$$P(Y_i = y_{ij}|p_i, \mu_{ij}) = \begin{cases} p_i + (1-p_i)(\frac{\theta}{\mu_i+\theta})^{\theta} & y_i = 0 \\ (1-p_i)\frac{\Gamma(y_i+\theta)}{\Gamma(\theta)y!}\frac{\mu_i^y \theta^{\theta}}{(\mu_i+\theta)^{y+\theta}} & y_i = 1, 2, 3, \dots \end{cases} \tag{2}$$

Eq. (1) presents the model structure for the logit part of the model, where the x_i represents the covariates vector, and β represents the parameters vector. The probability of the excess zero (denoted as p_i), and the probability of the other counts is $(1 - p_i)$ follow a negative binomial distribution, with a mean of μ, and following a Gamma distribution (Γ). The mean of the ZINB distribution $E(y_i) = (i - p_i)\mu_i$, and variance $Var(y - i) = (i - p_i)\mu_i(1 - p_i\mu_i + \mu_i/\Gamma)$. The ZINB distribution is given by Eq. (2); where θ is the shape parameter that allows for the over dispersion (Rodrıguez, 2013; Long, 1997).

Given a very high number of variable resulting from the use of the above presented datasets, we followed the notion of Duran-Rodas et al. (2019) for the model building process, to examine variables upon their correlation and used only non-collinear variables in an iterative process, removing insignificant variable during model structure examination, to reach the most parsimonious models.

4. Analysis

This section presents the analysis performed to compare the demand and trip characteristics on temporal and spatial levels. The main aim of comparing the different cities' data is to investigate the differences and similarities of scooter use patterns in the subject cities and investigate if scooters' use pattern is similar for the different cities or not.

4.1. Seasonal temporal demand

Descriptive statistics were derived for the seasonal temporal demand (Table 2 and Fig. 2). At the beginning of the scooter's deployment, the demand increased rapidly for about two weeks until it reached a steady trend that exhibited seasonal demand patterns. In general, the demand during the pilot projects drops near the end of the project, which is not observed for Austin and Louisville, where scooters continue to operate to date. Minneapolis exhibited a different trend, which has a surge in the demand one

Table 2
Scooter demand summary statistics.

City	Mean	SD	25th Percentile	Median	75th Percentile	Max.	Highest demand day	Start Date	End Date
Austin, pilot	1,950	1,400	994	1,708	3,130	5,530	Fr.	03-Apr-18	03-Jul-18
Austin	11,919	6,248	8,427	11,073	14,150	4,6974[a]	Sat.	04-Jul-18	31-Jan-20
Calgary	5,556	2,241	4,566	6,160	6,927	9,952	Fr.	02-Jul-19	30-Sep-19
Chicago	4,749	1,280	4,190	4,780	5,575	7,716	Sat.	15-Jun-19	15-Oct-19
Louisville, pilot	363	140	260	346	433	807	Sat.	09-Aug-18	09-Nov-18
Louisville	794	573	342	644	1,185	2,659	Sat.	10-Nov-18	31-Jan-20
Minneapolis	1,460	759	945	1,330	1,794	3,562	Thu.	10-Jul-18	01-Dec-18

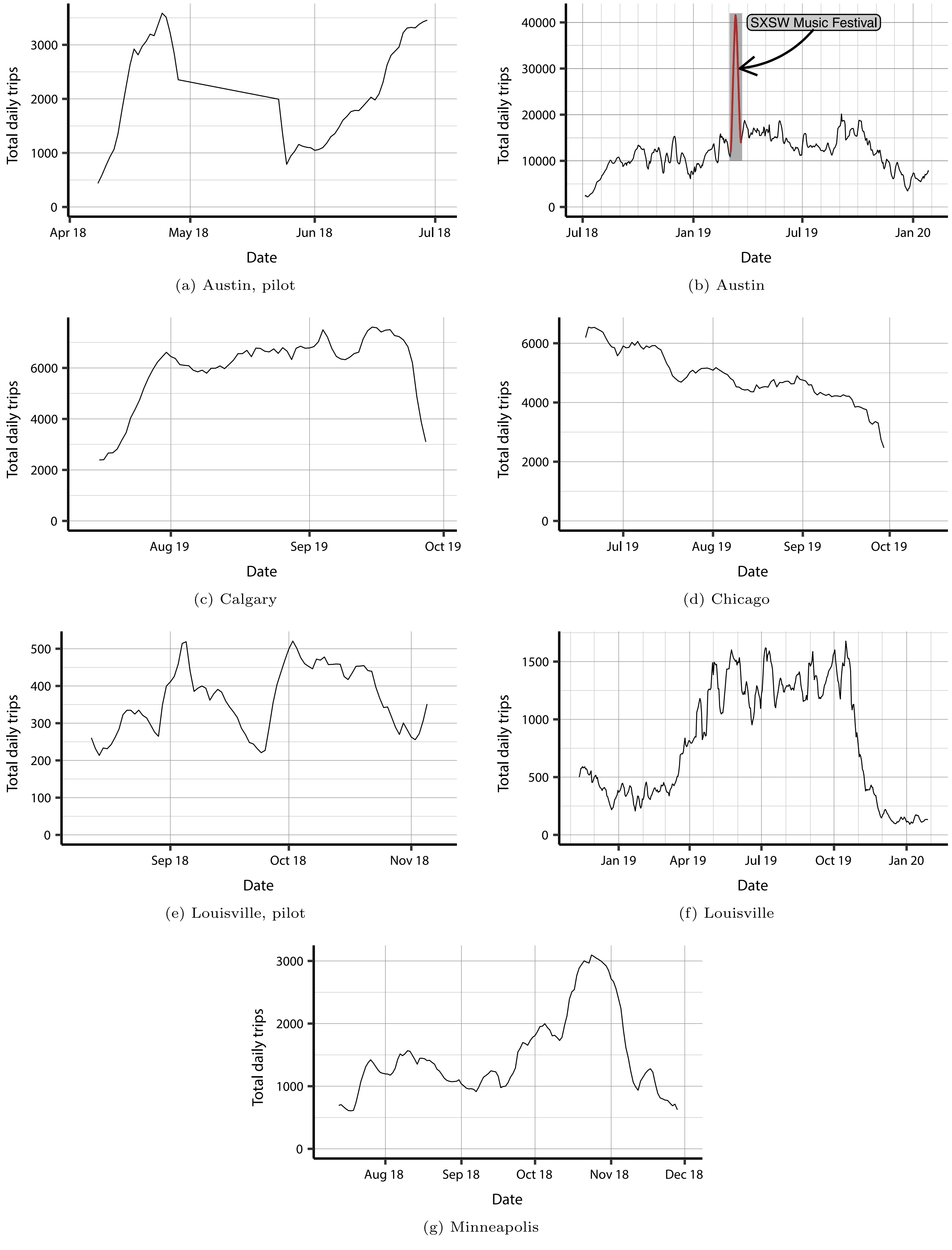
[a]The average daily demand in Austin, during SXSW was 38,868 trip per day.

month before the end of the pilot, where the demand almost doubled in November with no special events observed in the city during this period and despite the cold weather. Also, Chicago had a different demand trend than the other cities, where the demand starts from a high value, and it decreased over time by a steady slope till two weeks before the end of the pilot, where the decreasing slope of the demand is steeper, which we believe was resulted or partially aided by the severe weather conditions during the end of the project period (CDOT, 2020). To compare the demand in the different cities, we controlled for the fleet size by calculating the number of trips per vehicle (average daily trips/number of vehicles). There was no change in the controlled demand pattern compared to the total demand, specifically in Minneapolis. Chicago showed a different trend when comparing the absolute demand with the number of trips per vehicle. The number of trips per vehicle started from a high number, over two trips per vehicle, and then dropped over time; the absolute minimum is around one trip per vehicle. Austin and Louisville's regular use demand has similar trends, with increased scooter demand during the summer and decreased demand during December and January. Comparing pilots with regular use demand in Austin shows an increase in the average daily use between the two use stages; however, it is not the case when controlling for the number of vehicles. It is also worth noting that from March 8 to 17, 2019, Austin hosted the South by Southwest (SXSW) conference and festival, which increased the demand for the scooters almost four times compared to the regular daily average demand. This showcases that events can significantly impact scooter demand, and scooters are more likely used for leisure purposes, which was also observed in other studies (McKenzie, 2019). Similarly, in Washington, DC, during the Cheery Blossom Festival (March 20–April 12, 2019), scooter use demand increased sharply compared to average days (Zou et al., 2020). Also, average demand tends to increase during Fridays and weekends, consistent with findings from other cities (Zou et al., 2020; Liu et al., 2019), except for the case of Minneapolis, where Thursday is the day with the highest average demand. The increased demand during the weekends is another indication that scooters are mainly used for leisure activities, Table 2.

As the exact daily number of available vehicles is not reported in any collected trip datasets, we used the maximum fleet size during the examined period to control the impact of vehicles available on the number of generated trips per vehicle. Fleet sizes changed over time in Austin and Louisville, but the fleet size was fixed for the other three cities, primarily due to the short pilot project duration. Fig. 3 shows the daily number of trips per vehicle trends after controlling the demand for the fleet size in the five examined cities. The overall number of trips per vehicle trend is almost similar to the absolute demand trend. However, the average number of trips per vehicle nearly doubled in Austin compared to the pilot period, which is the opposite case in Louisville, where the pilot period trips per vehicle are almost double the rate in later stages. The maximum utilization of the fleet was found in Calgary, with an average of approximately four trips per vehicle per day, almost 2–4 times the average ridership in other examined cities. The examination of the number of trips per vehicle prompts the need to monitor the number of available scooters and their utilization to avoid unnecessary, unused vehicles in the public right of way. Underutilized scooters can be a hazardous obstacle in public spaces.

4.2. Hourly and daily temporal demand

In the second stage of the temporal demand analysis, we analyzed and compared the aggregated average hourly demand for weekdays and weekends. We calculated the percentage of the hourly trip in reference to the average daily demand to normalize the impact of the vehicle's supply in the different cities and to be able to compare the hourly demand trends between the different cities. It is to be noted that shared mobility demand is a direct impact of the supply (Gammelli et al., 2020), which was another reason to consider controlling for the vehicular supply. Interestingly, the maximum hourly demand is almost consistent among all the cities, and it ranges between 8%–12% of the total demand as per Fig. 4. The only exception to the previous finding was in Minneapolis, where the average maximum hourly demand is high and it is around 15%. The general hourly demand in the different cities can be described as a bipolar distribution with two different sizes of peaks; one minor morning peak (between 8:00–10:00) in Austin, Chicago, and Calgary, during the weekdays, and the prime peak (in general between 16:00–18:00). On weekends, scooter demand has one peak during the afternoon and a higher percentage of early morning trips, starting after midnight, compared to the rest of the week. The only exception is Minneapolis, where the weekend and weekday demands are almost identical. Still, these observed patterns in Minneapolis could be because trips' starting times were coarsely aggregated to the nearest half-hour (Fig. 5).



(a) Austin, pilot

(b) Austin

(c) Calgary

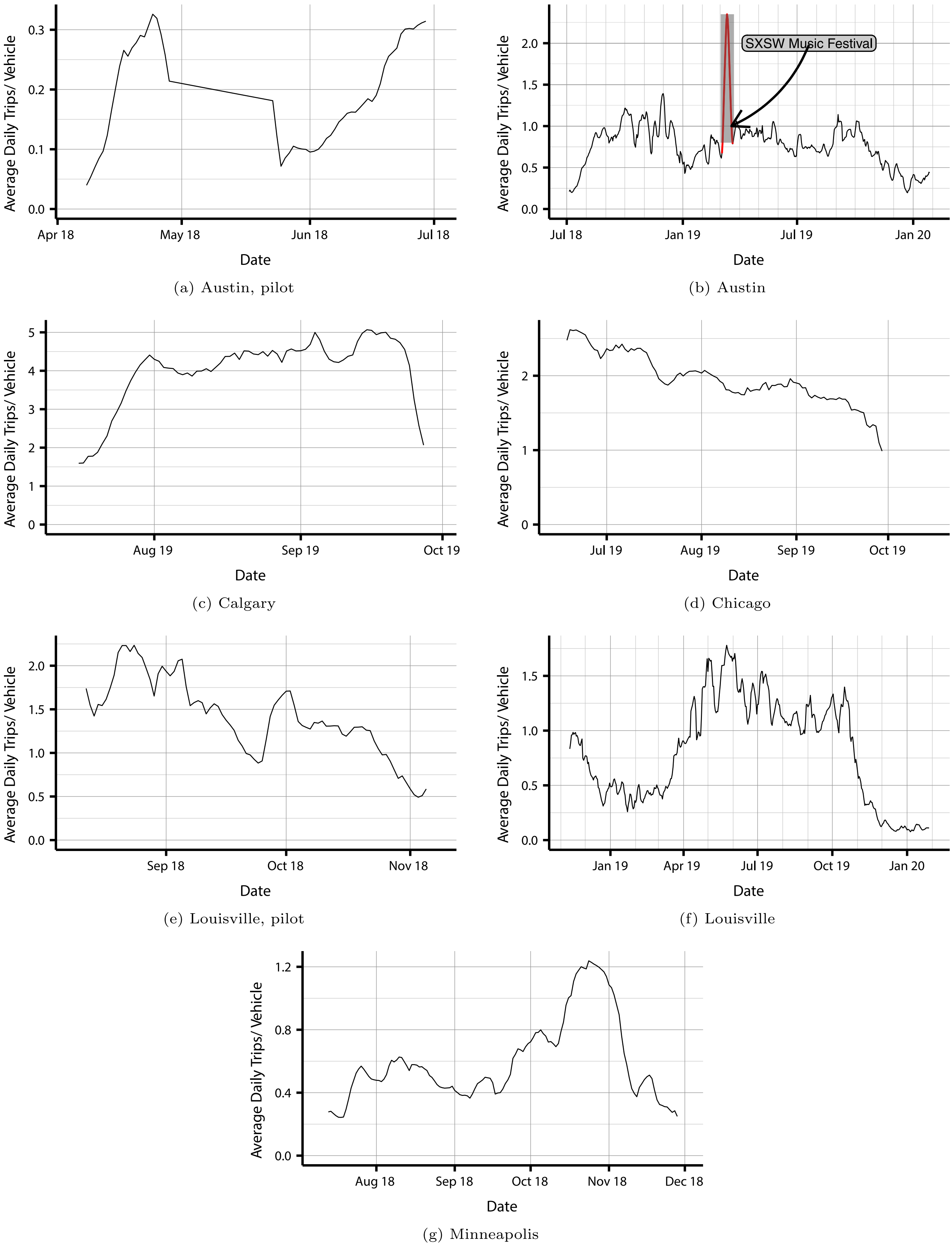
(d) Chicago

(e) Louisville, pilot

(f) Louisville

(g) Minneapolis

Fig. 2. Total daily demand, 7 days running average.



(a) Austin, pilot

(b) Austin

(c) Calgary

(d) Chicago

(e) Louisville, pilot

(f) Louisville

(g) Minneapolis

Fig. 3. Average daily trips/vehicle, 7 days running average.

The explored hourly demand trends suggest that scooters are mainly used for leisure or shopping trips and maybe for commuting to work outside of the regular 9 am to 5 pm jobs. Zou et al. (2020), Liu et al. (2019) reached a similar conclusion, analyzing the temporal distribution of trips in Washington DC and Indianapolis, IN, where during weekdays, the demand peaked between 12:00–17:00 and 16:00–19:00, respectively. The minor morning peak in Austin, Chicago, and Calgary is an indication that, in these cities, scooters might be used for commuting purposes during the morning hours or as a first and last-mile solution. This finding is consistent with the fact that, in these cities, the public transport modal share for work trips is high, as in Chicago, it is 28% of the total trips, which is almost six times the average rate for work trips in the USA.[5] Calgary also exhibits a high public transport use share of 16%, which is (40%) higher than the national average of 11.5%.[6]

Comparing the hourly trip distribution of Austin and Louisville with their pilots period reveals a change in demand pattern during the weekdays; refer to Fig. 4. The peak hour use in Austin shifts from noon in the pilot to 17:00 in the regular use. The peak hour shifts from 16:00 during the pilot to 13:00 in the post-pilot stage in Louisville. Interestingly, the overall demand distribution per hour changes, allowing for more late-night and early morning trips. It is not clear if the lack of late-night and early morning trips in Louisville's early stages is due to certain restrictions on operating hours. We did not find any evidence of this in the information in the operation documents published by the city. It is also worth mentioning that Chicago's pilot restricted the scooters' use from 5:00 am to 10:00 pm. The temporal demand analysis answers the first part of the first research question, and it gives additional insights into the scooter's temporal demand patterns.

4.3. Spatial demand analysis

In this subsection, we investigated the spatial demand characteristics, the similarities and differences of the demand between the different cities, and the change in demand over time in the same city. The temporal demand analysis results suggested a significant difference between the weekdays and weekend travel patterns; we differentiated between the weekdays and weekends when analyzing the spatial demand. We performed the spatial demand analysis in two steps. In the first step, we aggregated all the trips temporally into weekend and weekday trips; secondly, we aggregated the trips spatially to the census tracts corresponding to their starting locations. It is worth mentioning that the delineation of the tracts in the USA and Canada has a similar concept of being identified by committees of the local expert following visible features and encompass between 2500 to 8000 residents.[7] We normalized the difference between the weekend and weekday average trips per census tract to compare the examined cities' results. Figs. 6 and 7 present the results of the spatial analysis showing the geographically dominant areas by weekday. The spatial analysis of scooter demand reveals other exciting findings. In all cities, spatial demand exhibits a very similar pattern: during weekdays, the demand is concentrated outside the downtown area, especially around educational institutes, schools, and universities. During the weekends, demand is concentrated in downtown areas and around specific points of interest POIs, areas known for leisure activities, such as bars and restaurants, recreational areas, parks, and lakes.

We can describe the spatial demand pattern as, during weekdays, the University of Texas campus in Austin, the University of Minnesota in Minneapolis, and the University of Louisville in Louisville are the area of trip concentration. The weekdays trips concentration areas in Chicago are confined by West Harrison Street from the north side and West Taylor Street from the south side, where there are two ample size schools. In Austin and Louisville, the downtown areas are the main attractions during weekends. In Louisiana, Baxter avenue, a concentration area for restaurants and nightlife, and Louisville champions park by the Ohio River are prominent attractions during weekends. Minneapolis also illustrates a similar spatial demand distribution, except that the downtown area is split into two zones. The first zone is the area around the U.S. Bank Stadium, which generates more trips on weekdays. The other zone is the north loop neighborhood, a concentration area for restaurants, bars, and nightlife spots, and this area is an attractive area for weekend trips. The only exception to the previous pattern is Calgary, where the downtown area generates more trips during the weekdays. We believe that the high demand in Calgary's downtown area during weekdays is because several universities' campuses are located in the downtown area, creating a different spatial demand pattern than the other four cities.

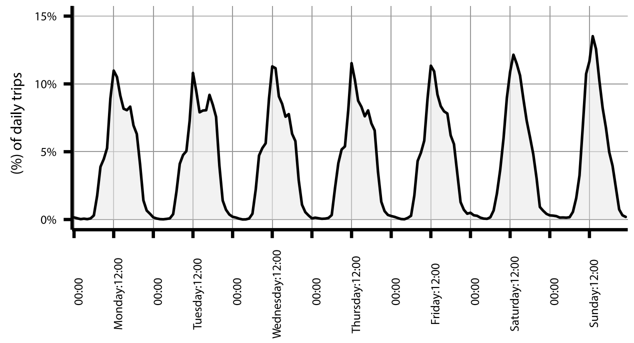
In Minneapolis and Calgary recreational areas play a significant role in attracting trips. In Minneapolis, the area around Lake Calhoun west of the city, where there are parks and scenic bike trails, generates a significant share of the city's trips on the weekends In Calgary, the Inglewood Park area generates more weekend trips than the downtown area, dominated by weekday trips. Also, in Chicago, the area around Wicker park, where there is a concentration of restaurants, pubs, and bars, is a trip concentration area during the weekends.

To check if there is a change in the spatial use pattern over time, we compared the early use stage pattern to the later use pattern in Austin and Louisville. Comparing the generated trips in the pilot period and the latter use stage reveals a change in the use pattern, as trips are more clustered in the later use stage than in the pilot period, where trips are spread over a larger area. In Austin, the change in the spatial use pattern over time is noticeable, especially in the downtown area and south of the Colorado River. Weekdays trips dominated the downtown area, and weekend trips dominated the south of the Colorado River. This pattern is reversed in the after-pilot period. The weekend trips dominate the downtown area, and the difference between the weekend and weekday trips almost vanished in the south of the river.

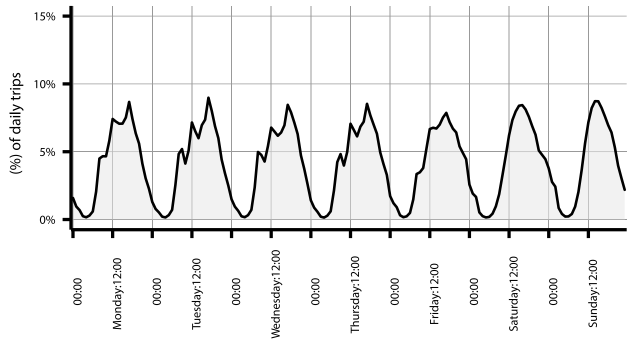
[5] censusreporter.org

[6] calgary.ca, www12.statcan.gc.ca

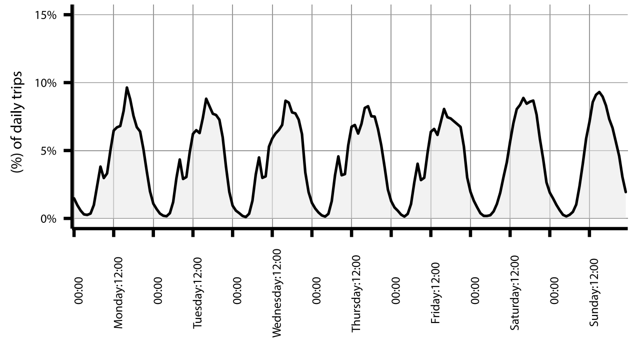
[7] www2.census.gov and www150.statcan.gc.ca, last accessed 15/03/2022.



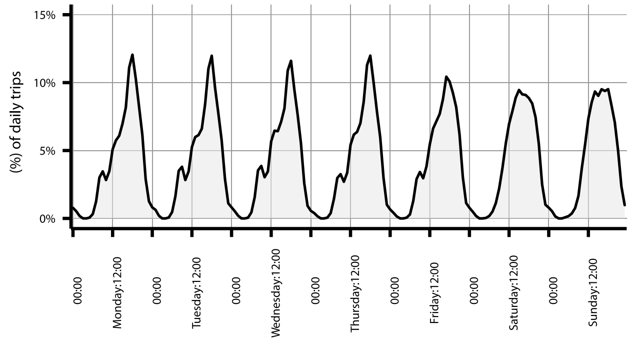
(a) Austin, pilot



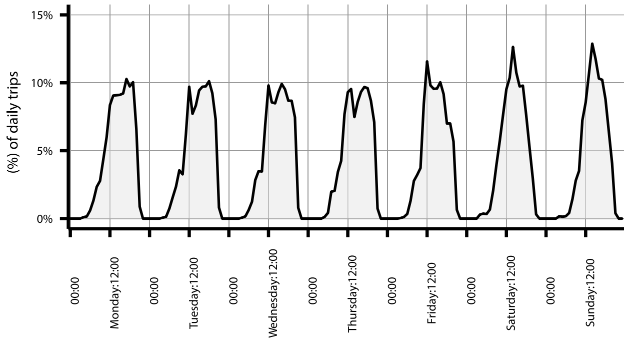
(b) Austin



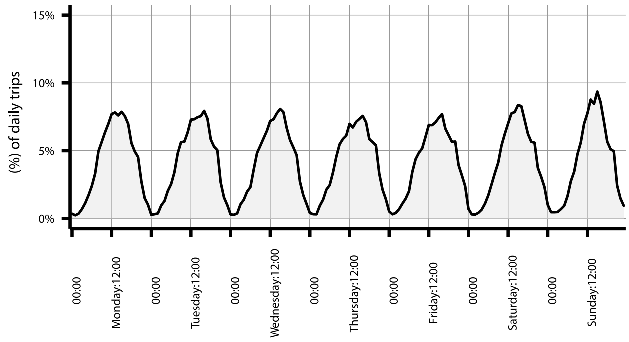
(c) Calgary



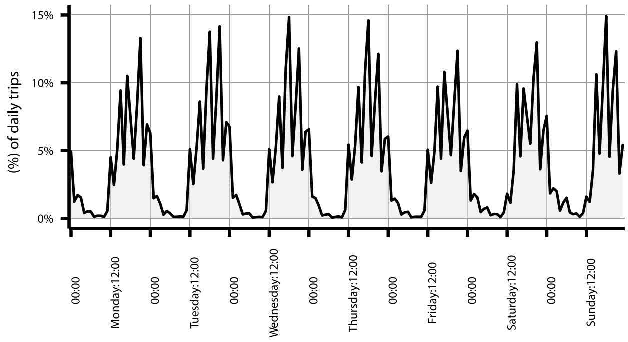
(d) Chicago



(e) Louisville, pilot

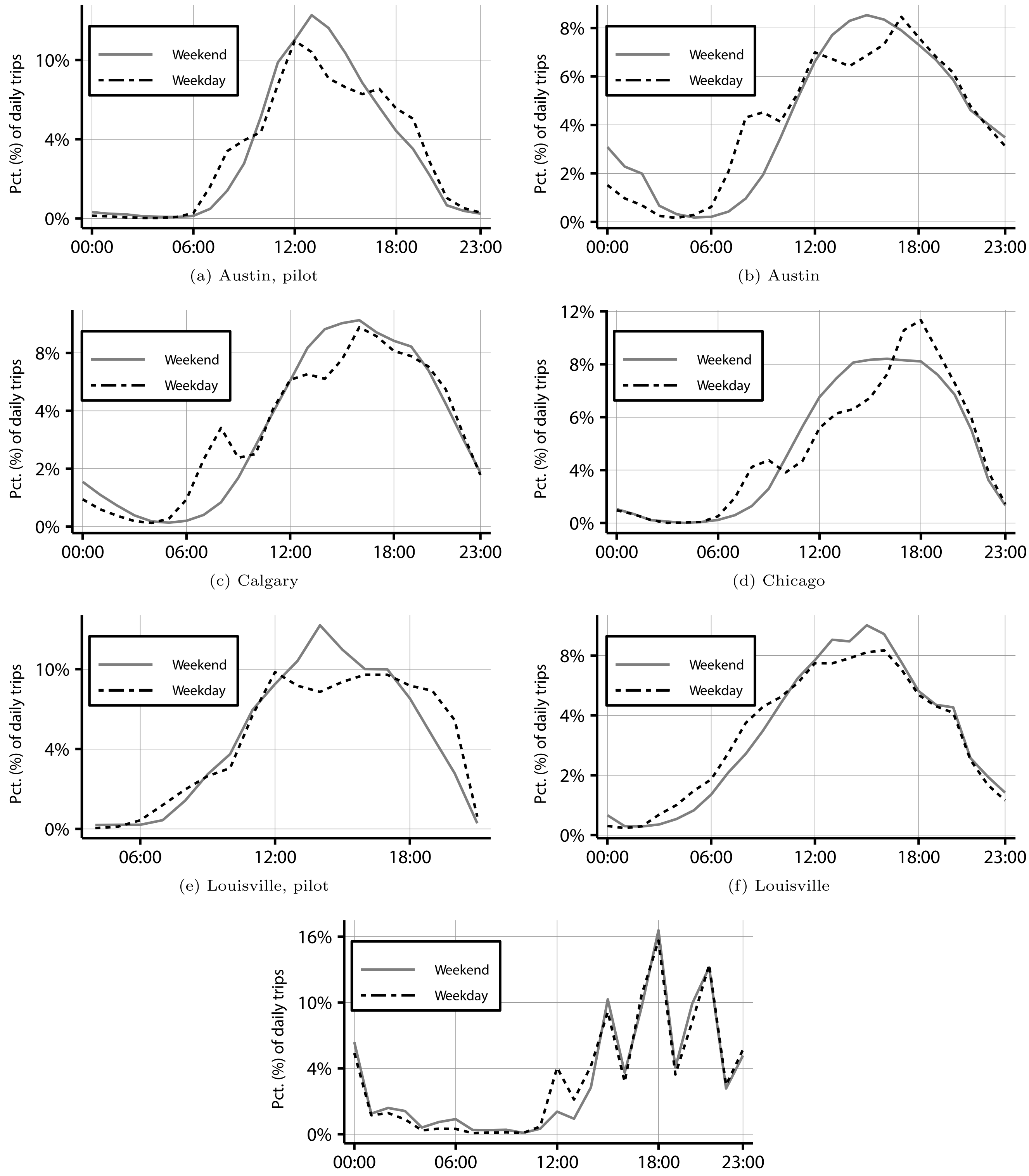


(f) Louisville



(g) Minneapolis

Fig. 4. Daily average hourly demand.



(a) Austin, pilot (b) Austin

(c) Calgary (d) Chicago

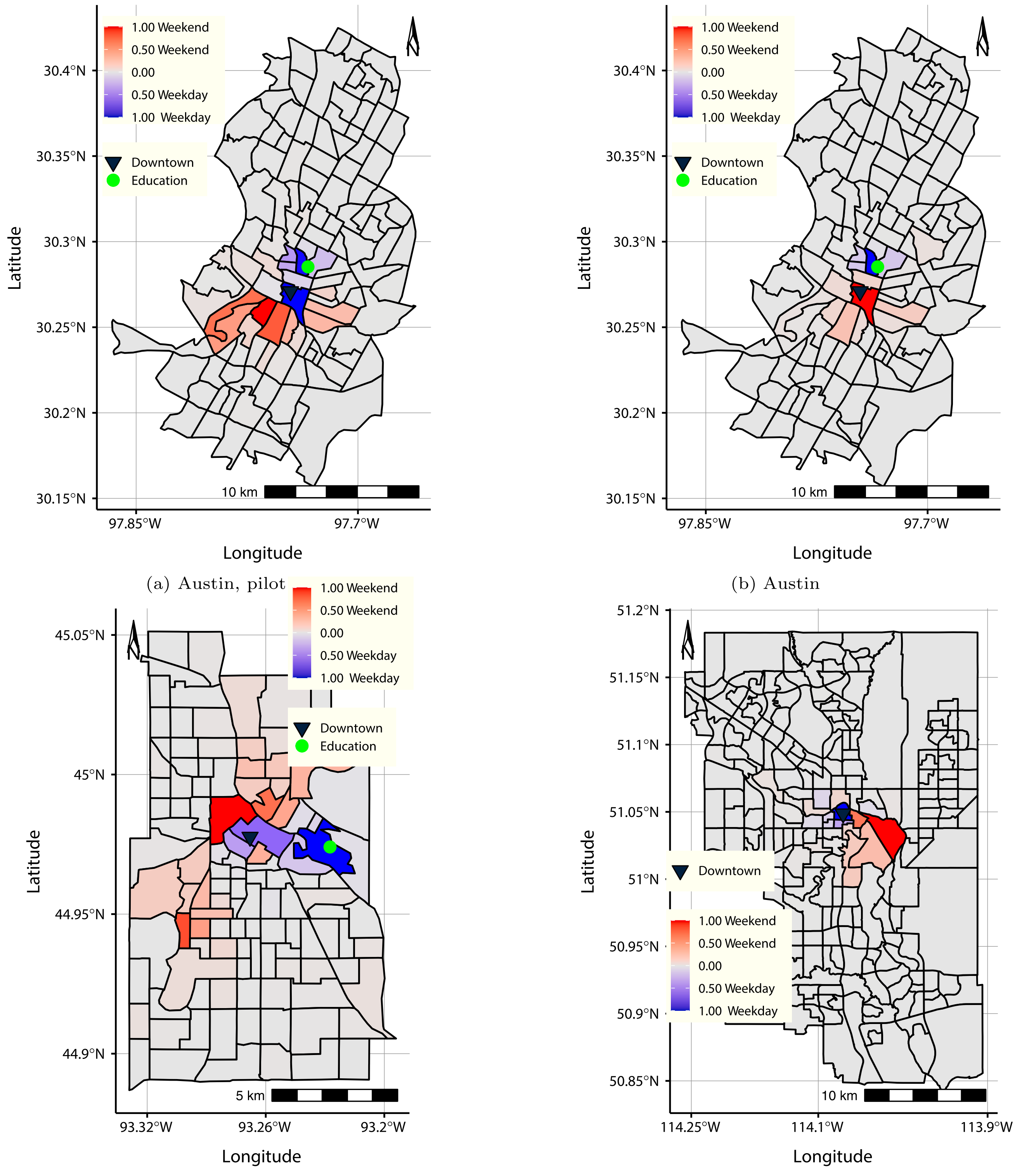
(e) Louisville, pilot (f) Louisville

(g) Minneapolis

Fig. 5. Aggregated average hourly demand distribution, weekdays vs. weekends.

4.4. Trip characteristics analysis

In this section, we analyzed the trip speed, distance, and duration distribution in the five cities, as shown in Table 3. The overall average trip distance is around 1.7±2 km. Interestingly, the pilot projects presented a longer average trip distance than those observed in later use stages in Austin and Louisville. In the discontinued pilot of Chicago, the average trip distance was longer than in other cities. Similar behavior holds for trip duration and trip speed, where pilots' trips are longer and faster than in the later



(a) Austin, pilot

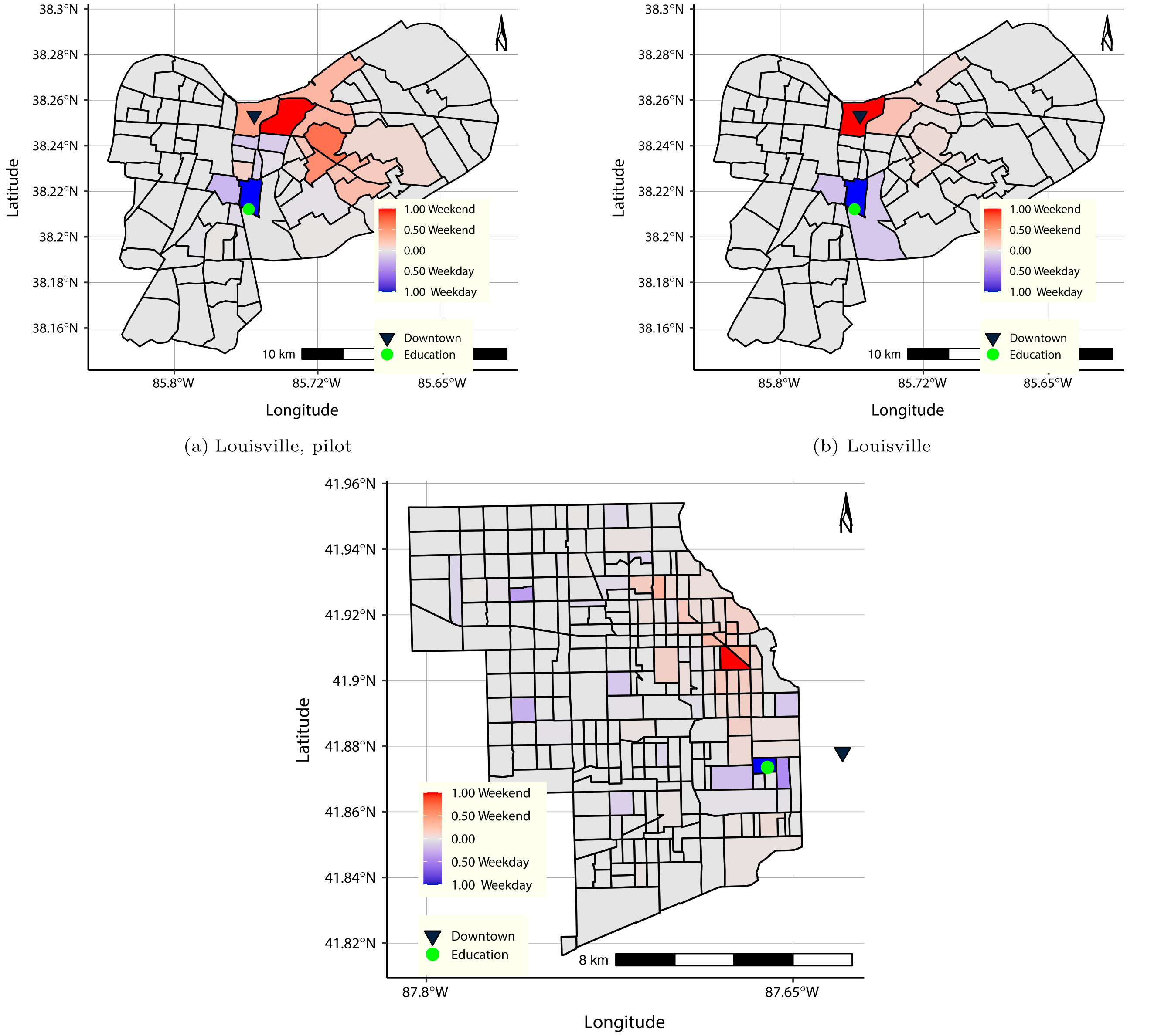
(b) Austin

(c) Minneapolis

(d) Calgary

Fig. 6. Spatial distribution of the dominance difference between weekends and weekdays trips aggregated by tract (continued).

use stage. Also, Chicago has the fastest trips on average, and Louisville has a long trip duration. Also, the trips' characteristics in the examined five cities are similar to the trip characteristics of Washington DC analyzed by Younes et al. (2020), Zou et al. (2020). It is worth mentioning that the average trip cost in all cities during the data collection period was 1$ for unlocking the vehicle and, on average, 0.33$ per minute; the price in Louisville was slightly lower than the other cities (1$ for unlocking the vehicle + 0.15$ per minute), which could be a reason for observing longer trips in Louisville (Noland, 2019).



(a) Louisville, pilot

(b) Louisville

(c) Chicago

Fig. 7. Spatial distribution of the dominance difference between weekends and weekdays trips aggregated by tract.

We had an initial hypothesis that scooter behavior might be different in terms of trip characteristics at different times of the day. Also, Abouelela et al. (2021a) noticed a different parking behavior for scooters based on the hour of the day. Therefore, we examined the average speed distribution per hour. Fig. 8 shows the average speed per hour per city. All cities exhibit a similar speed trend during the day, with a noticeable speed increase during the early morning and morning hours between (2:00–10:00), except for Minneapolis and Chicago. Minneapolis shows a slightly different hourly speed profile that departs from the average between 10:00 and 16:00. Chicago follows the same trend but with a different speed profile. The speed on average is around 12 km/hr, but still, it exhibits an increase in the early morning and morning hours between (2:00–10:00) to approximately 15 km/hr. The rise in the speed during the early morning hours in all the cities might be encouraged by the low traffic volume, which is a factor that might increase injury probability during that time of the day. However, it is not the only contributing factor to the increased likelihood of crashes and injuries among users; other factors, such as the high intoxication rates and users' familiarity with the service use, were reported by the patients (Störmann et al., 2020; APH, 2019).

5. Exogenous factors impacting trip generation

The dependent variable of the modeling process was the number of daily trips per census tract zone, as discussed in detail in Section 3.2. Tables 5 and 6 show the estimation results for each city's models, as well as a model estimated on the pooled data.

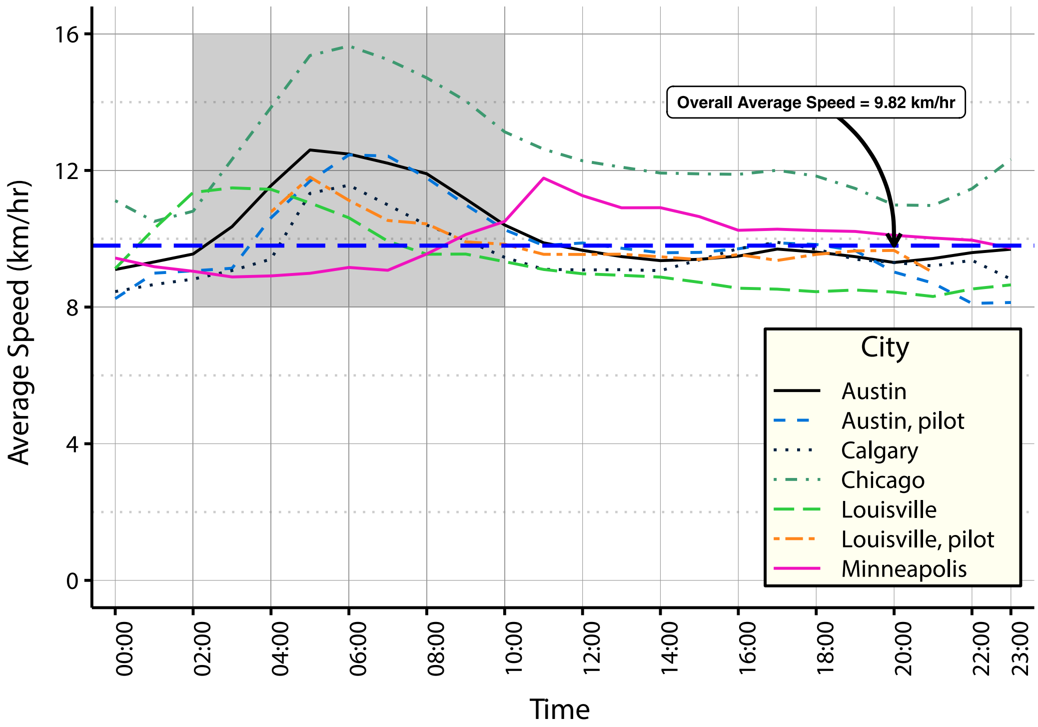


Fig. 8. Hourly Speed Profile.

Table 3
Trips characteristics summary statistics.

City	Distance (km)							
	Mean	SD	Min	25th Percentile	Median	75th Percentile	99th Percentile	Max
Austin, pilot	2.0	2.0	0.1	0.8	1.4	2.5	5.8	31.9
Austin	1.6	1.5	0.1	0.6	1.1	2.0	4.4	45.7
Calgary	1.8	1.9	0.1	0.6	1.3	2.3	5.6	27.0
Chicago	2.3	2.2	0.1	0.9	1.6	3.0	6.8	40.5
Indianapolis[a]	1.8	2.0	0.0	0.6	1.1	2.2	–	38.8
Louisville, pilot	2.8	2.9	0.1	0.8	1.7	3.6	8.9	26.5
Louisville	2.0	2.2	0.1	0.6	1.2	2.5	6.5	32.2
Minneapolis	2.1	2.3	0.1	0.7	1.3	2.5	6.8	38.1
	Duration (min)							
Austin, pilot	13.8	15.1	1.0	4.9	8.4	16.5	44.6	120.0
Austin	11.0	11.8	1.0	4.5	7.2	12.9	32.8	120.0
Calgary	12.8	12.9	1.0	5.1	8.5	15.4	38.7	119.9
Chicago	13.2	13.9	1.0	4.8	8.6	16.1	39.9	120.0
Indianapolis[a]	13.9	16.4	0.1	4.3	8.0	16.0	–	120.0
Louisville, pilot	18.4	18.8	1.0	6.0	11.0	24.0	59.0	120.0
Louisville	15.4	17.1	1.0	5.0	9.0	19.0	52.0	120.0
Minneapolis	14.3	17.1	1.0	4.6	7.7	16.3	50.7	120.0
	Speed (km/hr)							
Austin, pilot	9.9	4.0	0.1	7.0	9.8	12.7	16.6	25.0
Austin	9.8	4.6	0.1	6.4	9.3	12.7	18.1	25.0
Calgary	9.5	5.0	0.1	5.7	8.8	12.6	18.6	25.0
Chicago	12.0	5.5	0.1	7.9	11.9	15.7	21.2	25.0
Indianapolis[a]	8.8	4.1	1.6	5.6	8.4	11.5	–	40.2
Louisville, pilot	9.6	4.1	0.1	6.5	9.4	12.4	16.6	24.1
Louisville	9.0	4.5	0.1	5.7	8.5	12.0	17.1	24.1
Minneapolis	10.2	4.2	0.1	7.1	10.3	13.2	17.0	25.0

[a]Indianapolis summary data were retrieved from Liu et al. (2019).

Table 4 summarizes the models' significant variables and their units. Also, it is to be mentioned that all numeric variables were standardized to compare the magnitude of the different coefficients.

5.1. Coefficient interpretation

Weather and weekdays

Rainy days and snowy days reduce the probability of scooter use. On the other hand, warmer days increase the likelihood of scooters' use, except in Chicago, where the average daily temperature coefficient is not statistically significant. Wind speed has a mixed effect. In Austin, windy days increase the likelihood of scooter use; however, the wind speed coefficient is not statistically significant in Minneapolis. In Chicago and Louisville, windy days reduce the possibility of scooter use. Also, scooter use increased on the weekend compared to weekdays in all cities. It is a statistically significant factor in all cities except Minneapolis. The weekday temporal demand analysis showed the same results. Refer to Fig. 5.

Accessibility, infrastructure, and land use

Zones with higher transit accessibility (higher LITA value) generate more trips than other zones; the increase in the number of shared bike stations and the length of the bike lanes per zone increases the likelihood of scooters' use, except in Minneapolis; the coefficient of bike lanes is not statistically significant. Only in Louisville do the bike lanes have a negative sign coefficient indicating the reverse impact. This can be attributed to the geographic distribution of bike lanes in the northwest and southeast of the scooter operation zones, with fewer trip rates than in the downtown area. Sidewalk length per zone has a mixed impact on the probability of scooter use: in Austin, where it is permitted to ride on sidewalks, the increase in sidewalk length increases the trip generation; in other cities, however, it is not allowed to ride on the sidewalk, it reduced the trip generation rate. Residential land use reduces the probability of the number of generated trips in the area compared to other land uses.

Zero count model part

The zero count model part is the part of the model that predicts the excess zero, or –in other words– the factor that results in zero trips in the different zones. The previously estimated parameters were also significant for reducing trip generation, with opposite signs indicating the adverse effects, except for population density and bike lanes. These were not significant in all the estimated models and were thus removed from the zero count part.

6. Discussion and conclusion

This study used around nine million scooter trips from five North American cities to investigate scooters' demand, trip characteristics, and the factors impacting their use. Several findings suggest the consistency of scooter use in different cities, despite their size and population, urban structure, and the general travel demand behavior. The conclusions revealed could help organize the shared-e-scooter service in other cities, or they can be used as guidelines before deploying the service in other cities. The main findings' impacts on operation policies are discussed in the following subsections.

6.1. Demand patterns

Weekdays scooters' hourly demand has similar patterns in all the examined cities; the hourly demand can be described as a bimodal distribution exhibiting two peaks, one in the morning and the other in the evening. The weekend demand pattern is different from the weekday demand, as it has only one peak in the late afternoon. Maintenance and redistribution work should consider spatiotemporal demand patterns. Demand patterns should be synchronized with maintenance and vehicle redistribution work to allow the vehicles to be present during peak demand hours. Moreover, the predefined scooter demand patterns would utilize the vehicle redistribution work to minimize the empty VKT.

Scooter demand shows several individuals' atypical temporal patterns. For example, in cities that allow late-night operation, late-night use typically increases during the weekends. This increase in late night/ early morning hours scooter demand is an indication that scooters could extend the temporal accessibility for travel options, especially if the vehicles are available in high-demand places during these times. Moreover, scooters' demand increase was found to be associated with the increase in accessibility to PT, as indicated in the estimated regression models, and micromobility has received increased attention as a viable mode for the first/last mile dilemma (Abouelela et al., 2021a; Bai and Jiao, 2020; Jiao and Bai, 2020). That said, micromobility can be used as a mode that would encourage the concept of multimodality, especially in addition to the previous facts there are a significant amount of car trips that are shorter than the average scooter's trip (FHWA, 2014). An initiative such as subsidizing scooters' trip costs for PT users and making scooters available in the park and ride facilities should be considered methods for encouraging scooter use and multimodality. Also, another proposal to increase the integration between PT and last-mile services could be extending the validity of the PT tickets to include the use of micromobility services. However, encouraging scooter use, approaches should be carefully planned, as it should consider avoiding attracting users of other active modes, which is already noticed as the majority of scooters; replaced trips are active mobility trips (6-t, 2019; ADOPT, 2019; Sanders et al., 2020).

Furthermore, seasonal demand trends indicate an increase during warmer months and a demand drop around January. Considering such patterns could help dynamically adjust the fleet size over the year to optimize operating costs and allow for vehicle maintenance during the low demand periods. Scooters' demand is sensitive to special events; in Austin, the daily demand

Table 4
Independent variable summary statistics.

Variable	Unit	Austin				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.17	0.08	0.00	0.17	0.36
Age 18 to 24 years	pct %	0.11	0.15	0.01	0.08	0.95
Bike lane	length Km	1.14	2.54	0.00	0.00	14.72
Sidewalk length	length Km	37.01	18.28	1.67	33.06	125.04
Shared bike station	count	0.25	0.97	0.00	0.00	6.00
LITA	–	5.50	0.76	4.38	5.40	9.72
Male Pct	pct %	0.52	0.06	0.40	0.51	1.00
Median income	Thousand U$	65.24	30.06	8.75	60.88	171.19
Population density	person/km2	2,372.16	1,685.12	35.53	2,080.17	11,028.64
Mean daily temperature	Fahrenheit	69.4	14.93	33.00	71.18	92.78
Wind Speed	mph	5.53	2.45	0.96	5.19	13.50
Land use (Residential)	pct %	0.38	0.18	0.00	0.4	0.71
Snowy days	pct %	0.00	–	–	–	–
Rainy days	pct %	16.00	–	–	–	–
Variable	Unit	Chicago				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.23	0.08	0.04	0.23	0.45
Age 18 to 24 years	pct %	0.11	0.06	0.02	0.10	0.48
Bike lane	length Km	0.62	0.85	0.00	0.34	6.80
Sidewalk length	length Km	22.24	12.45	1.51	19.08	87.86
Shared bike station	count	5.96	6.49	0.00	4.00	50.00
LITA	–	5.50	0.76	4.04	5.42	9.54
Male Pct	pct %	0.49	0.05	0.31	0.49	0.90
Median income	Thousand U$	54.90	30.30	13.74	47.78	159.02
Population density	person/km2	7,253.87	3,132.64	879.49	7,271.78	16,069.96
Mean daily temperature	Fahrenheit	71.0	6.48	47.16	71.42	85.95
Wind Speed	mph	7.80	2.53	2.78	7.54	14.37
Land use (Residential)	pct %	0.37	0.15	0.00	0.4	0.60
Snowy days	pct %	0.00	–	–	–	–
Rainy days	pct %	30.00	–	–	–	–
Variable	Unit	Louisville				
		Mean	SD	Min	Median	Max
Age under 18	pct %	0.11	0.10	0.02	0.09	0.79
Age 18 to 24 years	pct %	0.21	0.08	0.04	0.21	0.43
Bike lane	length Km	2.79	4.86	0.00	1.84	36.19
Sidewalk length	length Km	4.54	7.90	0.00	1.23	45.80
Shared bike station	count	0.34	1.91	0.00	0.00	16.00
LITA	–	5.51	0.81	4.47	5.37	10.75
Male Pct	pct %	0.48	0.04	0.37	0.48	0.62
Median income	Thousand U$	44.49	25.40	9.64	35.62	158.21
Population density	person/km2	2,023.63	816.15	492.33	1,953.60	4,019.25
Mean daily temperature	Fahrenheit	56	18.04	7.96	53.48	86.51
Wind Speed	mph	7.23	3.18	0.97	6.55	19.91
Land use (Residential)	pct %	0.42	0.18	0.02	0.45	0.71
Snowy days	pct %	2.00	–	–	–	–
Rainy days	pct %	22.00	–	–	–	–
Variable	Unit	Minneapolis				
		Mean	Sd	Min	Median	Max
Age under 18	pct %	0.21	0.10	0.01	0.21	0.43
Age 18 to 24 years	pct %	0.11	0.13	0.02	0.08	0.89
Bike lane	length Km	2.09	3.98	0.00	0.20	27.96
Sidewalk length	length Km	5.57	7.75	0.00	2.39	46.05
Shared bike station	count	0.89	1.82	0.00	0.00	12.00
LITA	–	5.87	0.91	5.21	5.68	12.30
Male Pct	pct %	0.51	0.04	0.38	0.50	0.67
Median income	Thousand U$	62.70	29.67	18.23	57.14	155.11
Population density	person/km2	3,697.53	2,129.68	611.81	3,216.84	14,118.84
Mean daily temperature	Fahrenheit	55.7	18.90	14.16	61.17	81.12
Wind Speed	mph	7.98	2.94	2.45	7.84	15.93
Land use (Residential)	pct %	0.20	0.16	0.01	0.15	0.73
Snowy days	pct %	6.00	–	–	–	–
Rainy days	pct %	19.00	–	–	–	–

Table 5
ZINB model results-A.

	Pooled			Austin			Chicago		
	Count model coefficients (negbin with log link):								
	β	Std. Error	Z value	β	Std. Error	Z value	β	Std. Error	Z value
(Intercept)	2.65	0.01	227.51	2.93	0.01	200.18	3.20	0.03	111.38
Mean Temperature	0.03	0.01	5.17	0.08	0.01	11.76	–	–	–
Mean Wind speed	0.05	0.01	8.13	0.05	0.01	8.51	−0.03	0.01	−1.94
Precipitation Yes vs No	−0.26	0.01	−18.19	−0.25	0.02	−13.69	−0.08	0.03	−2.55
Snow Yes vs No	−2.46	0.09	−26.69	–	–	–	–	–	–
Weekend Vs Weekday	0.31	0.01	24.57	0.35	0.01	24.68	0.09	0.03	2.96
Population Density	0.53	0.01	64.76	0.74	0.01	59.12	0.63	0.02	32.33
Bike lane length	0.23	0.01	26.47	0.43	0.01	38.46	0.52	0.02	23.51
Sidewalk length	0.45	0.01	67.45	0.59	0.01	74.34	−0.04	0.02	−2.04
Shared Bike station	0.29	0.01	45.98	0.22	0.01	28.48	0.17	0.02	9.91
LITA	0.31	0.01	50.05	0.42	0.01	48.19	0.04	0.02	2.17
Gender Male vs Female	0.28	0.01	22.50	0.41	0.01	28.65	−0.79	0.04	−18.84
Age under 18 Pct.	−0.59	0.01	−60.37	−0.87	0.01	−67.15	−0.51	0.02	−22.39
Age 18 to 24 pct.	0.08	0.01	9.77	−0.12	0.01	−9.89	−0.09	0.02	−4.96
Median Income	0.06	0.01	6.46	0.24	0.01	18.28	−0.16	0.02	−7.84
Land use Residential vs other	−0.85	0.02	−47.53	−1.06	0.02	−51.46	−1.03	0.05	−22.79
Log(theta)	−1.09	0.01	−177.60	−0.66	0.01	−79.36	−1.11	0.02	−60.88
	Zero-inflation model coefficients (binomial with logit link):								
	β	Std. Error	Z value	β	Std. Error	Z value	β	Std. Error	Z value
(Intercept)	−1.66	0.03	−59.28	−2.21	0.04	−50.32	−1.55	0.08	−19.65
Mean Temperature	−0.05	0.01	−4.03	0.50	0.02	29.05	−0.11	0.03	−4.39
Mean Wind speed	0.05	0.01	4.73	−0.03	0.02	−2.11	0.09	0.02	3.75
Precipitation Yes vs No	0.19	0.03	6.89	0.33	0.04	8.22	0.15	0.05	2.82
Snow Yes vs No	2.45	0.14	17.57	–	–	–	–	–	–
Weekend Vs Weekday	−0.02	0.02	−0.97	–	–	–	−0.14	0.05	−2.52
Sidewalk length	−0.23	0.02	−14.80	0.24	0.02	13.31	−0.39	0.04	−9.10
Shared Bike station	−1.88	0.05	−37.54	–	–	–	−1.50	0.08	−18.90
LITA	−1.49	0.02	−66.51	−2.57	0.04	−63.78	−0.26	0.03	−8.54
Gender Male vs Female	−0.91	0.02	−37.36	−0.87	0.03	−27.29	0.17	0.06	3.00
Age under 18 Pct.	0.24	0.01	16.26	0.08	0.02	3.34	–	–	–
Age 18 to 24 pct.	−1.12	0.04	−31.81	−2.21	0.08	−27.43	–	–	–
Land use Residential vs other	0.25	0.03	9.83	0.58	0.04	15.38	−0.53	0.08	−6.72
Median Income	−0.60	0.02	−33.31	−1.35	0.03	−43.33	−1.35	0.06	−22.90

was around four times the average demand during the South by the Southwest (SXSW) music festival; similar behavior was also observed in Washington DC during the Cherry Blossom festival (Younes et al., 2020). Therefore, the supply should be coordinated to serve such events. A potential advantage of deploying shared-e-scooters versus "heavier" shared mobility system vehicles, such as carsharing, is that they are easier to transport and deploy, require less infrastructure, contribute less to congestion and take up less public space. However, the deployment of scooters should also include consideration for supplemental services, such as fleet redistribution and maintenance. When comparing the daily demand in the Austin and Louisville pilots, there is an apparent change in the hourly demand distribution with the later use stage. This pattern indicates the dynamic nature of the scooter use, which requires the operators to continuously re-plan the service design based on monitoring the temporal changes in the demand use patterns.

Spatial demand patterns are generally consistent between the examined cities, regardless of their urban structure differences. Spatial demand is concentrated around leisure activities, such as restaurants, bars, and parks during weekends, while on weekdays, around the downtown area and educational institutes. Also, the demand is more geographically dispersed on the weekends than the more compact and clustered weekday demand. The distribution and maintenance operations should consider these locations as hot spots, while after the weekend, the redistribution process should cover more expansive areas to retrieve the scooters.

Chicago, Calgary, and Minneapolis pilot projects have witnessed a drop in demand near the end of the project. The severe weather justified this drop by the end of the pilot duration in Chicago. At the same time, there is no evidence of why the demand dropped in the Minneapolis and Calgary cases. The reasons for demand dropping should be widely investigated, as it could have resulted from the lack of adequate publicity of the project's period or even the reduction of the provided vehicles by the operators towards the end of the pilot project; or users' loss of interest, which might be a negative indicator to further go with the full-service deployment stages.

6.2. Trip characteristics and service use progress

Average trip speed, distance, and duration are consistent among the five examined cities. Pilot projects and early use stages exhibited slightly higher speeds and longer trip distance and duration, possibly due to new users' excitement. Considering that

Table 6
ZINB model results-B.

	Louisville			Minneapolis		
	Count model coefficients (negbin with log link):					
	β	Std.Error	Z value	β	Std.Error	Z value
(Intercept)	1.56	0.02	75.14	1.20	0.03	43.23
Mean Temperature	0.49	0.01	44.86	−0.12	0.02	−6.91
Mean Wind speed	−0.07	0.01	−6.50	–	–	–
Precipitation Yes vs No	−0.13	0.02	−5.38	−0.15	0.03	−4.44
Snow Yes vs No	−0.80	0.12	−6.90	−1.02	0.09	−11.88
Weekend Vs Weekday	0.20	0.02	9.51	–	–	–
Population Density	−0.01	0.01	−1.26	0.03	0.01	1.74
Bike lane length	−0.28	0.01	−26.47	–	–	–
Sidewalk length	–	–	–	–	–	–
Shared Bike station	0.12	0.02	7.20	0.47	0.02	21.39
LITA	0.50	0.02	21.70	0.34	0.02	17.80
Gender Male vs Female	−0.07	0.02	−3.07	0.19	0.03	6.18
Age under 18 Pct.	−0.62	0.01	−42.25	−0.52	0.01	−35.46
Age 18 to 24 pct.	0.45	0.01	49.85	0.45	0.01	32.05
Median Income	0.20	0.02	10.18	−0.05	0.02	−2.57
Land use Residential vs other	−1.28	0.04	−34.70	−0.19	0.05	−3.69
Log(theta)	−0.13	0.02	−7.84	−0.10	0.02	−4.66
	Zero-inflation model coefficients (binomial with logit link):					
	β	Std.Error	Z value	β	Std.Error	Z value
(Intercept)	−0.26	0.04	−6.53	−1.79	0.09	−20.46
Mean Temperature	−0.81	−0.02	34.87	−0.59	0.04	−14.28
Mean Wind speed	–	–	–	−0.11	0.03	−3.18
Precipitation Yes vs No	0.27	0.05	5.36	0.25	0.09	2.90
Snow Yes vs No	–	–	–	2.11	0.19	10.97
Weekend Vs Weekday	−0.11	0.04	−2.48	−0.13	0.07	−1.76
Sidewalk length	−1.51	−0.07	22.65	–	–	–
Shared Bike station	–	–	–	−1.81	0.11	−16.35
LITA	−1.88	−0.05	40.78	−1.64	0.12	−13.57
Gender Male vs Female	−1.03	−0.05	20.99	–	–	–
Age under 18 Pct.	0.50	0.03	16.31	0.58	0.04	14.03
Age 18 to 24 pct.	−1.02	−0.05	19.10	−1.36	0.12	−11.54
Land use Residential vs other	–	–	–	−1.86	0.46	−4.06
Median Income	0.10	0.04	2.84	0.12	0.04	2.84

accidents are highly correlated with a lesser familiarity with service use (APH, 2019), which has a higher probability during the scooter introduction period, strict monitoring for vehicle speed should be applied. Furthermore, both cities and operators should provide educational marketing plans to educate the users about how they would use the service adequately and the rules for using the vehicles, identifying the hazards that could arise from the improper use.

6.3. Factors impacting the demand

External factors impacting the demand are almost the same in the different cities; however, their magnitude might differ from one city to another. Meteorological conditions play a significant role in demand generation, with snow and rain being decisive factors. Therefore, seasonal maintenance and fleet size control should be utilized dynamically based on the short and long-term weather forecast to avoid excessive vehicle deployment that is not needed to cater to the expected low demand. They most likely will be occupying public spaces that might impair accessibility. Land use, PT accessibility, and infrastructure are also essential factors impacting the demand, and they are hard to change factors. The previous factors need long-term high capital investment to alter; therefore, scooter deployment should be coordinated to utilize scooter use and decrease disturbance for the other elements of the urban environment. For example, scooter deployment should be reduced in dominantly residential areas. In areas with high PT accessibility, the supply should be increased to encourage scooters' use as a first and last-mile solution.

Finally, sociodemographics such as age and income level affect scooter demand; therefore, scooter deployment should consider the population distribution; for example, areas with a younger population might require more vehicles than areas with older population groups. Income-level impact on scooter demand has been observed in different studies (Bai and Jiao, 2020; Jiao and Bai, 2020); that said, the effect of income level raises the question: is scooter use equitable or not? Cities such as Louisville and Chicago implemented measures to improve scooter use equity. Louisville operators have provided options for cash payment and discounts for people with no credit cards or smartphones. Also, some operators provided discounts for the people who receive public aid (Louisville Open Data, 2022). In Chicago, operators were asked to deploy a certain percentage of their scooters in inequitable access to transportation areas and provide accessibility to scooter use for the unbanked population (CDOT, 2020). There is no evidence that these measures used to increase equity were successful. Chicago's pilot program reported that only on average, five trips from every 10,000 completed trips (.05%) were made by the unbanked population (CDOT, 2020). Authorities in different cities should ensure that the recommendations to increase scooter equity are effective using personal interviews and surveys. The investigation of equity of use should target minority and marginalized groups such as groups with low income, ethnic minorities, non-drivers, and geographical places with reduced transit accessibility, to investigate the users' service use pattern and what factors impact their use, to include them within the system regular users group.

The optimum scooter deployment process is complicated; it should consider multi-dimensions (weather, built environment, and sociodemographics) holistically and dynamically. However, the scooter can be a policy tool that is used by the city to close the gap in the transportation system in a spontaneous low-cost fashion.

6.4. Study limitations

There is no available data reflecting the exact daily number of scooters available in the public right of way; the only available information is the fleet size for each city, reflecting the maximum allowable number of scooters. Therefore, when controlling for the number of vehicles, the exact daily number of scooters was not used, which might affect the actual number of trips per vehicle rate; however, we do not think the overall observed demand trend might have been affected by the lack of the exact number of vehicles. We also did not consider the influence of the re-balancing and redistribution of the vehicle processes that might impact the demand. There was no available information regarding these processes. We assumed that scooters are uniformly distributed through the study area, especially for the datasets where trip Geo-location was aggregated. We believe that the availability of such information should enhance our understanding of the demand pattern. The data used are collected through different periods with no complete overlap, which is expected due to the nature of such data; however, it still represents a limitation.

6.5. Conclusion

This research analyzed scooter trips from four US and one Canadian city to answer three main research questions regarding the different demand patterns and the exogenous factors that impact the demand. The answers to the research questions have helped us better understand and provide insights into the current scooter use on different levels. Cities and operators may find these insights helpful in planning the operational schemes for current or future scooter-sharing projects. Based on the demand patterns, both cities and users are satisfied with scooter use, as expressed by the demand increase and the continuation of the pilot projects in cities like Minneapolis and Chicago. Future research can provide additional insights into this topic, which is only now gaining momentum.

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Exploring the Potentials of Open-Source Big Data and Machine Learning in Shared Mobility Fleet Utilization Prediction

Mohamed Abouelela[1] · Cheng Lyu[1] · Constantinos Antoniou[1]

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Abstract

The urban transportation landscape has been rapidly growing and dynamically changing in recent years, supported by the advancement of information and communication technologies (ICT). One of the new mobility trends supported by ICT is shared mobility, which has a positive potential to reduce car use externalities. These systems' recent and sudden introduction was not adequately planned for, and their rapidly growing popularity was not expected, which resulted in the urgent need for different stakeholders' intervention to ensure efficient services' integration within the urban transportation networks and to grant an effective system operation. Several challenges face shared mobility, including fleet size management, vehicle distribution, demand balancing, and the definition of equitable prices. In this research, we developed a practical, straight-forward methodology that utilizes big open-source data and different machine learning (ML) algorithms to predict the daily shared-e-scooter fleet utilization (the daily number of trips per vehicle) that could be used to drive the system's operation policies. We used four ML algorithms with different levels of complexity, namely; Linear Regression, Support Vector Regression, Gradient Boosting Machine, and Long Short-Term Memory Neural Network, to predict the fleet utilization in Louisville, Kentucky, using the knowledge the models get from the training data in Austin, Texas. The Gradient Boosting Machine (LightGBM) was the model with the best performance prediction based on the different evaluation measures. The most critical factors impacting daily fleet utilization prediction were temporal time series features, sociodemographics, meteorological data, and the built environment.

Keywords Shared mobility · Micromobility · Shared-E-scooter · Machine learning · Demand prediction · Open source data

Introduction

The urban population is rapidly growing at an unexpected rate led by the increasing urbanization movement; the UN expects that by 2050, 80% of the world population will live in urban areas, compared to 49% in 2010 (United Nations Department of Economic and Social Affairs 2018). The urban population growth is coupled with a substantial increase in travel demand, air pollution, accidents, and more congested urban networks (Zannat and Choudhury 2019). Investment in infrastructure and significant land-use changes might be required to meet the expected growth of travel demand; however, such solutions need significant investments and long time processes to materialize, which are not always viable solutions (Bhattacharya et al. 2012; Estache 2010). Innovative solutions supported by the latest advancement in information and communication technologies (ICT) could represent a smart, efficient way to cater to the increased demand. The advancement of ICT already supports (fully or partially) the revolutionizing of the urban transportation systems; in the main developing areas of transportation; electrification, sharing, and automation (Sperling 2018).

Shared mobility services are one example of the recent innovative solutions that could cater to the expected increase in travel demand. These services provide commuters with access to different vehicle types or the ability to share rides based on the users' needs (Shaheen et al. 2016; Shared and

✉ Mohamed Abouelela
Mohamed.abouelela@tum.de

Cheng Lyu
cheng.lyu@tum.de

Constantinos Antoniou
c.antoniou@tum.de

[1] Chair of Transportation System Engineering, Technical University of Munich, Arcisstrasse 21, 80333 Munich, Germany

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Digital Mobility Committee 2018). The umbrella of shared mobility services covers different service types that can be split into two main categories; (i) sharing of rides based on different operational schemes such as the case of e-hailing, ridesharing, ride pooling, and alternative transit systems. (ii) The direct use of the vehicle based on need, such as the case of carsharing and micromobility services, e.g., bikesharing and shared-e-scooter, which are the focus of this research. Shared mobility services have many positive potential impacts on the urban environment, including reducing vehicular traffic (Abouelela et al. 2021b, 2023), reducing energy consumption, and increasing transport system efficiency by achieving saving in travel time and travel costs (Becker et al. 2020). Notwithstanding the possible positive effects of shared mobility services, some of them have integration, planning, and policies challenges following their sudden and novel introduction to the urban environment, such as the case of shared-e-scooters, we will refer it as *scooters* in the rest of the article. Scooters are one of the youngest members of the shared mobility services family, launched in July 2017 by Lime (www.li.me) in Santa Monica, California. 38.5 million trips were completed by scooters in the USA by the end of 2018, representing 45.8% of the total micromobility trips for the same year. In the following year, 2019, the number of scooter trips raised to 88.5 million in 109 cities in the USA, representing an exponential increase of 130% of the previous year's trips (NACTO 2019). Scooter use and growth were not limited to the US, but it was a global phenomenon observed in Asia, Europe, and Australia (Santacreu et al. 2020; Heineke et al. 2019; Møller and Simlett 2020). The micromobility market is expected to grow to between \$330 and \$500 billion by 2030 (Heineke et al. 2019). However, the growth of scooters faces several challenges, such as the increase in related injuries (Yang et al. 2020a; Namiri et al. 2020), defining the optimal fleet size, vehicles optimal redistribution strategies, speed limits enforcement, and equity regulations (Janssen et al. 2020). In order to further study these problems and define their causes and factors leading to them, more data is required.

Recently, the term big data has gained popularity and attracted more effort from the industry and the research sides to explore the opportunities it can create. The advancement of ICT has also opened the horizon for collecting and analyzing new types of data in large quantities, or so-called big data (Stojanović and Stojanović 2020; Chaniotakis et al. 2020). Other factors have helped in the collection of large amounts of data, such as but not limited to; the increase in the computational power of computers, the decreasing cost of data storage, and the exciting direction towards smart cities platforms, have also enriched the interests in big data (Iliashenko et al. 2021; Xin et al. 2020; Torre-Bastida et al. 2018; Zhu et al. 2018). Big data have been examined in many applications related to transportation research, e.g., estimating transit network origin–destination flows (Liu et al. 2021a), availability of parking supply using sentiment analysis of the location-based social network data (LBSN) (Chaniotakis et al. 2022; Jiang and Mondschein 2021), improve traffic management and traffic planning (Haghighat et al. 2020), and the impact of pricing schemed changes on bikesharing use (Venigalla et al. 2020). Different entities, primarily operators and cities' authorities, are currently sharing their data (big based on volume, velocity, or variety) openly to encourage the innovation of new methods and ideas to improve the urban environment, to increase integration between the different transportation services, and to help in regulating and dynamically adjusting the operation of various shared mobility services within the urban environment (Durán-Rodas et al. 2020a; Iliashenko et al. 2021).

In this research, we use the publicly available scooter trips data from two American cities, Louisville, Kentucky, and Austin, Texas, in combination with other open data sources, discussed in detail in the methodology sections to explore the potential and accuracy of using open-source data and machine learning (ML) techniques to predict the scooter daily fleet utilization (number of trips per vehicle). The main goal of this research is to create and develop a framework that could help the different stakeholders involved in the operation, organization, and governance of the micromobility services to integrate the service in the urban environment efficiently and to facilitate the policy-making process.

The main contribution of this research comes from developing a framework for scooter fleet utilization prediction (daily number of trips per vehicle) using different sources of publicly available data and how this information is processed (including feature engineering) to obtain the optimum prediction results in terms of prediction error minimization.

The contribution of this work can be summarized as follows:

- Using open-source big data and ML techniques to predict the daily scooter fleet utilization (daily number of trips per vehicle).
- Compare the prediction results using different ML techniques; Gradient boosting decision tree (GBDT), Linear regression (LR), Support Vector Regression (SVR), and more complex deep learning techniques such as Long Short-Term Memory Neural Network (LSTM-NN).
- The prediction period was more extended than 1 year, which is longer than the periods used in most previous research, representing a long-term forecast horizon of operation.
- The prediction model showed accurate results when used to predict the test dataset, discussed in more detail in the following sections; therefore, it could be implemented in

real-life and the scooter deployment, organization, and governance processes.

- The proposed methodology is a practical yet simple[1] method to transfer the scooter fleet size utilization prediction learned from one city to another; which implies that same frame work could be used for other cities.
- The developed methodology, with its capabilities to be transferred to other cities, is to be used to define the daily,[2] weekly, or seasonal fleet size based on the predicted utilization rate for the existing services and the planned one, which could help in more efficient system operation by dynamically predicting and then deploying the number of vehicles needed to cater for the demand and not to deploy a fixed number of vehicles that do not account for the demand seasonality and fluctuation. In addition, deploying the vehicle based on the actual demand could reduce the number of ideal vehicles and facilitate vehicle re-balancing, distribution processes, and the subsequent vehicle kilometer traveled resulting from the distribution process.

The rest of this paper is organized as follows; "Literature Review" section discusses the current literature related to the discussed topic, "Methods, Data, and Case Study" section shows the data used and methodology, "Analysis Results" section shows the analysis for the collected data and estimated models. Finally, "Discussion, and Conclusion" section discusses the results and the conclusion of the research.

Literature Review

The literature review is organized as follows; in the first part, we define the reasons to use shared mobility services, their potential positive impacts, factors impacting their demand, and challenges shared mobility faces. The second part summarizes the potential of new sources of data and different ML techniques used in shared mobility studies, focusing on shared vehicle systems (carsharing, bike sharing, and shared-E-scooters) and their potential for demand prediction compared to traditional regression models.

Shared mobility is a rapidly growing trend in recent years encouraged by many factors such as but not limited to, travel time savings, ease of payment, fare transparency, trip cost, comfort and security, or even health benefit such as in the case of bikesharing (Abouelela et al. 2022; Tirachini and del Río 2019; Tirachini 2020; Tirachini and Gomez-Lobo 2020; Cerutti et al. 2019; Circella et al. 2018; Nikitas et al. 2015; Schaefers 2013), the popularity of smartphones and the development of mobile applications, or the general advancement of ICT (Spinney and Lin 2018; Schmöller et al. 2015). Moreover, shared mobility supports sustainability goals, or at least they can be described as more sustainable transport systems than private vehicle use; for example, the use of carsharing systems could have the positive potential for reducing negative traffic externalities (Kostic et al. 2021). Also, shared mobility could reduce the vehicular kilometer traveled (VKT) as in the case of bikesharing, shared-e-scooter, and pooled rides (Ting et al. 2021; Abouelela et al. 2021b; Tirachini and Gomez-Lobo 2020; Ricci 2015). Integrating shared mobility services in the urban environment faces several challenges, mainly tied to the systems' governance and management. These operational problems are more avid and critical for vehicle-sharing systems (scooter sharing, bikesharing, and carsharing), especially for free-floating systems, compared to other forms of shared mobility. The main problems are; fleet size management, spatial and temporal demand prediction and estimation, fleet geographical distribution and re-distribution, deciding on the optimal pricing schemes, use equity, accessibility of the service, operational hours, and geographical limits (zonal fencing) (Duran-Rodas et al. 2020b; Turoń et al. 2019; Liu et al. 2018; Ko et al. 2019; Shaheen and Cohen 2013; Weikl and Bogenberger 2013). It is to be noted from the previously mentioned challenges faced by the shared mobility services that most of the challenges are directly linked to the travel demand; therefore, understanding factors impacting the demand and demand prediction is a must to improve shared mobility operations and integration.

Several exogenous factors impact the use of shared mobility, and they can be categorized into four main groups. The first group is related to the shared vehicle's systems (bike sharing, scooter, and carsharing), such as the presence of docking stations and vehicles availability (Reck et al. 2021; Raux et al. 2017; De Lorimier and El-Geneidy 2013). The second group of factors is the infrastructure-related factors, including the availability of bike lanes, the density of road intersections, and the availability of parking lots (Müller et al. 2017; Chen et al. 2018; Hu et al. 2018). Meteorological conditions also play a significant role in shared mobility use, which is evident in the case of bikesharing, carsharing, and scooters. In contrast, adverse weather conditions significantly reduce bike sharing and scooter sharing use; it increases the use of carsharing (Yoon et al. 2017; Lin et al. 2018; Shen et al. 2018; Abouelela et al. 2021b). The last group is the land use and built environment and points of interest (POI), where different land uses impact the various

[1] Refer to "Methods, Data, and Case Study" section, and "Model Transfer" section, where we explain the used transfer methodology namely label differencing and sample normalization.

[2] We predicted the fleet utilization rate daily so that it can be aggregated to courser time units, e.g., weekly, monthly, or season based.

services. For example, mixed land uses are associated with carsharing use, commercial land use[3] is linked to bikesharing, scooter sharing and carsharing use (Kim et al. 2015; Hu et al. 2018; Abouelela et al. 2021a). Also, POI impact the use of shared mobility, where educational institutes, schools, and universities, were found to be associated with the increased use of carsharing and bikesharing (El-Assi et al. 2017; Mattson and Godavarthy 2017; Sun et al. 2017; Kim et al. 2012; Sun et al. 2017).

The generation and availability of big data, sometimes publicly available, from new sources supported by the advancement of ICT, in addition to the advancement in processing and data-storing methods, has facilitated data use and the further development of applications. Several examples can be referred to, such as the use of big spatial data to evaluate the relation between housing rental and carsharing use in Korea (Choi and Yoon 2017), identifying scooter users' segments from trip data in Germany (Degele et al. 2018), predicting the demand for bikesharing systems using a combination of weather data and bike booking data from New York (Cantelmo et al. 2020), the use of smartphone applications to understand pedestrian route choice behavior (Sevtsuk et al. 2021), and using news report to investigate scooters' crashes (Yang et al. 2020a).

The capabilities of ML with the combination of big data use have already been explored in the research related to shared mobility use; for the different shared vehicle services. For example, shared micromobility, which is mainly praised for its potential to solve the last mile problem (Baek et al. 2021; Fearnley et al. 2020; Luo et al. 2021), where Yang et al. (2016) proposed a spatio-temporal mobility model of bike-sharing and present an OD demand (check-in and check-out demand) prediction mechanism based on historical bike-sharing and meteorological data. They used a probabilistic model for the check-in demand, while a random forest (RF) model was introduced for check-out demand. Factors such as time of the day, day of the week, holidays, and weather conditions were found to be significant in predicting demand. Gammelli et al. (2020) proposed a general method for censorship-aware demand modeling by devising a censored likelihood function; censorship-aware demand is used to simulate reality. Transport demand is highly dependent on supply for shared mobility services, where services are often limited. Predictive models would necessarily represent a biased version of the actual demand without explicitly accounting for the supply restriction. The censored likelihood within a Gaussian Process model was incorporated and validated the limiting effect of supply on bike-sharing demand data to counter the previous problem. ML was also used in the case of scooter sharing, but not extensively as used for other modes; Saum et al. (2020) combined Box-Cox transformation, seasonal autoregressive moving average (SARIMA), and family of generalized autoregressive conditional heteroskedasticity (GARCH) models to predict hourly demand and volatility for scooter demand, for a limited period in; Thammasat University, Thailand. Deep learning models are also becoming more popular and widely used in transport. Gao and Lee (2019) propose a moment-based model with a new hybrid approach that combines a fuzzy C-means (FCM)-based genetic algorithm (GA) with a back propagation network (BPN) to predict bikesharing rentals. Xu et al. (2018) developed a long short-term memory (LSTM) model based on different data types (trip data, weather data, air quality data, and land use data) to predict the bikesharing trip generation and attraction for different time intervals (10, 15, 20, and 30 min). They also compared the model with other popular ML models, including one-step forecast, ARIMA, optimized gradient boosting algorithm (XGBoost), support vector machine (SVM), artificial neural network (ANN), and recurrent neural network (RNN).

Also using deep learning, Yang et al. (2020b) focused on graph features; they extracted time-lagged variables describing graph structures and flow interactions from bike usage data. These variables include graph node Out-strength, In-strength, Out-degree, In-degree, and PageRank. The results proved that different machine learning approaches (XGBoost, MLP, LSTM) improve the prediction accuracy when time-lagged graph information is included. Zhang et al. (2019) used a deep learning model to predict the hourly travel demand using an LSTM model and compared it with different ML algorithms such as support vector regression (SVR), autoregressive integrated moving average model (ARIMA) for carsharing systems. The results demonstrated that LSTM performs better in terms of performance and precision. Also, Luo et al. (2019) predicted dynamic demand based on graph features. The model was tested on real-world shared electric vehicle (EV) data, showing accurate prediction results. It is worth mentioning that, in comparison with traditional regression techniques, regression models generally show a poor prediction power when compared to ML algorithm; for example, in the case of carsharing, Müller et al. (2017) used a negative binomial statistical model to predict the vehicles demand, and the models' R-squared (ρ^2) were around (0.07). Also, Younes et al. (2020) used negative binomial models to predict the average hourly trips for bikesharing and shared-e-scooter with (ρ^2) ranging between (0.14–0.20). These examples show the poor prediction capabilities of regular regression models compared to ML, which supports the potential of using ML techniques for further research. Table 1 shows a summary of some selected studies and the used ML techniques, used performance evaluation matrices, and the recommended technique if applicable.

[3] According to the American Planning Association APA (planning.org), commercial land use is the land use that contains commercial retail and wholesales, business offices; while mixed land use is the combination of more than one land use in the same area such as residential, public and semi-public, and parks and open spaces.

Table 1 Selected examples of ML techniques used in selected studies for different shared vehicle systems from selected studies

References	ML technique	Performance evaluation metrics	Best performing ML*
Micro-mobility			
Yang et al. (2016)	Check-in: probability model for the undocked bikes; Check-out behaviour: RF	RMLSE	NA
Saum et al. (2020)	SARIMA + GARCH and their variation	MAE, MSE, MAPE	Modified SARIMA (BoxCox-SARIMA and SARIMA-PGARCH) outperformed other models
Yang et al. (2020b)	Feature extraction + XGBoost/MLP/ LSTM	MAPE, RMSE	LSTM
Gao and Lee (2019)	FCM-based GA with BPN	RMSE, MAE	NA
Xu et al. (2018)	LSTM; HA, ARIMA, XGBoost, SVM, ANN, RNN	RMSE	LSTM
Car-sharing			
Zhang et al. (2019)	LSTM; SVR, ARIMA, smoothing	MSE, R^2	LSTM
Luo et al. (2019)	Multi-graph Dynamic GCN	RMSE, Error Rate	NA

* NA refers to no comparison between the different models was performed

Methods, Data, and Case Study

Methods

Problem Statement and Framework Overview

Figure 1 shows the overview of the proposed methodology framework. We employed in this research the model transfer problem for time series prediction to predict scooters' fleet utilization (Zhang et al. 2020). Given the historical demand data in the source city (Austin) alongside the pilot stage[4] demand data in the target city, Louisville, a time series model was trained and applied to predict the future fleet utilization in the target city. The source city is the city that provides us with the long-term patterns of historical demand and fleet utilization changes, whereas the target city only has information on demand changes over a short pilot stage.

The historical data of a city is denoted as $\boldsymbol{D} = \{\boldsymbol{d}_i\}_{i=1}^{Z}$, where Z is number of census tracts (demand aggregation zones). $\boldsymbol{d}_c = \{\boldsymbol{t}_c, z_c\}$[5] is the data of census tract c, consisting of both historical time series $\boldsymbol{t}_c \in \mathbb{R}^L$ and auxiliary census tract attributes $z_c \in \mathbb{R}^N$, where L is the length of the time series and N is the length of auxiliary attributes. The data of the source city and the target city can be respectively denoted by $\boldsymbol{D}_S$ and $\boldsymbol{D}_T$. The two lengths L and N can be determined based on the richness of data rather than fixed. For example, longer pilot stage duration and more accessible land use attributes allow the choice of larger L and N.

An autoregressive formulation was adopted for the time series prediction problem, such that it was transformed into a supervised ML problem. The raw data was split into two samples for model training and testing. A sample is described by a vector pair $(\boldsymbol{x}_i, y_i)$, where i is the index of the sample. The first element $\boldsymbol{x}_i = \{x_i^j\}_{j=1}^m \in \mathscr{X}$ is an m-dimensional feature vector, which is comprised of m features extracted through feature engineering from the census tract attributes and the time series data of w consecutive days in a specific census tract c, i.e., $\boldsymbol{t}_c^{(i:i+w)}$. The label $y_i \in \mathscr{Y}$ is the succeeding time series value in census tract c, i.e., $t_c^{(i+w)}$.

The ordinary time series prediction problem aims at learning an accurate mapping $f : \mathscr{X} \to \mathscr{Y}$ on future time steps in the same time series as in $\boldsymbol{D}_S$. However, the model transfer of the time series prediction problem aims at learning another mapping $f' : \mathscr{X} \to \mathscr{Y}$ from $\boldsymbol{D}_S$, but still performs well on the time series of $\boldsymbol{D}_T$. The foremost difficulty in model transfer lies in the inconsistency between the distributions of data in $\boldsymbol{D}_S$ and $\boldsymbol{D}_T$, also known as the covariate shift. To address this problem, we proposed a simple yet effective approach to align the distributions of time series in two cities and minimize the generalization error of the time series prediction model. Following the common ML procedures, the four-step pipeline of (*sample construction—feature engineering—model training—inference*) was adopted. Two strategies were used to facilitate the transfer of the time series prediction model, namely the sample normalization and the label difference. Note that the proposed framework

[4] We considered the first 3 months the service deployed in the source city as a pilot stage, as commuters are generally trying to get familiar with the service, and it is the same period used by other cities to evaluate scooters' deployment such as Minneapolis, MN (Abouelela et al. 2023)

[5] The length of $\boldsymbol{t}_c$ depend on the available amount of historical time series data, and z_c depends on the other auxiliary variables length.

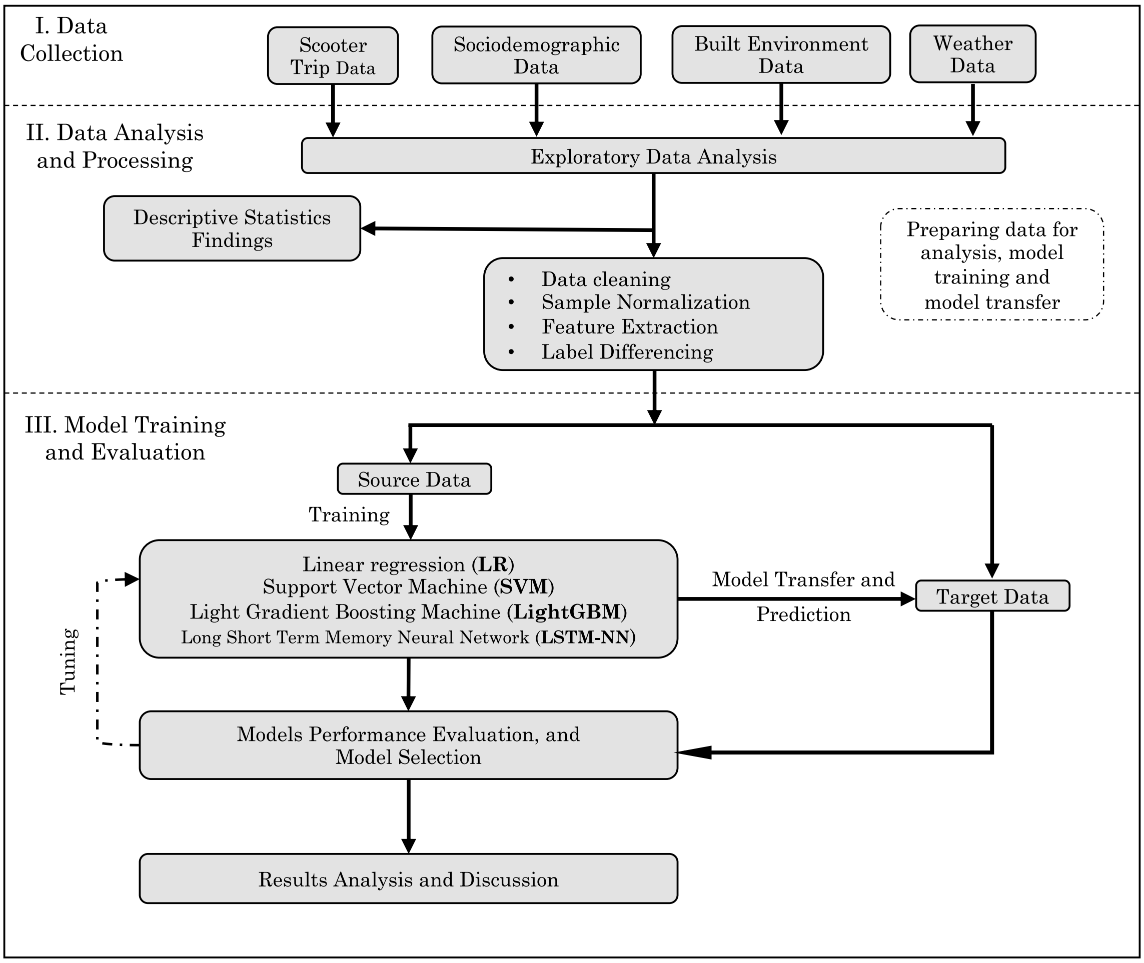


Fig. 1 The used methodological framework

is compatible with various base ML models, which will be discussed in "Base Models" section.

Feature Engineering

Feature engineering is an important step for ML model development. Raw data were examined and processed to predict important information before using it in the modeling process. Our model incorporated two categories of features, namely time-series features and auxiliary features. Historical time series characteristics were included in the feature set so that the model could learn the patterns of time series dynamics from them. Liu et al. (2020), Zhang et al. (2016) recommend considering; (i) neighboring information, (ii) periodical information, and (iii) trend information for accurate time series prediction. Neighboring information contains the demand values on the neighboring days of the target prediction day, informing the model of the recent level of demand. In this study, the number of neighbors is set as five. Periodical information contains historical demand values on a weekly basis, as repetitive weekly peaks can be observed from Fig. 3. Trend and seasonality needed to be removed through differencing before applying classical time series prediction tools like ARIMA (Kwiatkowski et al. 1992). Although ML models do not explicitly assume stationarity for time series prediction, a nonstationary time series is not always suitable for prediction without preprocessing, especially for decision-tree-based models, which is explained in the following section. Therefore, a first-order differencing[6] was applied to the demand data as prediction labels. Table 2 shows the summary of the statistics of the time series features. Apart from time-series features, auxiliary information was proven to be of great help in prediction tasks (Liu et al. 2021b; Lyu et al. 2020; Wessel

[6] First-order differencing refers to computing the difference between two consecutive values in the time series. Denote the i-th observation of a time series as x_i, the transformed label y_i will be defined as follows; $y_i = x_i - x_{i-1}$.

Table 2 Time series feature summary statistics

Feature	Type[a]	Austin		Louisville	
		Mean	StD	Mean	StD
Demand (previous day) (×10^{-3})	N	6.36	33.91	9.67	53.24
Demand (2 days ago) (×10^{-3})	N	6.37	33.94	9.69	53.30
Demand (3 days ago) (×10^{-3})	N	6.37	33.96	9.71	53.36
Demand (4 days ago) (×10^{-3})	N	6.38	33.99	9.73	53.41
Demand (5 days ago) (×10^{-3})	N	6.38	34.00	9.74	53.47
Demand (1 week ago) (×10^{-3})	P	6.39	34.03	9.78	53.59
Demand (2 weeks ago) (×10^{-3})	P	6.43	34.18	9.92	54.00
Demand (3 weeks ago) (×10^{-3})	P	6.48	34.35	10.06	54.42
Demand (4 weeks ago) (×10^{-3})	P	6.52	34.51	10.21	54.85
Demand (difference between 1 and 2 days ago) (×10^{-3})	T/N	0.00	12.18	– 0.02	24.89
Demand (difference between 2 and 3 days ago) (×10^{-3})	T/N	0.00	12.19	– 0.02	24.91
Demand (difference between 3 and 4 days ago) (×10^{-3})	T/N	0.01	12.20	– 0.02	24.94
Demand (difference between 4 and 5 days ago) (×10^{-3})	T/N	0.01	12.21	– 0.02	24.97
Demand (difference between 5 and 6 days ago) (×10^{-3})	T/N	0.01	12.22	– 0.02	25.00
Demand (difference between 6 and 7 days ago) (×10^{-3})	T/N	0.01	12.23	– 0.02	25.02
Demand (difference between 8 and 9 days ago) (×10^{-3})	T/P	0.00	12.24	– 0.02	25.08
Demand (difference between 15 and 16 days ago) (×10^{-3})	T/P	0.00	12.29	– 0.02	25.28
Demand (difference between 22 and 23 days ago) (×10^{-3})	T/P	0.00	12.35	– 0.02	25.48
Demand (difference between 29 and 30 days ago) (×10^{-3})	T/P	0.01	12.41	– 0.02	25.69
Demand (average of the past week) (×10^{-3})	T	6.40	31.99	9.72	49.04
Demand (variance of the past week) (×10^{-3})	T	0.16	3.10	0.52	6.24
Demand (range of the past week) (×10^{-3})	T	6.49	32.93	13.44	61.36
Citywide demand (previous day) (×10^{-2})	N	76.95	36.96	80.28	54.56
Citywide demand (2 days ago) (×10^{-2})	N	77.02	36.96	80.42	54.53
Citywide demand (3 days ago) (×10^{-2})	N	77.10	36.95	80.58	54.49
Citywide demand (4 days ago) (×10^{-2})	N	77.16	36.95	80.73	54.46
Citywide demand (5 days ago) (×10^{-2})	N	77.21	36.96	80.88	54.42
Citywide demand (1 week ago) (×10^{-2})	P	77.29	37.00	81.21	54.32
Citywide demand (2 weeks ago) (×10^{-2})	P	77.78	36.93	82.37	53.98
Citywide demand (3 weeks ago) (×10^{-2})	P	78.37	36.77	83.49	53.70
Citywide demand (4 weeks ago) (×10^{-2})	P	78.92	36.67	84.72	53.27
Citywide demand (difference between 1 and 2 days ago) (×10^{-2})	T/N	0.06	25.50	– 0.16	33.54
Citywide demand (difference between 2 and 3 days ago) (×10^{-2})	T/N	0.06	25.52	– 0.16	33.57
Citywide demand (difference between 3 and 4 days ago) (×10^{-2})	T/N	0.06	25.54	– 0.16	33.61
Citywide demand (difference between 4 and 5 days ago) (×10^{-2})	T/N	0.08	25.56	– 0.16	33.65
Citywide demand (difference between 5 and 6 days ago) (×10^{-2})	T/N	0.09	25.58	– 0.17	33.68
Citywide demand (difference between 6 and 7 days ago) (×10^{-2})	T/N	0.09	25.60	– 0.17	33.72
Citywide demand (difference between 8 and 9 days ago) (×10^{-2})	T/P	0.02	25.62	– 0.16	33.80
Citywide demand (difference between 15 and 16 days ago) (×10^{-2})	T/P	0.05	25.72	– 0.15	34.07
Citywide demand (difference between 22 and 23 days ago) (×10^{-2})	T/P	0.05	25.86	– 0.17	34.34
Citywide demand (difference between 29 and 30 days ago) (×10^{-2})	T/P	0.07	26.00	– 0.18	34.62

[a]We use type N for neighboring information, P for periodical information, and T for trend information

2020). In the used models, we incorporate four auxiliary features, (i) temporal features, (ii) meteorological features, (iii) built environment features, and (iv) sociodemographic features. Temporal and meteorological features vary across different days (dynamic data); built environment and sociodemographic features are static for each census tract, in addition to the road network and

Table 3 Variables summary statistics aggregated by census tracts

Variable	Unit	Austin		Louisville	
		Mean	StD	Mean	StD
Demographics[a]					
Population	Count	2372.16	1692.12	2023.63	821.10
Median income	10^3\$	65.24	30.18	44.49	25.56
High education	(%)	0.47	0.20	0.27	0.21
White ethnicity	(%)	0.51	0.23	0.58	0.33
Male	(%)	0.52	0.06	0.48	0.04
Age under 18	(%)	0.17	0.08	0.21	0.08
Age between 18 and 29	(%)	0.26	0.16	0.2	0.11
Age between 30 and 39	(%)	0.20	0.06	0.14	0.05
Age between 40 and 59	(%)	0.23	0.07	0.25	0.05
Age over 60	(%)	0.14	0.07	0.20	0.08
Modes used to travel to work					
Drove alone	(%)	0.70	0.09	0.73	0.12
Taxi	(%)	0.01	0.01	0.03	0.04
Transit	(%)	0.05	0.05	0.07	0.07
Walked	(%)	0.03	0.06	0.04	0.05
Work from home	(%)	0.08	0.05	0.04	0.03
Bicycle	(%)	0.02	0.02	0.01	0.01
Carpooled	(%)	0.09	0.06	0.08	0.04
Infrastructure					
Census tract area	km^2	2.57	2.12	2.10	1.76
Sidewalk length	km	37.01	18.36	4.54	7.95
Number of signal	Number	8.21	10.97	8.12	12.52
Length of bike lane	km	1.14	2.55	2.79	4.89
Bikesharing station	Number	0.25	0.98	0.34	1.92
Distance to downtown[d]	km	7.16	3.77	5.61	2.59
LTAI		5.50	0.76	5.51	0.82
Land use[b]					
Residential	(%)	0.43	0.16	0.42	0.18
Civic	(%)	0.08	0.12	0.10	0.09
Commercial	(%)	0.07	0.07	0.08	0.07
Industrial	(%)	0.03	0.07	0.06	0.09
Mixed	(%)	0.01	0.02	0.00	0.00
Office	(%)	0.04	0.05	0.00	0.00
Parks	(%)	0.08	0.09	0.07	0.13
Meteorological					
Max temperature	$^\circ F$	70.44	16.17	61.18	19.05
Mini temperature	$^\circ F$	70.44	16.17	61.18	19.05
Precipitation[c]		0.02	0.13	0.03	0.18
Wind speed	km/h	5.70	3.81	6.93	4.39

[a]For the definition of the different demographics, please refer to the United States Census Bureau (ensus.org)

[b]For the definition of the different land uses categories, please refer to the American Planning Association APA (planning.org)

[c]Rainy days coded as (1), and non-rainy days coded as (0)

[d]Measured from the centroid of each tract

infrastructure attributes. Table 3 shows the summary of the statistics of the used auxiliary features.

Base Models

This subsection introduces four ML techniques that we applied using the proposed methodological framework. We choose the models based on four different types of ML. Linear regression (LR) depends on the assumptions of the linear relationship between the features and the outputs. Support vector regression (SVR) uses a kernel method to impose the non-linearity of the data; gradient-boosting decision tree models the data using an ensemble of if-else rule sets based on tree representation. Finally, we used a deep learning technique to capture the non-linearity of the relationship between the features and the output. We explain the details of each of these models as follows;

Linear Regression (LR) LR is a classical machine learning model that assumes a linear or affine relationship between input features and output labels. The simple linear regression takes the following formulation,

$$f(\boldsymbol{x}_i) = \boldsymbol{w}'\boldsymbol{x}_i + b, \tag{1}$$

where $\boldsymbol{w} \in \mathbb{R}^m$ is the coefficient vector, and $b \in \mathbb{R}$ is the intercept. The residual $y_i - f(\boldsymbol{x}_i)$ is assumed to follow a Gaussian distribution. Also assuming the independence of training samples, the parameters can be estimated through the least squares method, which is equivalent to maximum likelihood estimation. It aims at minimizing the sum of squared error, formulated as follows,

$$\min_{\boldsymbol{w},b} \sum_i \left(y_i - f(\boldsymbol{x}_i)\right)^2. \tag{2}$$

Support Vector Regression (SVR) SVR is an extension of ordinary support vector machine (SVM) for solving regression problems, which was originally designed for classification. To make binary classification, SVM adopts a separating hyperplane $\boldsymbol{w}'\boldsymbol{x} + b = 0$ to split the feature space $\mathscr{X}$ into two half-spaces. In the regression case, the hyperplane is turned into a real-valued function $f(\boldsymbol{x}_i) = \boldsymbol{w}'\boldsymbol{x}_i + b$ resemblant to linear regression. Instead of least squares, SVR is trained based on the ϵ-insensitive loss, as formulated below,

$$\ell_\epsilon(z_i) = \begin{cases} 0, & \text{if } |z_i| \le \epsilon, \\ |z_i| - \epsilon, & \text{otherwise,} \end{cases} \tag{3}$$

where $z_i = y_i - f(\boldsymbol{x}_i)$. Unlike squared loss in least squares, there is no penalty when the absolute prediction error is not greater than threshold ϵ. The complete optimization objective of SVR is given by,

$$\min_{w,b} C \sum_i \ell_\epsilon(z_i) + \frac{\|w\|^2}{2}, \tag{4}$$

where $C > 0$ is a trade-off coefficient between the ϵ-insensitive loss and the regularization term (Scholkopf and Smola 2001). In addition to the linear formulation, SVR can deal with non-linearity by introducing the kernel trick, which projects the input features into a high-dimensional space using a kernel function $\phi(\cdot)$; thus the prediction function becomes $f(\boldsymbol{x}) = \boldsymbol{w}'\phi(\boldsymbol{x}) + b$. Common kernel functions include the polynomial kernel, spline kernel, and Gaussian kernel (Scholkopf and Smola 2001; Wendland 2004). Despite the strong expressive power of non-linear kernels, the time complexity of model estimation can be worse than $O(N^3)$ (Platt 1998).

Gradient boosting decision tree (GBDT) Decision tree (DT) has a superior prediction performance and good interpretability (Wu et al. 2008). Each decision rule corresponds to an exclusive path from the root node to a leaf node in the tree, while each leaf node is associated with a group of samples in the training set. The rule set of a DT actually partitions a subspace $\mathscr{S}$ of the feature space $\mathscr{X}$ into many sub-regions. For each input feature vector, DT searches for the sub-region to which this vector belongs, and prediction can be made based on the samples associated with the leaf node in the corresponding decision rule. The training process of a DT is a search for a satisfactory set of decision rule, i.e., a partition of $\mathscr{S}$. It has early been proven that finding an optimal rule set for a DT is *NP-Complete* (Kwiatkowski et al. 1992); hence a greedy heuristic algorithm is often used for model training and the resulting DT is suboptimal. But, concerning a DT for regression problems with a determined feature space partition, the optimal output value of a specific leaf node can be concluded as the average labels of all the associated samples (Bishop 2006). Therefore, it is noteworthy to mention that the output of a DT is limited between the minimum and maximum of labels of its training data. Despite the inability in extrapolation, DT is competitive over many other machine learning models in interpolation. Despite the boom of deep learning research in the recent decade, it has been found that deep learning is not a panacea for all tasks. For example, Shwartz-Ziv and Armon (2022) pointed out that DT outperforms deep models on many tabular data, which is the case for the auxiliary information in our experiment. In addition, according to a research (Bojer and Meldgaard 2021) on the winning solutions of forecasting competitions on Kaggle,[7] DT is the most competitive one over other machine learning models. Similar results can be observed from the latest survey conducted by Kaggle[8]; DT is the most popular method among its users on top of linear models. To further improve its generalization ability and reduce the risk of over-fitting, ensemble learning is combined with DT, and GBDT is one of the representatives (Friedman 2001). The principal idea of Boosting is to express the model as a summation of multiple base models. There are a number of improvements made on GBDT in terms of engineering implementation, including XGBoost (Chen and Guestrin 2016), CatBoost (Dorogush et al. 2017) and LightGBM (Ke et al. 2017). In this paper, we adopt LightGBM, a highly efficient GBDT framework, which utilizes two specially designed techniques, namely Gradient-based One-Side Sampling and Exclusive Feature Bundling, to ease the computational burden of large-scale data involved in model training without sacrificing the prediction accuracy.

Long Short-term Memory Neural Network (LSTM NN) LSTM is a recurrent neural network (RNN) model for modelling sequential data. In contrast to most non-recurrent neural networks, RNN allows loop connections in its architecture, which feed the outputs of a layer to itself as its inputs in the following time step (LeCun et al. 2015). An ordinary RNN layer maintains a hidden state $\boldsymbol{H}$ along time; in each time step t, it is fed with the current feature vector $\boldsymbol{x}_t$ and the previous hidden state $\boldsymbol{H}_{t-1}$. The hidden state of time step t is updated by the non-linear transformations of the two inputs, while the output is given by another non-linear transformation of the hidden state. LSTM improves RNN's ability of modelling long-term relationship by introducing three gated units (i.e., input gate, output gate, and forget gate) and an additional memory state $\boldsymbol{C}$ in the recurrent layer. The three gated units apply different non-linear transformations on the two inputs, whereby the memory state and the hidden state are also updated,

$$\begin{aligned}
\boldsymbol{I}_t &= \phi(\boldsymbol{w}_I'\boldsymbol{x}_t + \boldsymbol{v}_I'\boldsymbol{h}_{t-1} + b_I),\\
\boldsymbol{O}_t &= \phi(\boldsymbol{w}_O'\boldsymbol{x}_t + \boldsymbol{v}_O'\boldsymbol{h}_{t-1} + b_O),\\
\boldsymbol{F}_t &= \phi(\boldsymbol{w}_F'\boldsymbol{x}_t + \boldsymbol{v}_F'\boldsymbol{h}_{t-1} + b_F),\\
\boldsymbol{C}_t &= \boldsymbol{F}_t \otimes \boldsymbol{C}_{t-1} + \boldsymbol{I}_t \otimes \psi(\boldsymbol{w}_C'\boldsymbol{x}_t + \boldsymbol{v}_C'\boldsymbol{h}_{t-1} + b_C),\\
\boldsymbol{H}_t &= \boldsymbol{O}_t \otimes \phi(\boldsymbol{C}_t).
\end{aligned} \tag{5}$$

where $\phi(\cdot)$ and $\psi(\cdot)$ are sigmoid and hyperbolic tangent activation functions, respectively; $\boldsymbol{w}$, $\boldsymbol{v}$ and b are parameters; $\otimes$ is the Hadamard product. The training of LSTM NN can be realized via back-propagation through time, which unfolds

[7] A platforms for hosting data science competitions (kaggle.com).

[8] https://www.kaggle.com/competitions/kaggle-survey-2022, accessed 25/11/2022.

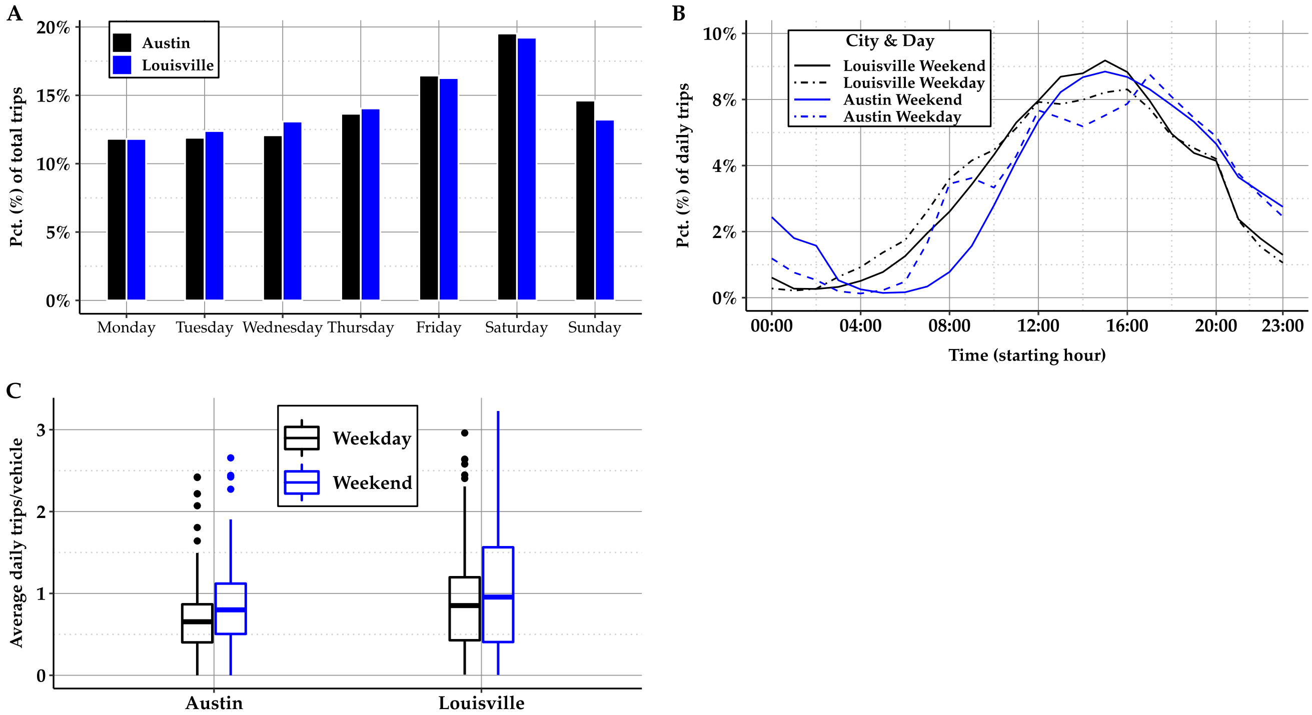


Fig. 2 Average **A** daily, **B** hourly demand distribution, **C** and fleet utilization (number of trips per vehicle) daily distribution. Weekend includes Saturday and Sunday, weekdays are the rest of the days

the computation steps along time to allow the use of the chain rule (Hochreiter and Schmidhuber 1997).

Model Transfer

Time series differencing is used to remove trends from the data (detrend) in response to GBDT's defect in extrapolation. Denote two consecutive time series values as x_{i-1} and x_i, the first-order differencing yields a transformed label y_i as follows,

$$y_i = x_i - x_{i-1}. \tag{6}$$

However, differencing alone is inadequate regarding the model transfer problem due to the uneven distributions between data in $\boldsymbol{D}_S$ and $\boldsymbol{D}_T$. Figure 2 compares the distributions of average daily trips per vehicle between two cities. The demand pattern of Louisville has a more significant dispersion than Austin's. If Austin was used as the source city and Louisville as the target city, the trained GBDT model might underestimate the demand in Louisville, as the model would not learn much information about high daily trip demand, and this was the main reason to use Austin, as the source city; which is called covariate shift. Covariate shift refers to the case when the probability distributions between training data and test data differ while the conditional distributions of labels on input data are the same (Sugiyama and Kawanabe 2012). Nevertheless, an implicit assumption of standard supervised learning models, including GBDT, is that the training and test data follow the same probability (Ben-David et al. 2010), refraining from dealing with covariate shift.

$\mathscr{D}_S$ and $\mathscr{D}_T$ denote the distributions of data in $\boldsymbol{D}_S$ and $\boldsymbol{D}_T$, respectively; denote the actual underlying functions mapping input feature vectors to labels on the two sets of data as f_S and f_T. Then, following Ben-David et al. (2010), we call $\langle \mathscr{D}_S, f_S \rangle$ the *source domain* and $\langle \mathscr{D}_T, f_T \rangle$ the *target domain*. The expected error on the source domain can be obtained by

$$\epsilon_S(g, f_S) = \mathbb{E}_{\boldsymbol{x} \sim \mathscr{D}_S} \left[\ell \left(g(\boldsymbol{x}), f_S(\boldsymbol{x}) \right) \right], \tag{7}$$

where $g(\cdot)$ is the model, $\ell(\cdot, \cdot)$ is the loss function. Similarly, the expected error on the target domain can be defined as $\epsilon_T(g, f_T)$.

In general, models are trained to minimize the empirical error on the source domain; nevertheless, in the model transfer problem, we minimize the error on the target domain. One option is transforming the data from $\boldsymbol{x}$ to $\boldsymbol{x}'$ such that the corresponding distributions $\mathscr{D}'_S$ is similar to $\mathscr{D}'_T$. Inspired by the batch normalization strategy in deep learning (Ioffe and Szegedy 2015), we proposed the sample normalization strategy to transport the knowledge learned from the source time series to the target time series. We implicitly assumed that time-series dynamics irrespective of the value scale conditional on given features. For each sample, before extracting time series features, the input time series segment was normalized to a mean of zero and a variance of one. Denote the time series segment as $\boldsymbol{t}$, the normalized segment $\tilde{\boldsymbol{t}}$ can be obtained by:

$$\tilde{\boldsymbol{t}} = \frac{\boldsymbol{t} - E(\boldsymbol{t})}{D(\boldsymbol{t})}, \tag{8}$$

where $E(\boldsymbol{t})$ and $D(\boldsymbol{t})$ are the mean and the standard deviation of $\boldsymbol{t}$ respectively.

Sample normalization was adopted to reduce the covariate shift for the studied model transfer problem. The feature construction procedure with sample normalization was presented in Algorithm 1. Feature vectors are constructed for data in each census tract following the FeatureConstuction procedure. It should be noted that a complete training sample consists of a feature vector and a label, where the label also needs normalization. Recall that sample normalization takes a time series segment of consecutive (w) days; the label corresponds to the day right after this segment and needs to be normalized using the mean and standard deviation of the previous segment. As the label represents the day when the demand is predicted, it should not be combined with the previous segment when calculating the normalization parameters, i.e., the mean and standard deviation.[9]

Algorithm 1 Feature Construction (FeatureConstuction) with Sample Normalization

```
procedure SampleNorm(t)
    ▷ t is a time series segment.
    μ ← (1/|t|) Σ_{i=1}^{|t|} t_i
    σ ← ((1/|t|) Σ_{i=1}^{|t|} (t_i − μ))^{1/2}
    t̃ ← (t − μ)/σ
    return t̃
end procedure
procedure FeatureConstruction(w, t, x_tm, x_bs)
    ▷ w is the time window size^9, t is a time series.
    ▷ x_tm is the temporal and meteorological information.
    ▷ x_bs is the built environment and sociodemographical information.
    Initiate s ← ∅
    for i ← 1 to |t| − w do                          ▷ i is the index of day.
        t̃ ← SampleNorm(t^(i:i+w))                    ▷ Normalize the time series segment.
        r̃ ← FeatureExtraction(t̃)                     ▷ Extract time series features from t̃.
        u ← r̃ ∪ x_bs ∪ x_tm^(i+w)                     ▷ u is the feature vector of a sample.
        s ← s ∪ {u}
    end for
    return s
end procedure
```

Data Collection and Processing

We predicted the scooter's fleet utilization using different data sources; we used fleet utilization daily rates (daily number of trips per vehicle) of one city to predict the fleet utilization in the other city. The primary datasets are the scooter trip booking data from Austin; Texas, and Louisville; Kentucky; in Austin, the data spanned from April 2018 to January 2020, while in Louisville, the collected data spanned from August 2018 to January 2020. We used trip data in combination with other open-source data, specifically; (i) census sociodemographics information obtained

[9] The window size used for feature extraction is 28 days. In this paper, we assume there are only 1 month available in the target city, hence the choice of window size approximately 1 month.

Table 4 Summary of trip characteristics per city

	Mean	StD	Min	Q^{1st}	Median	Q^{3rd}	Max	City
Distance (km)	1.57	1.50	0.10	0.64	1.13	1.96	45.71	Austin
Distance (km)	2.07	2.26	0.10	0.64	1.29	2.61	32.19	Louisville
Duration (min)	11.09	11.83	1.00	4.45	7.20	12.92	120.00	Austin
Duration (min)	15.62	17.22	1.00	5.00	9.00	19.00	120.00	Louisville
Speed (km/h)	9.76	4.59	0.06	6.39	9.29	12.68	25.00	Austin
Speed (km/h)	9.05	4.47	0.07	5.79	8.59	12.00	25.00	Louisville
Fleet utilization (trip/vehicle)	0.71	0.40	0.00	0.44	0.69	0.93	2.66	Austin
Fleet utilization (trip/vehicle)	0.91	0.61	0.00	0.42	0.86	1.26	3.23	Louisville

Number of trips after the data cleaning process is in Austin = 7,038,490 trip, and in Louisville = 389,739 trip

from the United States Census Bureau[10] census data include sociodemographic information aggregated per census tract including age group, gender ratio, race and ethnicity, marital status, education level, household income, house price, and modes used to work. (ii) Built environment and infrastructure data from (openstreetmap.org); this data set included all the physical features of the built environment and POI, such as roads, bike lanes, intersections (both signalized and non-signalized), bikesharing stations, shops, banks, and educational institutes. (iii) Meteorological data from (visualcrossing.com), and this dataset included hourly atmospheric temperature, wind speed, rain, and snow conditions.

The collected data was processed and cleaned in several steps. Austin's data set contained scooter and e-bike trips; the latter were removed. Other procedures were similar to what McKenzie (2019), Liu et al. (2019), Zou et al. (2020) used were implemented to remove false entries and false trips; all trips shorter than 100 m and longer than 50 km were removed; trips shorter than one minute and more extended than 2 h duration were removed. Also, we removed trips with speeds higher than 25 mph. Build environment, infrastructure, and POI data were aggregated per census tract as it is the spatial aggregation unit. It is to be noted that we did not observe any problems in the sociodemographic census information and meteorological data.

Case Study

Scooter booking data from Louisville, Kentucky, and Austin, Texas, were obtained from the open city portals (Austin Shared Mobility Services 2022; Louisville Open Data 2022). Scooter fleet size in both cities is different, wherein Austin, the maximum fleet size is 15,000 vehicles (Austin Shared Mobility Services 2022) and in Louisville, it is 1200 vehicles (Louisville Open Data 2022). Also, the operational regulations for shared-e-scooters are slightly different in both cities. The speed limit is 20 mph in Austin, while it is 15 mph in Louisville; helmet use is advised and mandatory for under-18 users in Austin, while it is mandatory for all users in Louisville.

It is essential to mention that the two cities in this study are different in terms of population, where Austin's population (0.98 million) is approximately 1.5 times the population of Louisville. Also, Austin has several options for public transportation, compared to Louisville, which has only bus service; however, they have similarities in terms of modal share for work trips, as both cities are car-dependent cities, wherein Louisville (89%) of work trips are done in private cars, compared to 81.2 % in Austin (census.gov).

Analysis Results

As discussed in the literature review, "Literature Review" section, some of the challenges faced by the shared mobility service are directly linked to the spatial and temporal demand pattern; therefore, we start by analyzing the trip characteristics and then the demand patterns temporally and spatially to recognize the patterns in both cities, and compare them to define similarities and differences, after that, we show the results of the estimated models and its adequacy for fitting the data.

Trips Characteristics

After cleaning the data as discussed in "Methods, Data, and Case Study" section, the original 9 million trips in Austin were reduced to around 7 million trips (78% of original trips), and the initial 500,000 in Louisville were reduced to approximately 390,000 trips (77% of original trips). We analyzed and compared the characteristics of the cleaned trips in both cities as shown in Table 4. To investigate the differences and similarities between trips characteristics in both cities, a *t* test of the mean of two samples is performed for the trip distance, duration, and speed between the two

[10] ;census.gov, accessed 5 March 2022.

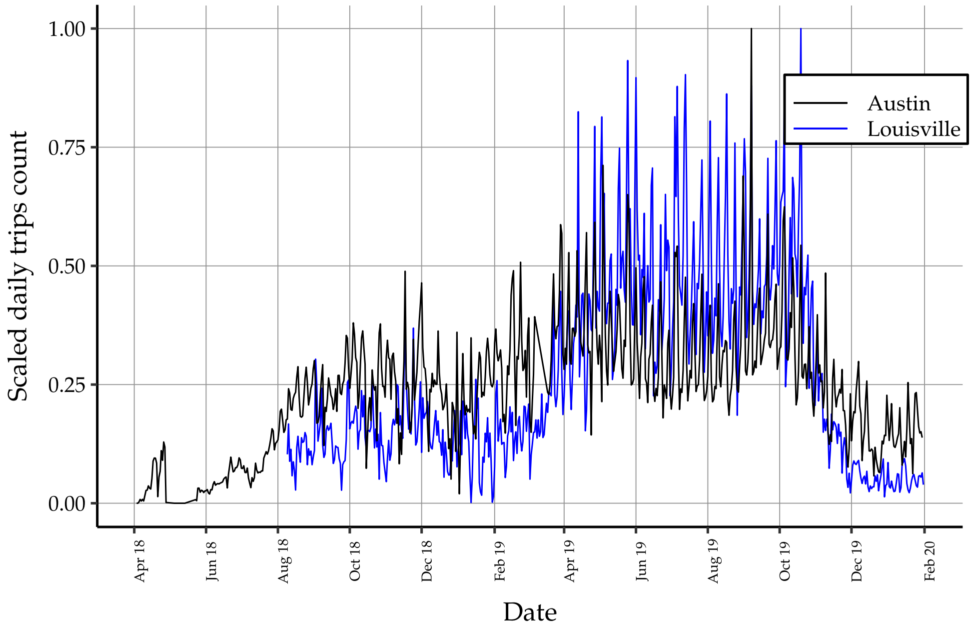


Fig. 3 Daily demand distribution, scaled demand

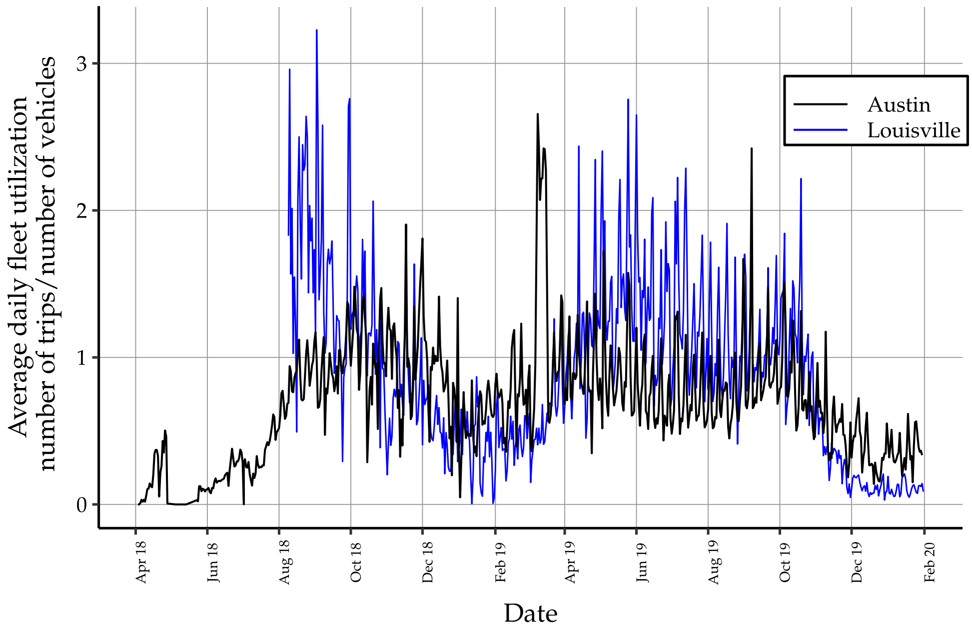


Fig. 4 Utilized fleet daily distribution, number of trips per vehicle per day

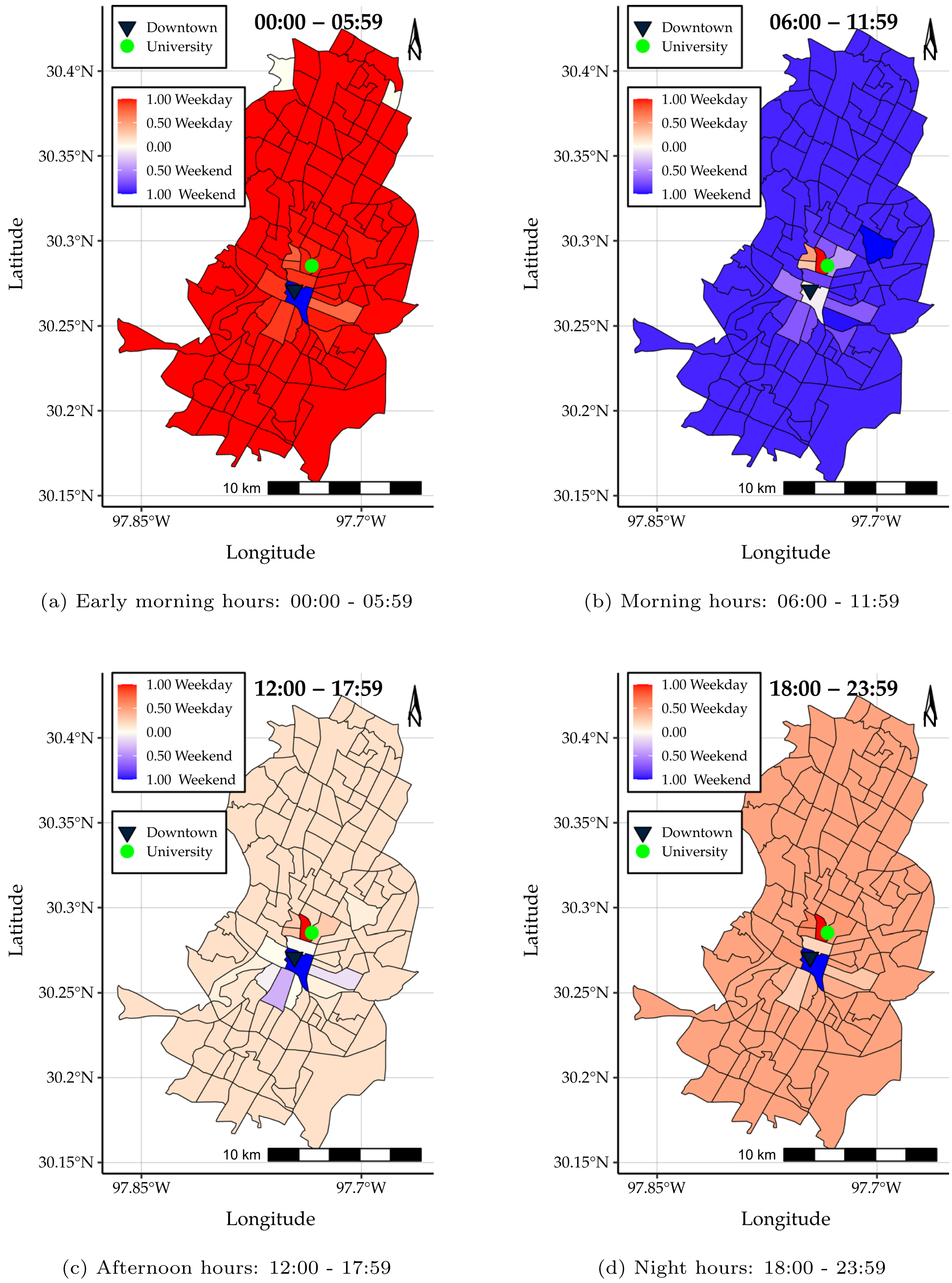
cities, and it shows that the difference between the two samples is significant for the three trip metrics ($P < 0.0001$). Louisville trips tend to be longer in distance and duration, but Austin trips tend to be faster. We investigated the average street slopes in both cities using Google Earth Engine (Gorelick et al. 2017) to explore if slopes impact the mean scooter trips' speed, with no significant difference found as both cities have almost flat terrain except for some localized areas. We also removed the demand data for the second week of March 2019 from the Austin dataset, as the SXSW music festival took place at that time, and the demand was (5–6) times the average demand for the rest of the data collection period, as extreme outlier removal is essential for improving model performance (Saum et al. 2020).

Demand Analysis

Temporal Analysis

To compare the demand trends and patterns in the two cities, we normalized the demand by scaling the daily demand; we divided it by the maximum number of trips for the

Fig. 5 Spatial distribution of the dominant difference between weekends and weekdays trips, Austin, TX



(a) Early morning hours: 00:00 - 05:59

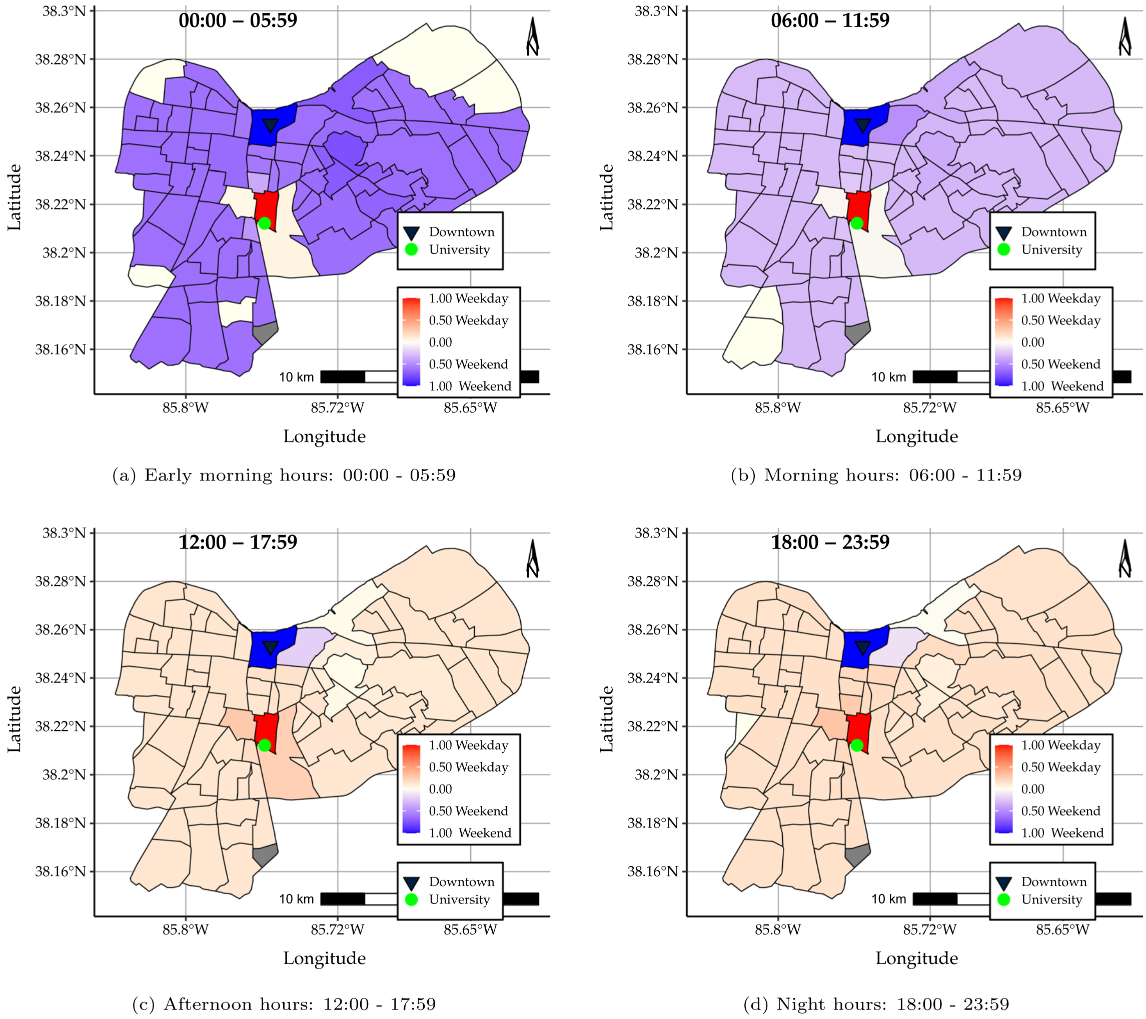
(b) Morning hours: 06:00 - 11:59

(c) Afternoon hours: 12:00 - 17:59

(d) Night hours: 18:00 - 23:59

investigated duration for each city, as shown in Fig. 3; similar to the procedures used by Schmöller et al. (2015). The scaled demand shows similar trends in both cities, where the demand increases in spring and summer, and it starts to drop from October (autumn) and continues to decline until January, when the lowest average of the year is observed. Following the same scaling procedures to control the different fleet sizes, we also compared the number of trips per vehicle in both cities. Interestingly, the number of trips per vehicle fluctuates in a different trend than the demand, with Louisville having higher trips per vehicle than Austin at the beginning of the deployment period, i.e., the first two months, and it decreases for the following 6 months. It almost matches in both cities for almost 7 months in 2019 (from April till November), despite the different fleet sizes in both cities. It is necessary to mention that the fleet size was not fixed during the data collection period, as mentioned and considered from Louisville Open Data (2022); Austin Shared Mobility Services (2022). Figure 4 shows the average daily number of trips per vehicle in both cities.

We also investigated the hourly and daily demand. In general, the demand patterns for weekdays are similar in both cities, where the demand per weekday as a percentage of the total weekly demand is stable from Mondays



(a) Early morning hours: 00:00 - 05:59

(b) Morning hours: 06:00 - 11:59

(c) Afternoon hours: 12:00 - 17:59

(d) Night hours: 18:00 - 23:59

Fig. 6 Spatial distribution of the dominant difference between weekends and weekdays trips, Louisville, KY

to Thursdays, with a slight increase on Fridays. The peak of the demand happens on Saturdays (around 20% of the total weekly demand and 50% more than the average weekday demand). Sundays' demand is slightly higher than the weekdays' demand, excluding Fridays; refer to Fig. 2. This trend in demand distribution shows an increase in scooter usage during weekends, which primarily indicates the use of scooters for leisure-related activities, which is the principal purpose of scooters (Abouelela et al. 2021a).

The last temporal element to investigate was the hourly demand. We aggregated the hourly demand for weekdays and weekends. We found that the hourly demand in both cities follows similar trends. In Austin, the weekday demand is a left-skewed Bimodal distribution, with one minor peak around 8:00 and the other peak of the day between 12:00 and 17:00, which is the primary demand peak. The morning peak (around 8:00) does not exist on weekends, and the only demand peak is around 13:00. The morning peak hour during the weekdays could indicate that scooters are used for commuting trips at this time of the day. It is also to be noticed that there is a high demand for trips on the weekends' early morning hours, which might indicate the use of leisure trips at these times of the day. In Louisville, the trends are similar except that there is no morning peak hour demand during weekdays, and there is a low number of early morning trips during the weekends; refer to Fig. 2.

Spatial Analysis

We analyzed the spatial demand in the two cities at different periods of the day and on different weekdays guided by the temporal analysis results. The demand was aggregated per each census tract, per weekday v.s. weekend, per time of the day. We divided the day into four primary time intervals, each 6 h long, as shown in Figs. 5 and 6. We investigated the weekday demand dominance by normalizing the difference between the number of weekday trips and weekend trips and scaled the difference from (-1 to $+1$). First,

Table 5 Models performance metrics

Label Differencing	Sample Normalization	Performance (×10^{-5})				
		Model	Train RMSE	Train MAE	Test RMSE	Test MAE
Models without transfer learning						
–	–	LightGBM	531.6	82.9	2195.7	**382.6**
–	–	LR	1017.2	185.5	2164.1	388.3
–	–	SVR	1064.8	242.9	**2092.5**	440.4
–	–	LSTM	1333.8	360.2	2366.2	484.9
Models after transfer learning						
✓	✗	LightGBM	469.3	97.9	2291.9	394.1
✗	✓	LightGBM	1059.0	174.1	2037.6	390.5
✓	✓	LightGBM	873.9	130.7	**1845.6**	**346.8**
✓	✗	LR	1017.3	185.7	2168.5	389.6
✗	✓	LR	1166.8	178.4	**2034.7**	**378.7**
✓	✓	LR	1263.6	185.4	2054.4	381.2
✓	✗	SVR	1064.0	215.1	2135.6	449.5
✗	✓	SVR	1212.7	181.4	2200.8	381.4
✓	✓	SVR	1296.4	177.8	**2208.3**	**371.3**
✓	✗	LSTM	1274.3	284.6	2647.4	515.8
✗	✓	LSTM	1176.5	182.1	2677.9	480.6
✓	✓	LSTM	1140.6	179.3	**2376.0**	**436.4**

Bold value indicates the best-performing models

we assigned each trip to the starting census tract; then we aggregated the trips temporally to the weekend trips that happened on Saturday and Sunday and weekday trips for the other five days of the week; then we calculated the difference between the average weekend, and weekday trips per week for each tract (i = number of weeks … $1 - m$, j = number of tracts … $1 - n$), after this we normalized the difference by dividing by the maximum difference for each tract;

$$T_{ij} = X \cdot \sum_{i=1,j=1}^{i=m,j=n} \frac{\mathrm{Avg}(\mathrm{Weekend}_{ij}) - \mathrm{Avg}(\mathrm{Weekday}_{ij})}{\max(\mathrm{Avg}(\mathrm{Weekend}_{ij}) - \mathrm{Avg}(\mathrm{Weekday}_{ij}))}, \tag{9}$$

where i = number of weeks, j = number of tract, and[11]

$$X = \begin{cases} -1, & \text{if } \mathrm{Avg}(\mathrm{Weekend}_{ij}) - \mathrm{Avg}(\mathrm{Weekend}_{ij}) \le 0, \\ 1, & \text{otherwise.} \end{cases} \tag{10}$$

The following spatio-temporal trends are observed. In Austin, the downtown area is mainly dominated by weekend trips at different times except before noon hours, where there is almost no difference in demand between weekday and weekend trips. A similar trend is noticed in the University of Texas at Austin area, which is dominated by weekday trips at different times of the day. Weekend trips dominate only the early morning hours, while the rest of the day is dominated by weekday trips by different ratios.

The spatio-temporal analysis shows interesting findings; both cities' downtown and university areas are two major attraction areas, and their spatial and temporal demand patterns are the same regardless of their use in the rest of the city. In Louisville, similar trends were also noticed. Weekend trips dominate the downtown area, and the University of Louisville area is dominated by weekday trips at all times of the day. For the rest of the city, the early morning hours

Table 6 Relative feature importance of top-10 features, LightGBM

Rank	Feature	Relative importance (%)
1	Demand (previous day)	6.6
2	Elapsed days since operation	6.3
3	Temperature	5.3
4	Day of the week	3.5
5	Demand (average of the past week)	3.1
6	Demand (difference between previous day and 2 days ago)	3.1
7	Demand (range of the past week)	3.1
8	Demand (7 days ago)	2.5
9	Distance to downtown	2.1
10	Citywide demand (difference between previous day and 2 days ago)	2.1

[11] X here is used for plotting positive values on the scale of Figs. 5 and 6.

Table 7 Relative feature importance of feature groups, LightGBM

Feature group	Importance (%)	Performance after feature removal ($\times 10^{-5}$)			
		Train RMSE	Train MAE	Test RMSE	Test MAE
Time series features	67.0	1243.7	199.8	2637.6	457.3
Temporal features	9.8	978.2	146.6	1976.0	362.4
Sociodemographical features	9.6	887.7	133.9	1873.3	350.4
Meteorological features	7.1	1051.2	169.0	2182.9	399.1
Built environment features	6.6	876.4	133.3	1869.3	349.7

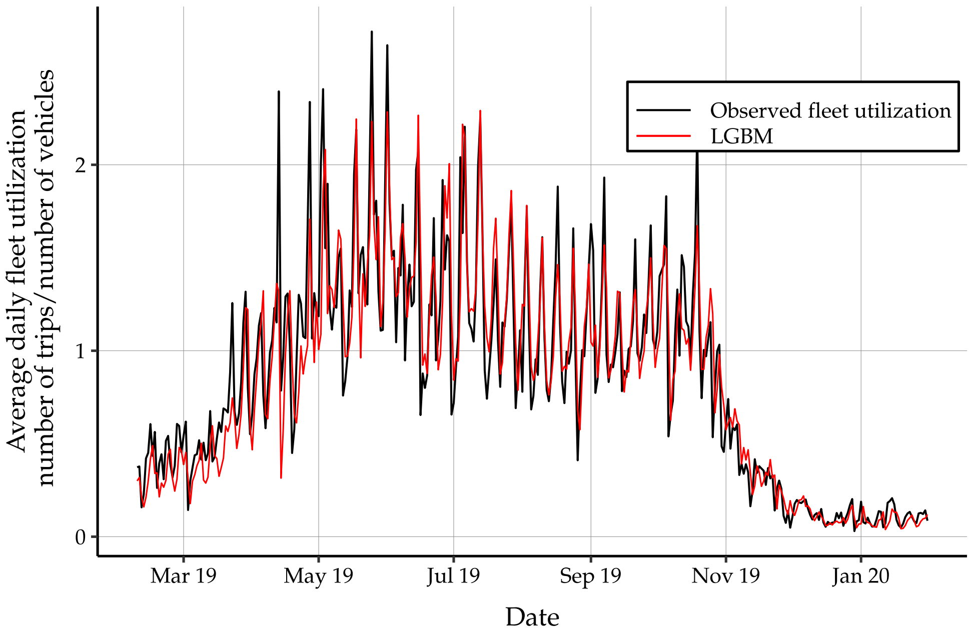


Fig. 7 Observed versus predicted fleet utilization using LightGBM

till before noon are dominated by weekend trips, and the rest of the day is dominated by weekday trips with different ratios. Although the temporal distribution of trips is almost the same in both cities, their geographical distribution is different, which we believe is due to the different urban structures of both cities.

Model Results, and Performance Evaluation

We investigated the effectiveness of the proposed methodology used for the model transfer problem for demand prediction. The prediction accuracy was evaluated using two metrics; root mean squared error (RMSE), and mean absolute error (MAE). The proposed framework was applied to the different used ML techniques. We first compare the performance of the models as shown in Table 5 upper part, and then we compared the performance of the model after the transfer (label differencing, and sample normalization), Table 5 lower part.

To further improve the transferability of the model, we applied the model transfer strategies to all the models. We applied the different transfer strategies as shown in Table 5 lower part, which shows the model's prediction results summary after applying the different transfer strategies. A time series prediction without treatment of the covariate shift issue suffers from low RMSE and MAE on the training set. However, when faced with unseen data in another city, the test set's performance suffers considerably because of distinct time series patterns. Firstly, we applied label differencing, but it did not improve accuracy as the distribution inconsistency in the input space was not addressed; similarly, only applying sample normalization was ineffective. The transfer error was finally reduced when the two strategies were used simultaneously, which is evident in the best-performing model, LightGBM. For LightGBM, The RMSE dropped from 2195.7 to 1845.6, which showed an improvement of the performance by approximately 15.9%. Meanwhile, a drop in accuracy on the training set was also observed, indicating a less severe over-fitting model; in other words, the proposed method was satisfactory in improving the generalization ability and robustness of the model in the

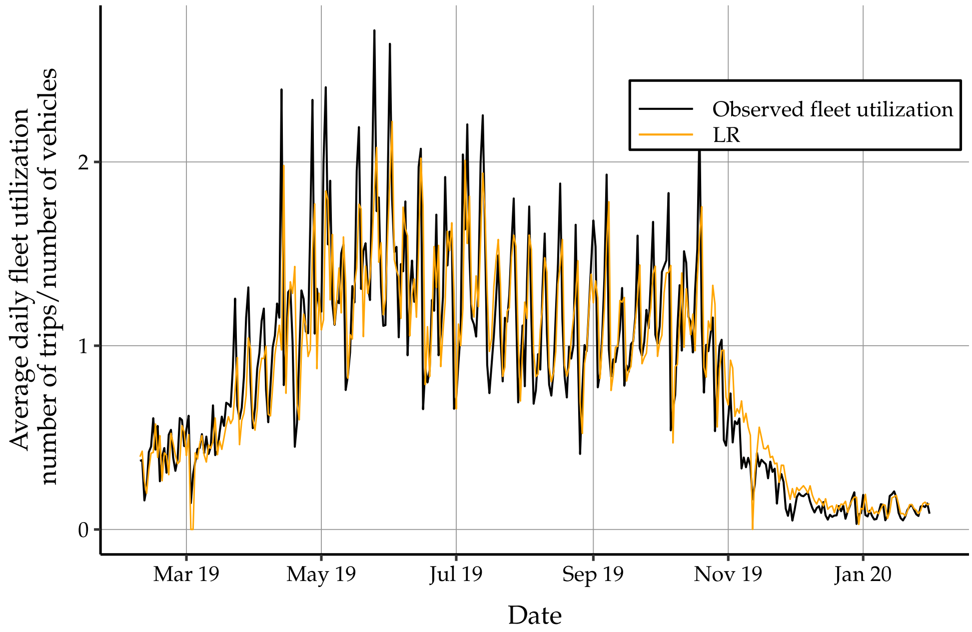


Fig. 8 Observed versus predicted fleet utilization using Linear Regression

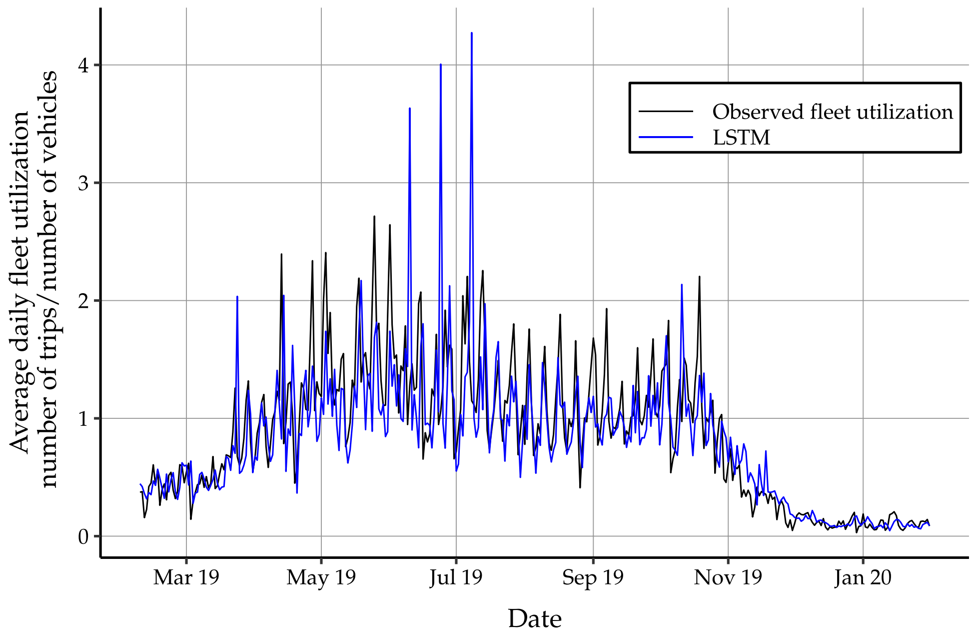


Fig. 9 Observed versus predicted fleet utilization using LSTM NN

transfer learning problem. Further error analysis is presented in the following section.

As The LightGBM model was the model with the best prediction performance, we evaluated the importance of factors influencing the prediction using the number of node splits corresponding to each feature in the trained LightGBM model. The more a feature was adopted for a split in the tree, the higher its contribution to the prediction (Liu et al. 2020). We ranked features by their relative importance, the top 10 listed in Table 6. As a time series prediction model, lagged demand values and their statistics are essential to the prediction, where the one-day lagged demand contributed the most, accounting for 6.6% of all feature splits in the trained decision trees. Among the top 10 features, three time-varying and one census tract-related auxiliary features, i.e., elapsed days since operation,[12] temperature, day of the

[12] The term "elapsed days since operation" here means the number of days from the first operation day of the service to the day corresponding with the sample to be predicted. This feature is used as the demand pattern of a shared mobility service can differ between its starting stage and later.

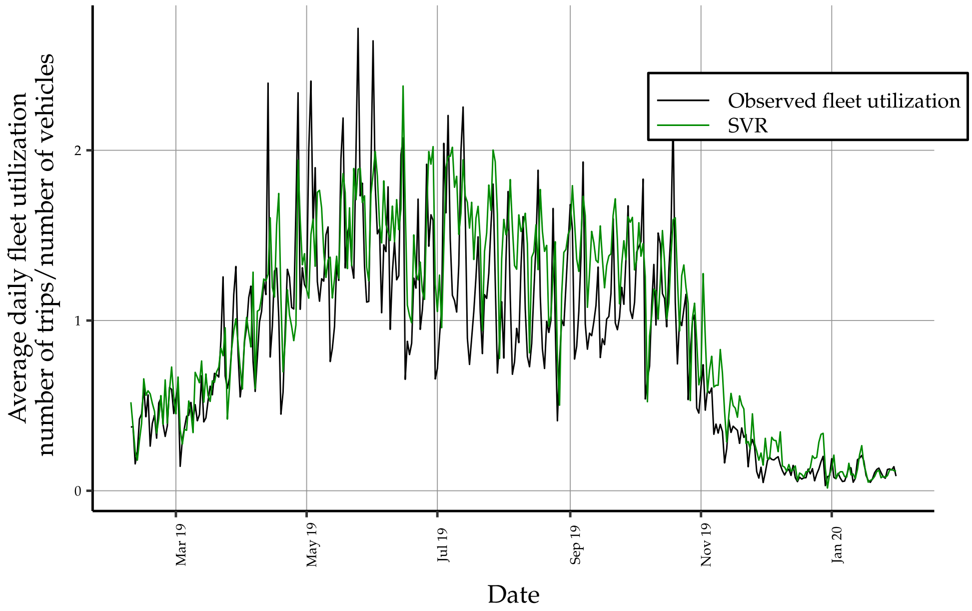


Fig. 10 Observed versus predicted fleet utilization using SVR

week, and distance to downtown significantly contributed to the prediction.

To quantify the influence of the different factors groups, we categorized the features into five main groups, refer to Table 7. Time series features accounted for 67.0% of node splits in the trees, whereas each category of auxiliary features accounted for approximately 6–10% of node splits. Further experiments were performed to see whether removing specific feature groups would significantly reduce prediction accuracy. We found that removing every feature group will more or less negatively impact the model performance. The results are generally consistent with their relative importance; the removal of time series features—the most critical group of features—resulted in a performance drop of around 43% in Test RMSE. Removing auxiliary features did not incur severe impacts, where the accuracy reduction caused by removing built environment features or sociodemographic features was less than 2% per group.

Error Analysis Description

We analyzed the prediction error, its value distribution, temporal distribution, and spatial location considering the test set Louisville's dataset. The actual and predicted number of trips per vehicle per day were plotted along the temporal axis in Figs. 7, 8, 9, and 10.

It can be observed that all the estimated models captured the overall demand pattern with some shortcomings. The LR model tends to overestimate the utilization rate between (1–1.75) vehicles per trip, and it underestimates the demand when it is higher than 1.75 trips per day; for the rest of the value, it is somehow able to estimate the fleet utilization rate.

SVR was consistently unable to predict the utilization rate; for rates below 1.25 vehicle/trip, the model underestimated the results, and for rates over 1.245 vehicle/trip, the model overestimated the utilization rates. Regarding the temporal distribution of the error, Fig. 10, SVR was the model with the least prediction capabilities. LSTM could not accurately predict the low utilization rate and tended to overestimate the utilization below 1.2 trips per day and underestimated the demand higher than 1.2; also, the model had some incidents where the estimated utilization rates were significantly higher than the actual rate. The LGBM model had the best performance among the four models. It can be observed that the prediction results of the proposed model capture most of the demand seasonal peaks and troughs dynamics without lag except for the several sudden spikes in the early stage of operation (e.g., the spike in mid-April). However, the model inclines underestimation regarding peak values, possibly an outcome of model regularization, as predictions of large values are more likely to be connected with high errors (error terms are increasingly proportional to the absolute demand value). Potential solutions include increased training data and additional information like special events and fine-grained weather forecasts. To be able to observe and understand the previous prediction trends, we plotted the predicted values in comparison to the actual values using three different graphs, where Fig. 11 shows the distribution of the predicted values in reference to the actual observed utilization rate, Fig. 12 shows the distribution of the difference between the observed utilization rate and the predicted utilization rate. Finally, Fig. 13 shows the predicted values against the actual values and the corresponding regression line.

We also spatially analyzed the difference between the predicted and actual fleet utilization rate; we plotted the difference between the average utilization rate and the predicted one per census tract. Figure 14 shows the prediction error spatial distribution; it can be observed that for all models, except SVR, the errors in most census tracts are low or even zero. SVR overestimates the utilization rate in all the tracts except the university area, where it underestimates the utilization rate. The errors have a distinctive pattern for the other three models, mostly occurring around downtown and the university area's tracts. The high demand can explain the relatively high errors in these two areas, and error is proportional to the absolute demand value and more events that make predictions difficult.

The conclusion of the error analysis process, which was done in multiple dimensions, shows that the LGBM model is superior in prediction accuracy compared to the other used ML models, including LSTM.

Discussion, and Conclusion

Discussion

The observed spatio-temporal scooters' demand patterns in the two examined cities show the demand and fleet utilization rate seasonality. The demand is different for the different hours of the day and the day of the week; also, the spatial demand distribution is different in the two examined cities, and it depends on the time of the day. Nevertheless, there is a significant spatial common phenomenon in both cities, with the demand spatially concentrated around the downtown and the university areas. Therefore, system operations such as vehicles' supply management and allocation and redistribution should consider such patterns in the deployment and redistribution process and ensure deploying the number of vehicles in the desired locations that are changing according to the actual demand. The used framework shows a simplified and effective way to predict the number of trips per vehicle (fleet utilization) for one of the rapidly expanding shared mobility services, shared-e-scooter, depending on open-source data. This framework could be used (after testing) for similar dockless, free-floating micromobility shared systems, which exhibited similar travel behavior, e.g., free-floating bike-sharing services (Zhu et al. 2020; McKenzie 2019). Moreover, similar data characteristics to the one used in this study should be available for other shared mobility services to implement the used framework; for each trip, trip starting and ending spatial points, starting and ending timings, trip speed, and trip distance. As the methodology section explains, the framework depends on employing the historical demand data combined with open-source data; therefore, different stakeholders could use the framework to predict the daily number of trips per vehicle and deploy the vehicles in the expected locations accordingly. The error analysis section ("Methods, Data, and Case Study" section) shows that the increase in the number of days used in the prediction process increases the accuracy of the models; therefore, the continuous use of such models would improve the model accuracy over time. It is also to be noticed that we used the ridership (the number of trips per vehicle per day) for the prediction task for two main reasons; firstly, we wanted to control the fleet size in both cities to be able to compare the demand and to normalize the impact of the supply. Secondly, demand is directly tied to supply in the case of shared mobility services, and estimating absolute demand will lead to a biased estimation (Gammelli et al. 2020). Moreover, the predicted fleet utilization rates should decide the fleet size. Table 4 shows that the median and mean daily average number of trips per vehicle in the two cities are under one trip/vehicle/day; therefore, more investigating measures need to be applied to define the reasons behind the low ridership. In addition, cities should study the consequences of making ridership rates a compelling factor for the number of deployed scooters. Based on our analysis, we believe fleet size should be dynamically decided, if not daily, which needs further research to determine its efficiency in vehicle balancing and redistribution and the generated additional VKT weekly according to the seasons. Special event periods, such as the SXSW music festival in Austin, should consider different supply and vehicle rebalancing operation schemes due to the increased demand compared to regular condition days.

Conclusion

The methodology and data show a promising approach that the stakeholders could implement and use to organize scooters and similar shared micromobility vehicle services. However, the model needs to be tested for the other service to validate user behavior differences. Also, publishing the trip booking data publicly by cities should be encouraged as it plays a vital role in encouraging researchers from industry and academia to investigate such services use behavior and discover innovative methods to enhance service operations.

Appendix 1: Additional Analysis

See Figs. 11, 12, 13 and 14.

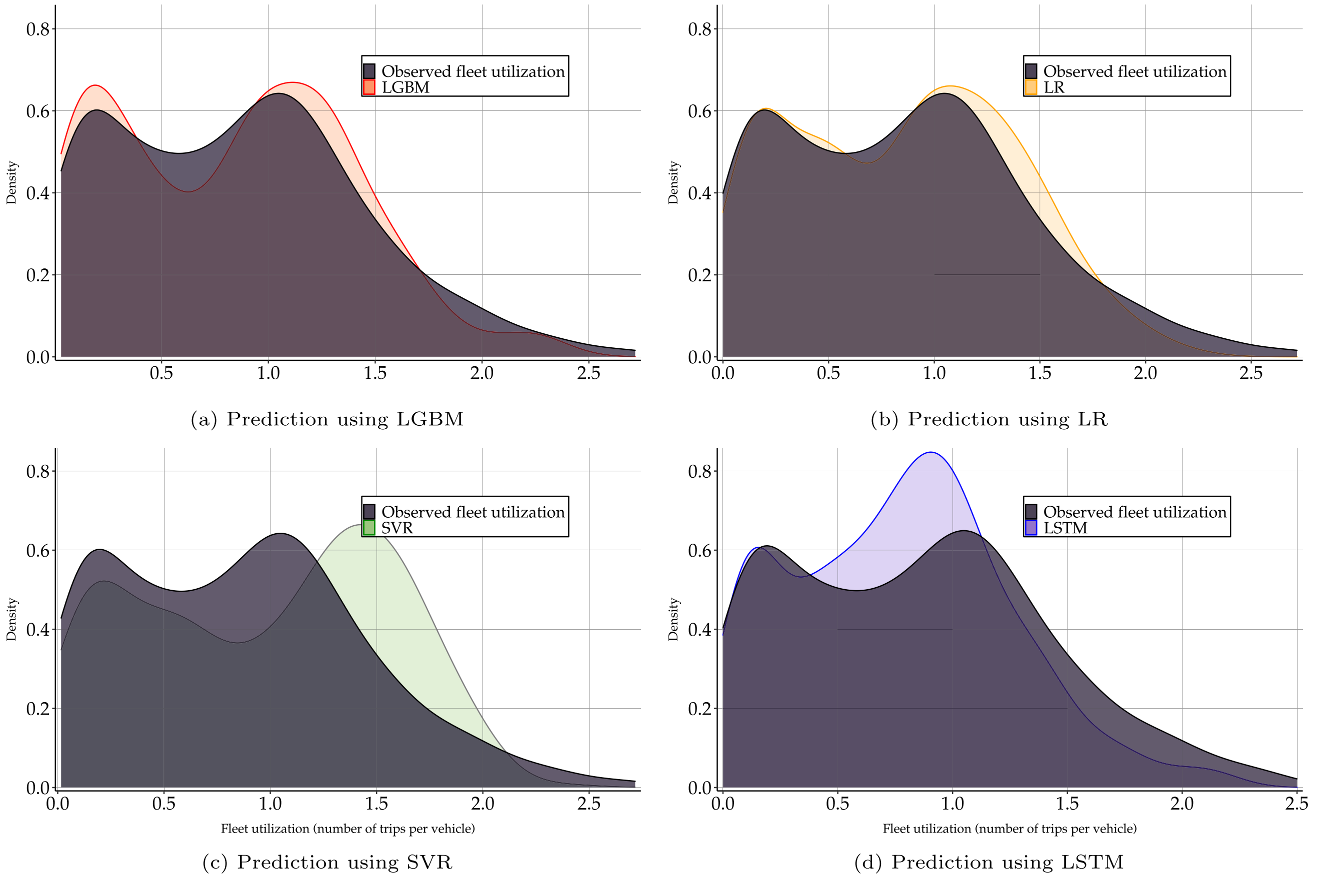
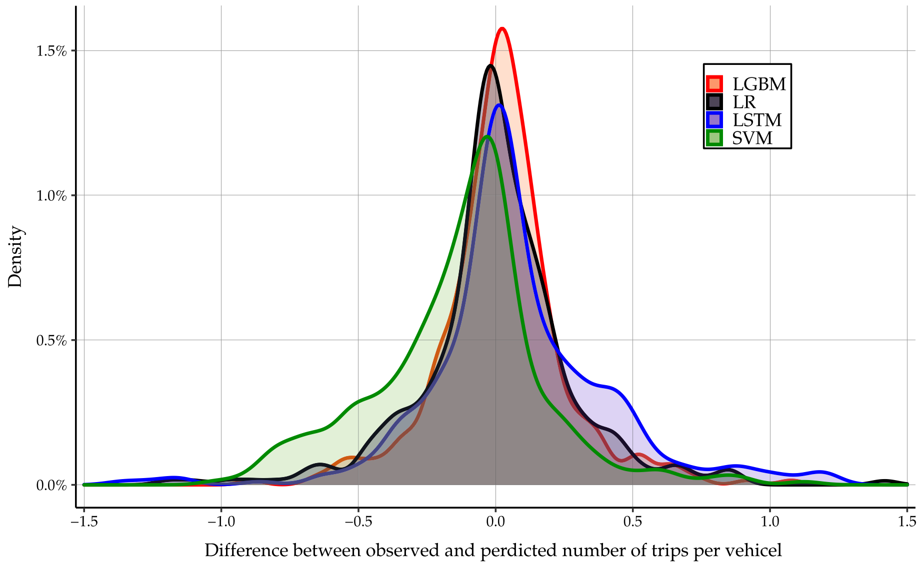
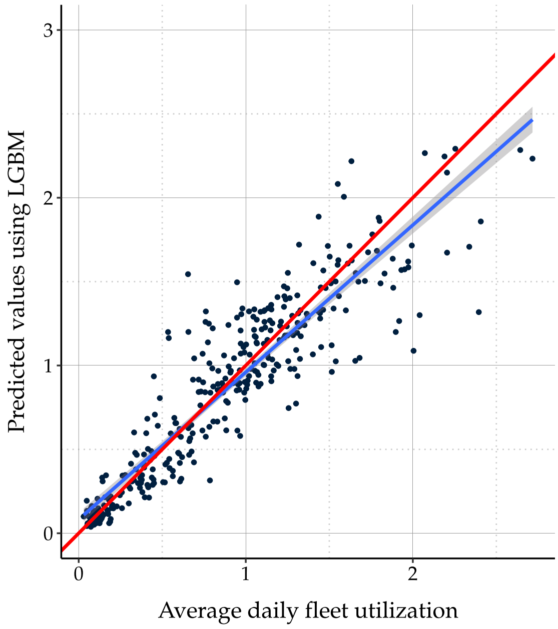


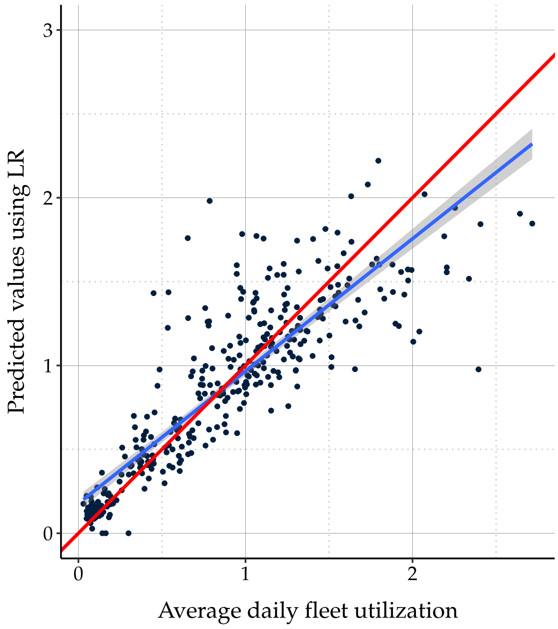
Fig. 11 Observed fleet utilization distribution versus predicted fleet utilization using different ML models

Fig. 12 Distribution of the difference between (Actual - predicted average daily trips per vehicle)

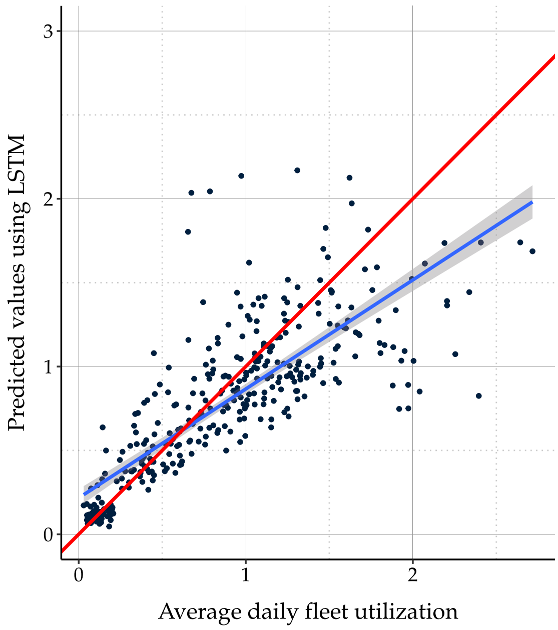




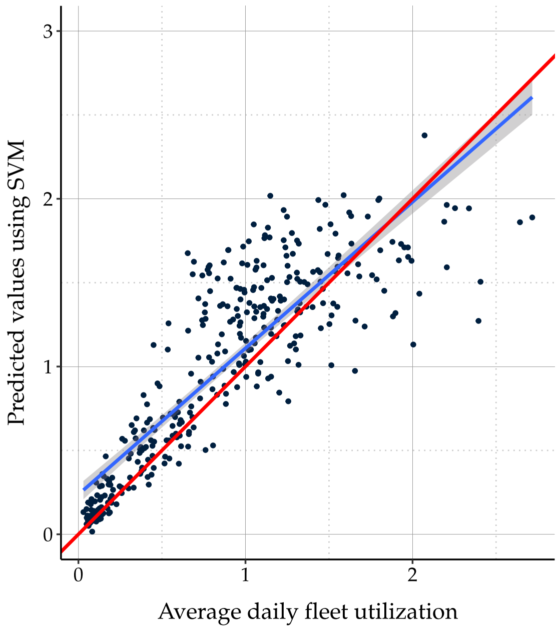
(a) Observed vs prediction daily fleet utilization; using LGBM



(b) Observed vs prediction daily fleet utilization; using LR

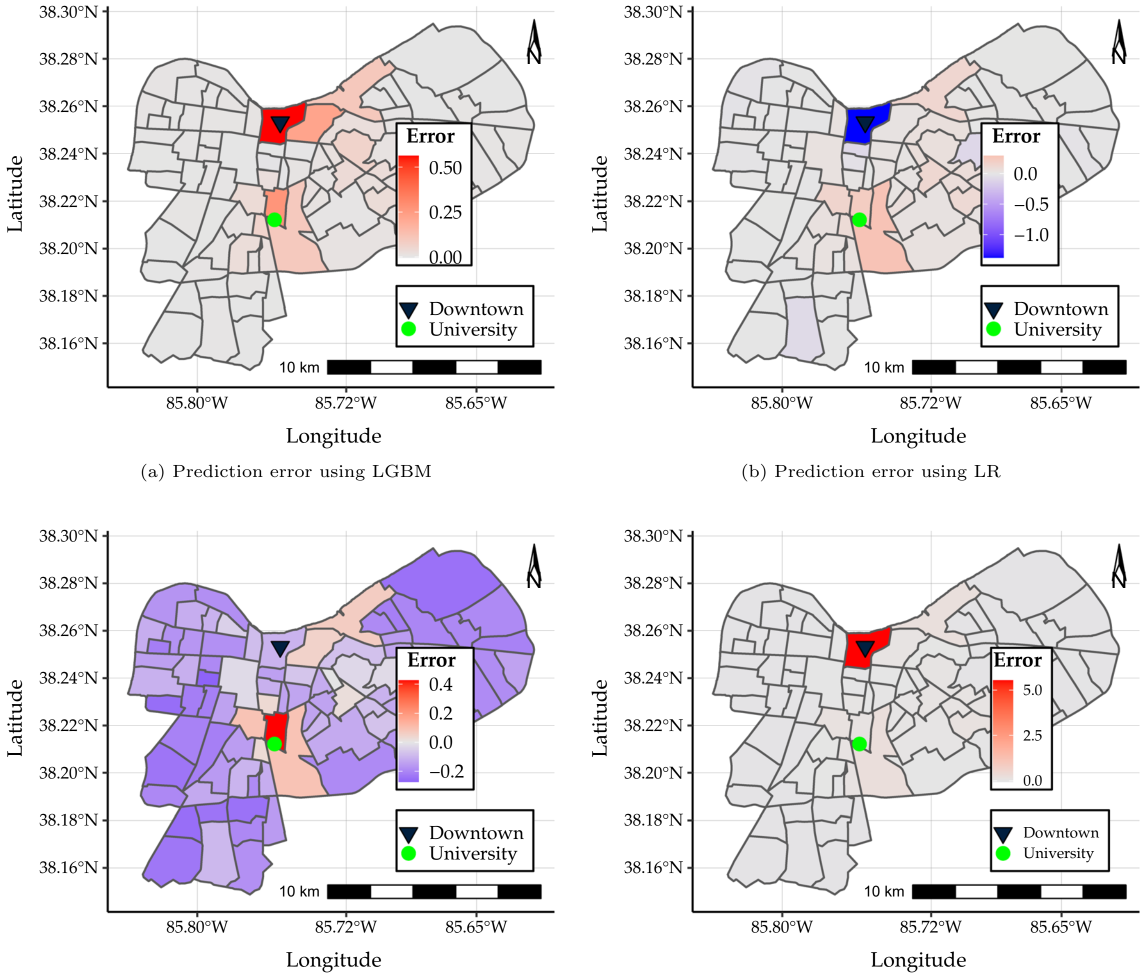


(c) Observed vs prediction daily fleet utilization LSTM



(d) Observed vs prediction daily fleet utilization SVR

Fig. 13 Observed average daily fleet utilization versus predicted fleet utilization, the blue line is regression line and the red line is 1:1 slope line



(a) Prediction error using LGBM

(b) Prediction error using LR

(c) Prediction error using SVR

(d) Prediction error using LSTM

Fig. 14 Spatial distribution of the mean difference between observed fleet utilization and predicted fleet utilization

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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Are young users willing to shift from carsharing to scooter–sharing?

Mohamed Abouelela, Christelle Al Haddad *, Constantinos Antoniou

Technical University of Munich, Arcisstrasse 21, Munich 80333, Germany

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ABSTRACT

Scooter–sharing has recently emerged as the newest trend in shared–mobility and micro––mobility; electric standing scooters are seen on the streets of major cities and are perceived as a fun, convenient mode of transport. However, there are also concerns regarding scooter safety, riding, and parking regulations. A motivation is to understand the impacts of scooters and their potential to disrupt existing systems. In this paper, the shift from carsharing to scooter–sharing is of particular interest. A stated preference survey targeting young individuals (18–34 years old) conducted in Munich was used to estimate a choice model between carsharing and scooter––sharing. The model was then applied to scenarios developed based on trip characteristics of a carsharing dataset. The model shift was then estimated for the scenarios, followed by a sensitivity analysis. In the best–case scenario, scooters were found to attract about 23% of carsharing demand.

1. Introduction

Transport systems have been recently witnessing unprecedented disruptions including shared mobility, autonomous mobility, and other forms of mobility that are shaping the way people move. Among these, micro–mobility has emerged as an attractive concept, for modes with low speed, short–term access, and on–demand trips, including both station–based and dockless or free–floating vehicles such as bikesharing, and scooter–sharing; the latter includes both standing electric scooter–sharing and moped–style scooter–sharing (Shaheen and Cohen, 2019). The increasing demand for standing electric scooters has seen considerable growth in various cities, particularly in the US where the market for scooter–sharing is expected to reach $300B (Shaheen and Cohen, 2019). Interest in micromobility has oriented research and policy–makers to investigate its impacts, understand the needs of its users/non–users, but also come up with responsible policy–making and guidelines for its integration to current systems (Shaheen and Cohen, 2019). Scooter trips are often seen as convenient, yet are associated with safety concerns (Sanders et al., 2020). When it comes to mode replacement, findings diverged: some argued that scooters have the potential to replace walking (Sanders et al., 2020; SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019; Portland Bureau of Transportation, 2019; Bloomington Planning & Transportation Department, 2020), while others highlighted a replacement of motorized vehicles such as taxi, access/egress trips (Lee et al., 2019), and ride–hailing trips (Chicago Department of Transportation, 2020b; SFMTA, 2020). Few studies, if any, addressed the impacts of scooter–sharing on carsharing, despite quite common characteristics mostly pertaining to shared–mobility. Moreover, to the best of the authors' knowledge, no previous study has conducted a stated preference (SP) experiment including scooter–sharing as a main mode of

* Corresponding author.
E-mail address: christelle.haddad@tum.de (C. Al Haddad).

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transport. Other researchers have conducted SP studies in an attempt to better understand scooter adoption (Aguilera-García et al., 2020) or developed scooter choice models, where scooters were introduced as a last mile transportation mode (Baek et al., 2021).

This study attempts to close this gap by i) conducting a stated preference study to estimate a choice model between carsharing and scooter–sharing[1], and ii) using the estimated model to predict the demand shift from carsharing using a carsharing dataset from a Munich operator. For the SP survey, young individuals (18–34 years old) were targeted, as they are most likely the potential users of scooter–sharing systems (SFMTA, 2020; 6-t, Bureau de recherche, 2019). In other words, the study aims to answer the following question: are young users willing to shift from carsharing to scooter–sharing?.

The remainder of this paper will be structured as follows. First, a literature review introduces research on both carsharing and e–scooters, and then concludes with the research gap motivating this study. The methodology is then presented in details including the different steps of estimation, prediction, and assumptions used. After that, results are given, including the stated preference results, the estimated models, and the prediction scenarios with the sensitivity analysis. This paves the way to a discussion of the main findings and contributions with insights for policy–makers. Finally, a conclusion wraps up the study findings and contributions, with a focus on possible future research steps.

2. Literature review

Since the aim of the paper is to study micromobility and benchmark it against carsharing, a literature on both sharing systems is needed, after which a gap analysis is drawn, with a focus on the objectives of this study.

2.1. Carsharing

The existing body of literature covers several aspects of carsharing and its impact on transportation systems. This comprises trip characteristics, factors affecting the use, and modes that carsharing would replace had it not been available. Already since 2003, a study by Cervero (2003) investigated the first carsharing program in the US. The authors found that carsharing could potentially stimulate motorized travel, since many users did not own a car, which meant that carsharing possibly replaced walking and biking, with trip purposes being mostly for personal business, and recreation.

More recently though, studies have benefited from rich datasets of carsharing including pilot data (Hui et al., 2017) and booking data in order to identify the factors of interest for carsharing demand (Schmöller et al., 2015; Müller et al., 2017). Factors affecting demand included weather conditions, time of the week, and socio–demographics. The latter is particularly notable for early adopters of carsharing, which according to Namazu et al. (2018) are rather wealthier and younger compared to late adopters. In addition to demographics like age and gender, De Luca and Di Pace (2015) identified cost, access time to carsharing parking lots, trip frequency, car availability, and trip type as the most significant attributes for carsharing. Trip type was also found to be significant in a study by Costain et al. (2012), particularly short trips where transit trips are less attractive. Besides pilot and trip data from real operators, carsharing studies often collected data from stated preference surveys to model user and non–user preferences (De Luca and Di Pace, 2015; Martin et al., 2010; Martin and Shaheen, 2011; Liao et al., 2020).

In terms of modal shift, carsharing was found to substitute motorized modes, but also complement transit where the latter was not efficient (De Luca and Di Pace, 2015). Similarly, a survey on North American carsharing (Martin et al., 2010) indicated that the average household car ownership would almost drop by half with carsharing introduction, highlighting as well the potential of private car substitution; overall more people increased transit use and non–motorized mode use (Martin and Shaheen, 2011). On the other hand, a case study in Montreal revealed that if carsharing was not available, users would have used transit, taxis, and walking instead (Wielinski et al., 2015), which goes against the findings of motorized vehicle reduction.

Findings from previous studies therefore reveal the importance of pilot and survey data to analyze carsharing trip characteristics, impacts, and factors affecting its demand; mostly time, cost, but also socio–demographics. Overall, carsharing was found to have the potential to reduce motorized modes, but also to complement or replace transit if the latter was inefficient or in poor conditions.

2.2. Scooter–sharing

The increasing interest in scooter–sharing has urged cities to better explore this system, understand its users, and the impact it has on existing modes of transport. Several cities have therefore conducted pilots to investigate scooter–sharing users and scooter impacts (Abouelela et al., 2020). In this section, we present findings from the analysis of city reports in Chicago, Bloomington, San Francisco, Portland, Calgary, and France (Paris, Lyon, Marseille). This analysis focused on different aspects including the means of data collection, trip purpose, modes replaced by scooters, reasons for using scooters (or not using them), the demographics of users, but also other pertinent remarks and learnings from these pilots.

In an attempt to understand the impact of e–scooters on existing systems, including insights of users and non–users, but also the potential they have to replace other modes, cities collected data from a variety of means. Data collected in the above–mentioned cities comprised data from pilots where cities introduced e–scooters, including company data (Chicago Department of Transportation, 2020b; SFMTA, 2020; Portland Bureau of Transportation, 2019), survey data or other stakeholder data (SPC on Transportation and

[1] In this study, the term "scooter–sharing", "e–scooters", and "scooters" will be used interchangeably to refer to free–floating standing electric scooters.

Table 1
Summary of findings from city pilots on scooter–sharing.

Study	Pilot data	Survey data	Riding and parking observations	Trip purpose	Mode replacement	Reasons to use	Reasons to not use	User demographics	Remarks
Calgary SPC on Transportation and Transit (2019)	✓	✓		Leisure	Walking	Access	Safety	Age: 25 to 44, males, high–income	
Chicago Chicago Department of Transportation (2020b)	✓	✓	✓	Commute, access to transit, leisure	Ride-hailing or personal vehicles	Access, curiosity, fun	lack of awareness on rules for riding and parking	White, high–income, educated	
Bloomington Bloomington Planning & Transportation Department (2020)		✓			Walking, personal car, ride–hailing				Users rarely use it
Paris–Lyon– Marseille -t, Bureau de recherche (2019)		✓		Leisure	Walking	Fun, timesaving	Price unsafe, weather	Age <35, mostly men	Regulations might reduce the use of e–scooters (parking, speed limit).
San Francisco SFMTA (2020)	✓	✓			Ride–hailing (Uber, Lyft)	Convenience	Use decreased in winter	Mostly males, young: 25–34	
Portland Portland Bureau of Transportation (2019)	✓	✓	✓	Access, leisure	Walking, personal car, ride–hailing		Discomfort with pedestrians and safety concerns		Data from other sources like police complaints, hospital reports was used.

Transit, 2019; Chicago Department of Transportation, 2020b; Bloomington Planning & Transportation Department, 2020; 6-t, Bureau de recherche, 2019; SFMTA, 2020; Portland Bureau of Transportation, 2019), and riding and parking observation data (Chicago Department of Transportation, 2020b; Portland Bureau of Transportation, 2019). Moreover, in Portland, data was enriched with police and hospital reports for complaints and injuries pertaining to e–scooter incidents. Data collection gave insights on trip characteristics, where most trips were done for leisure (SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019), commute or access (Chicago Department of Transportation, 2020b; Portland Bureau of Transportation, 2019). The trip average for most pilots showed that e–scooters were often used for trips of short duration: the average trip was just under 1 mile (1.6 km) in San Francisco, 1.15 miles (1.85 km) in Portland, and 1.5 miles (2.4 km) in Chicago. User characteristics in the different cities reflected similar user profiles: mostly young, males (SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019; SFMTA, 2020), with high income and education (Chicago Department of Transportation, 2020b). Users reported to use scooters, often for access (SPC on Transportation and Transit, 2019; Chicago Department of Transportation, 2020b), convenience (SFMTA, 2020), or perceived fun (Chicago Department of Transportation, 2020b; 6-t, Bureau de recherche, 2019). Non–users often reported safety concerns (SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019; Portland Bureau of Transportation, 2019), as well as price (6-t, Bureau de recherche, 2019), lack of awareness of rules for parking (Chicago Department of Transportation, 2020b), and weather (6-t, Bureau de recherche, 2019) as reasons for not using e–scooters; in San Francisco, the latter was not directly reported, but an observed decrease of e–scooter use is notable from November to February (winter season).

An interesting finding as well is the diverging perceptions when it comes to e–scooter regulations. In San Francisco, the introduction of regulations (on-street enforcement of the parking guidelines) helped reducing the number of complaints about scooters (SFMTA, 2020). On the other hand, in France, the enforcement of regulations (such as the obligation to wear a helmet, the regulation of parking, a speed limit reduction to 15 km/hr) was reported to reduce the use of scooters (6-t, Bureau de recherche, 2019).

Finally, pilots and surveys aimed to investigate the impact scooters have on existing modes, by quantifying their replacement of other modes; essentially, had scooters not been available for the trip they were used for, what other modes would users have used? This was divided among two main modes: walking [Calgary (SPC on Transportation and Transit, 2019), Bloomington (Bloomington Planning & Transportation Department, 2020), Portland (Portland Bureau of Transportation, 2019), Paris-Marseille-Lyon (6-t, Bureau

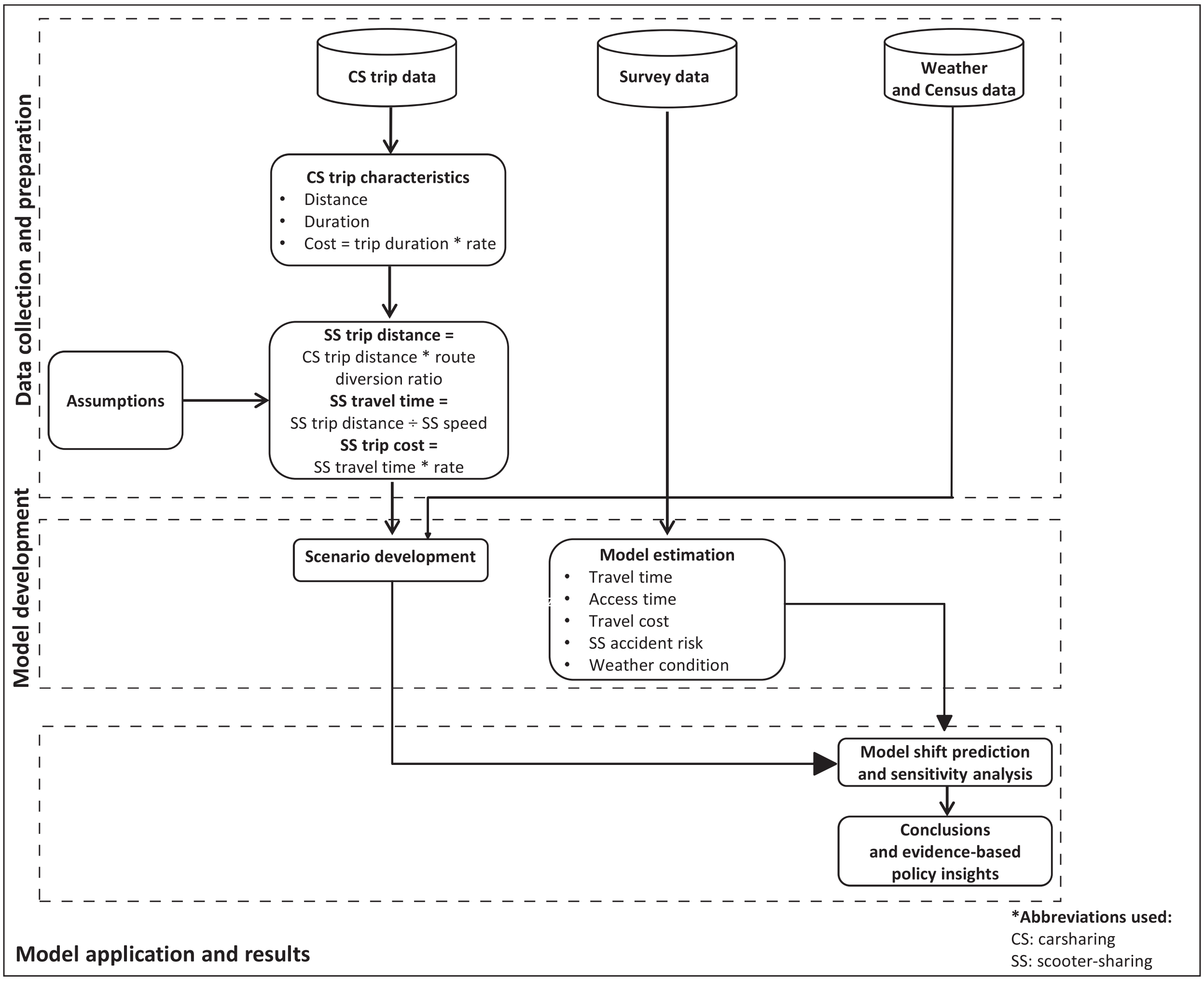


Fig. 1. Methodology workflow.

de recherche, 2019)], or motorized personal vehicles, particularly ride–hailing like Uber or Lyft [Chicago (Chicago Department of Transportation, 2020b), San Francisco (SFMTA, 2020)].

A summary of findings on scooter–sharing is given in Table 1.

2.3. Gap analysis

The above analysis leads to an understanding of the gaps in micromobility research. On the one hand, fewer studies have investigated scooter users and demand compared to carsharing, mostly SP studies; on the other hand, studies on micromobility replacement have not looked at the shift from carsharing, but rather focused on walking and ride–hailing. This was usually done by directly asking users about the mode they would have used had scooters not been available for the same trip. Moreover, previous reports did not include carsharing, which could serve as a motivation to study the preferences and therefore shift from carsharing to scooter–sharing. The estimation of a choice model for preferences between both modes can be then applied to understand scooter–sharing potentials based on trip characteristics (distance, duration, etc.).

3. Methodology

The overall methodology of this study is summarized in Fig. 1. In the following section, data sources are presented, including carsharing trip data, survey data, hourly weather data and German census data. Then, the methodology for the mode choice estimation, in this case the multinomial logit model, is given. Finally, the methods for the model prediction are presented, including the used assumptions and the developed scenarios, as well as a thorough sensitivity analysis.

3.1. Data sources

3.1.1. Carsharing data

The carsharing dataset is an hourly carsharing trips dataset from a carsharing operator in Munich, Germany for 2016. The dataset contains the average distance and average duration for each trip in addition to the starting zone number. A separate shape file containing the geo-information of the parking zones was also received to locate the trip origins in reference to the map of Munich. Fig. 2 shows the carsharing zoning system with respect to the boundaries from the Munich census. The carsharing dataset contains 972,459 trips; only trips within the scooter travel range were kept, to allow for model estimation, where competition with e–scooters is possible.

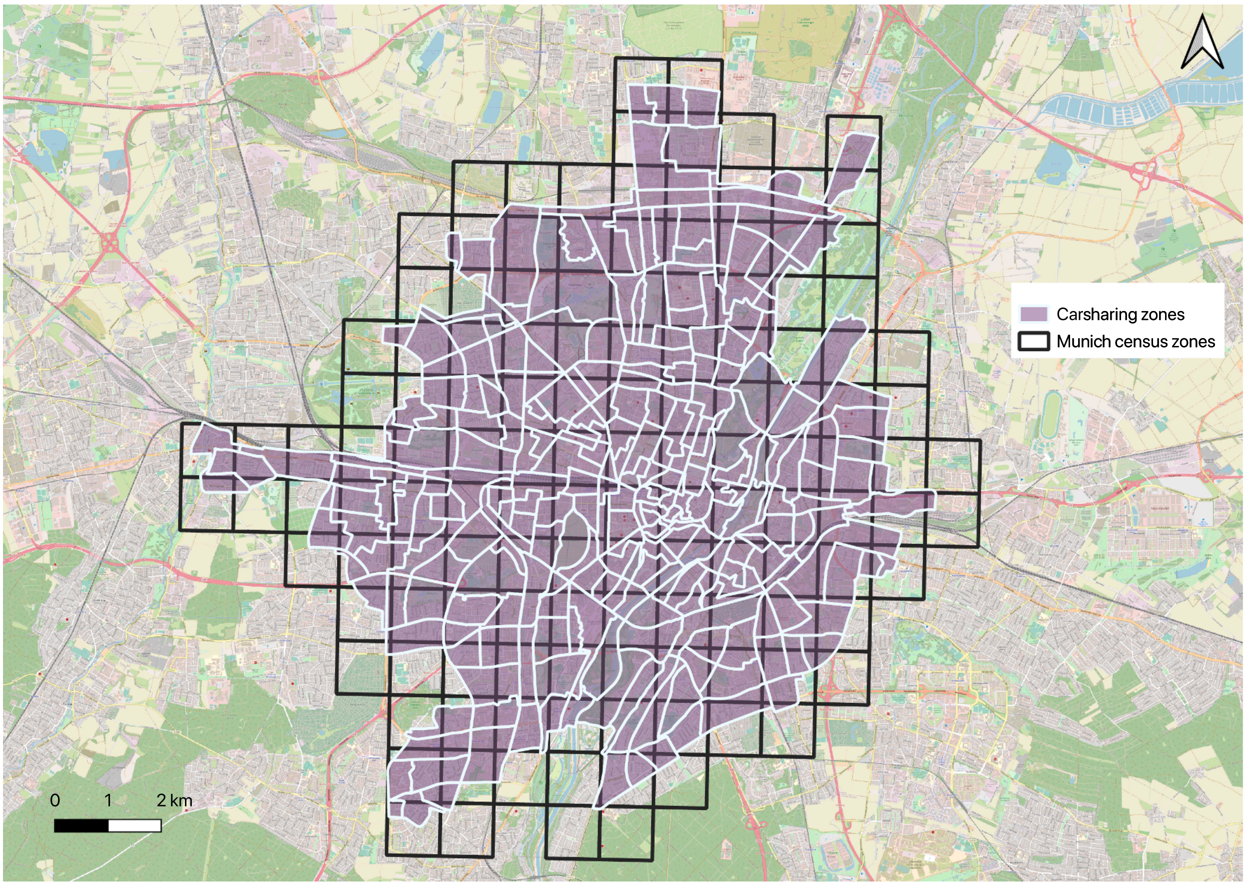


Fig. 2. Zoning system of the carsharing operator with respect to the Munich Census.

3.1.2. Survey data

To better understand user preferences for e–scooters compared to carsharing, a stated preference survey was conducted in Munich. The survey was shared online for two months starting December 2019 using Limesurvey Pro (limesurvey.org). It was distributed through channels of communication such as Facebook and Instagram as well as mailing lists via a snowball data collection method. The target population was young individuals from 18 to 34 years old, as they are most likely the potential users of scooter–sharing systems (SFMTA, 2020; 6-t, Bureau de recherche, 2019). Moreover, by focusing the target group that will most probably join scooter–sharing, sampling and coverage errors were reduced, as suggested by Efthymiou et al. (2013). To increase the response rate, the survey was further disseminated in the same social media channels.

The survey was designed with 11 blocks and 9 scenarios/block, using a random design, as previous literature did not find a strong evidence that efficient design outperforms random design (Kladeftiras and Antoniou, 2015; Walker et al., 2018). The attributes and levels used are summarized in Table 2.

The survey contained 31 questions and was structured in four parts. The first part included travel behavior questions, such as the main mode of transport, the ownership of a driver's license, the access to a car, and the overall satisfaction with the existing public transport system. The second part introduced carsharing and scooter–sharing as possible alternatives of a fictitious trip of 4 km between two points A and B. Here, nine choice scenarios were given and respondents had to choose for each one among: "Certainly carsharing", "Probably carsharing", "Indifferent", "Probably scooter–sharing", "Certainly scooter–sharing", or "none"; the 'none' option aimed to cover other modes, and therefore the bias of not including them in the stated preference study. Then, in the third part of the survey, questions pertained (but were not limited) to social media use, comfort with online services, willingness to share a ride, enjoyment of driving a car, environmental perceptions, and the previous involvement in a car crash (with different levels of intensity). Finally, the fourth and last part entailed socio–demographics such as age, gender, income, household size, higher level of education achieved, main occupation, etc.

To illustrate the second part of the survey, a survey block is given in Fig. 3.

3.1.3. Weather and Census data

In addition to the carsharing trip data and the survey data, external sources were used, namely the hourly weather data for 2016 (since the carsharing data was for the year 2016), and the German Census data. The former was retrieved from the German weather service online archive (dwd.de) and contains the hourly temperature and precipitation. The latter was obtained from the German federal statistical bureau (statistikportal.de). The data is available in 1 km × 1 km resolution raster format, and contains the average demographics distribution per zone, such as percentage of population, percentage of females, age distribution, and household size.

3.2. Model estimation

The collected stated preference (survey) data was used to estimate a mode choice model for the different alternatives. Since the aim is to use the model estimate to predict carsharing demand shift, responses were regrouped as follows: varying preferences for carsharing ("Certainly carsharing", "Probably carsharing") were grouped under the carsharing choice and varying preferences for scooter–sharing ("Certainly scooter–sharing", "Probably scooter–sharing") were grouped under the scooter–sharing choice. Moreover, responses with "indifferent" as a choice were removed following Antoniou et al. (2007), as they could not be attributed to either choices; moreover, these amounted to less than 1% of the sample size, and are therefore not believed to have an impact on estimation. Accordingly, three alternatives remained and were regrouped (carsharing, scooter–sharing, and none) and a multinomial logit model was estimated using the scenario attributes (time, cost, rain, risk of accidents), but also the respondents' demographics. The model was developed by first adding the mode attributes, and then, variables for demographics were added one by one. Cost and time coefficients were chosen as mode specific instead of generic, due to the improved model performance under this specification. While attitudinal questions could be used to better understand users' perceptions, they were not used in the model estimate, as the aim was to later use it to predict the shift for carsharing trips in Munich and it was not possible to obtain attitudinal data for the population of Munich. Models were estimated using Apollo package (Hess and Palma, 2019) under the statistical programming language R (R Core Team, 2020).

3.3. Model prediction

3.3.1. Assumptions

To test the attraction of carsharing users to e–scooters, we developed a number of scenarios based on different assumptions, with the aim to apply the estimate choice model to predict the carsharing to e–scooters. Cost and speed values were based on operator ranges in the city of Munich (case study). A comprehensive list of the used assumptions is given below:

- **Carsharing trip cost**: **(0.20, 0.28, 0.36)**, based on operator ranges from 0.19 to 0.36€/min (share-now.com).
- **Route diversion or scooter route/carsharing route**: **(−30%, −10%, 0%, 10%, 30%)**. Based on the carsharing trip (from the existing trip dataset), a hypothetical trip was created for the model prediction. To calculate the scooter's trip length for the same trip, a route diversion factor was considered. Despite the lack of references in the literature on a similar ratio, we used the diversion ratio with bike–sharing, as the closest proxy to scooters. According to Krenn et al. (2014), on average bike trips are 10% longer than the shortest path. Winters et al. (2010) found that car and bike trips are around 8% longer than the shortest path. To account for all possibilities of scooter to carsharing trip diversion ratios, we considered a conservative range the above–mentioned conservative scooters to carsharing ratios, ranging from −30% to 30%.

Table 2
Attributes and levels used in the survey.

Variable	Unit	Levels
Travel time of scooter–sharing	min	[8, 11, 14]
Travel time of carsharing	min	[5, 8, 11]
Access time of scooter–sharing	min	[1, 3, 5]
Access time of carsharing	min	[1, 3, 5]
Cost of scooter–sharing	€	[2.5, 3.1, 3.7]
Cost of carsharing	€	[2.5, 3.5, 4.5]
Scooter accident risk compared to carsharing	-	[1, 2, 4] * higher
Rain	-	[yes, no]

In this part of the survey, you are given 9 scenarios, designed to determine how your transportation choices would change if the attributes of the modes were altered.

You will be asked to choose from two available modes (car-sharing and electric scooter: e-scooter), given a set of attributes. Please base your evaluation only on the following attributes:

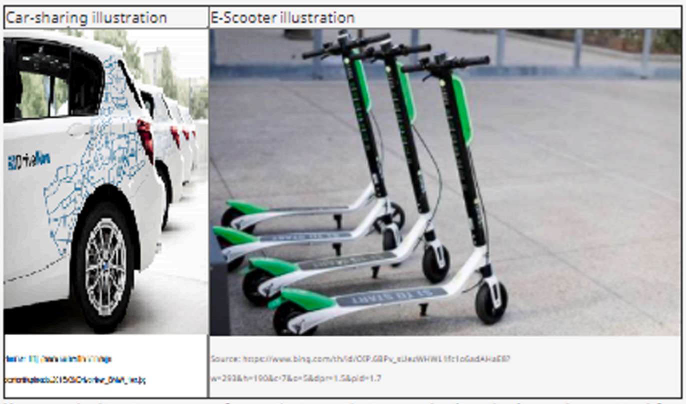
- **Travel time:** The time spent in the vehicle, to go from A to B.
- **Access & Egress time:** The total amount of time spent in **access** to the mode (at the beginning of the trip in reaching your car/scooter) and **egress** from mode (at the end, from where you park it to your destination); this is mostly walking time spent outside the vehicle.
- **Trip cost:** The amount of money you spend on this trip.
- **Safety level:** The likelihood of having an incident in an e-scooter compared to a car-sharing vehicle (which is at least as safe as e-scooters).

The travel process is therefore as follows: Access to mode (**access time**), Travel in-vehicle (**travel time**), Egress from mode (**egress time**).

We are aware that the options may be different from the ones that you would like to be offered, but we would like to know which option you would choose only if the mentioned choices were available.

If you would not choose either of the options, you can choose neither.

The given modes are illustrated below: a car-sharing scheme (such as DriveNow), or an electric scooter (such as Circ, Lime, etc.).



You are asked to state your preference between the two modes (car-sharing and e-scooters) for a set of scenarios, considering the following hypothetical situation:

-You are in Munich and you would like to do a short trip from point **A** to point **B**

-The distance between **A** and **B** is 4 km

-To access both services (car-sharing or e-scooter), you reserve a trip by smartphone application.
Please assume that the difference between the modes are only the ones that have been mentioned and keep in mind that there are no right or wrong answers: we are solely interested in your opinion.

5 Given the following options for the trip above, which would you choose **if it is a sunny day (without rain)**?

Scenario 1	Car-sharing (A)	E-scooter (B)
Travel time (min)	11	8
Access and Egress Time (min)	1	1
Travel cost (EUR)	2.5	3.7
Chance of having an incident (compared to car-sharing)	Reference level	2 x more likely of having an incident

Choose one of the following answers

Certainly A | Probably A | Indifferent | Probably B | Certainly B | None

Fig. 3. Scenario details and block example.

- **Scooter speed: (6,14,22,30).** Based on scooter trip data in five north American cities, scooter speed is 10±4 km/hr (Austin Shared Mobility Services, 2020; Calgary Open Data Portal, 2020; Chicago Department of Transportation, 2020a; Louisville Open Data, 2020; Minneapolis Public Works, 2020). The scooter speed levels were therefore considered to take the lower operational ranges (from the literature) and the upper ones (based on the speeds used in the SP).
- **Scooter trip cost: (0.15, 0.20, 0.25)+ 1€unlocking fees.** Based on operator rates in Munich: (0.15, 0.19, 0.20)€/min + 1€ (https://www.muenchen.de/freizeit/e-scooter-leihen.html).
- **Percentage of carsharing female members: 25%**, as reported by a carsharing report on users in Munich (WiMobil Ergebnisbericht, 2016).
- **Carsharing access and egress times: (1, 3, 5) min.**, based on the stated preference survey levels.
- **Scooter accident risks compared to carsharing: (1,2,4) times more**, based on the stated preference survey levels.
- **Rain condition** based on the real weather data of the given day.

3.3.2. Scenarios and sensitivity analysis

Based on the above assumptions, a combination of scenarios with the different levels was developed, amounting to a total of 1620 scenarios. These were tested and a sensitivity analysis was made to better understand the impact of scooter–sharing based on different parameter changes.

4. Results

4.1. Collected data

4.1.1. Survey data

The collected data led to 503 valid responses, amounting to 4527 observations (9 choice scenarios per response). The sample demographics are presented in Table 3 and benchmarked against the latest Munich Census for reference. The survey responses reflect some limitations in the representativeness compared to Munich. Overall, females are underrepresented (though not drastically), but the notable difference is in the age representativeness, where responses reflect a much higher percentage of a young, highly educated population, mostly students, with a lower income than the average net household income of 4220€.

Table 3
Summary of sample demographics and comparison with Munich Census (2011).

N = 503		Freq (Pct %)	Munich Census (2011)
Gender	Female	161 (32.0%)	48.3%
	Male	337 (67.0%)	51.7%
	Other	1 (0.2%)	-
	18–24	208 (41.3%)	8.1%
	25–34	295 (58.7%)	18%
Household size	1	182 (36.2%)	50%
	2	80 (15.9%)	29%
	3	65 (12.9%)	11%
	4	85 (16.9%)	7%
	5+	58 (11.5%)	3%
	I prefer not to answer	33 (6.6%)	-
Education	High school	34 (6.8%)	34.1%
	Apprenticeship	3 (0.6%)	40.7%
	Bachelor	271 (53.9%)	Bachelor/MS: 22.7%
	Masters	179 (35.6%)	
	PhD	7 (1.4%)	2.5%
	No answer	6 (1.2%)	-
Employment	Full-time employment	175 (34.8%)	Full/Part time: 87.1%
	Part-time employment	52 (10.3%)	
	Student	240 (47.7%)	2.9%
	Self-employed	10 (2.0%)	7.8%
	Unemployed	14 (2.8%)	2.2%
	Other	7 (1.4%)	-
	I prefer not to answer	5 (1.0%)	-
Income	Up to 500 €	87 (17.3%)	Avg: 4220 €/household
	500 to less than 1000 €	121 (24.1%)	
	1000 to less than 2000 €	69 (13.7%)	
	2000 to less than 3000 €	35 (7.0%)	
	3000 to less than 4000 €	29 (5.8%)	(Euromonitor International, 2017)
	4000 €or more	45 (9.0%)	
	I prefer not to answer	117 (23.3%)	

4.1.2. Carsharing data

Carsharing data was cleaned and filtered to keep only trips of interest for the model prediction. According to McKenzie (2019), charging a vehicle can propel it roughly for two hours, approximately 50 km at 25 km/hr speed. Therefore, carsharing trips over 2 h duration, and 50 km length were filtered from the original dataset and represented 27.2% of the received trips. Fig. 4 shows carsharing characteristics for trips by hour of the day, including trip distance, and trip duration, based on which trip cost can be calculated.

4.2. Choice model estimation

Survey data was used to estimate a mode choice model for the preferences between carsharing, scooter–sharing, and none of them, with the aim to use it later for predicting the modal shift of generated scenarios generated from carsharing to scooter–sharing. A multinomial choice model was then estimated with carsharing, scooter–sharing, and none as the three available alternatives (options given in the survey); the latter was considered to improve the model predictability, as reported in previous studies (Vermeulen et al., 2008; Fu et al., 2019). Considered attributes in the utility equations of the different alternatives were alternative–specific attributes that were part of the experimental design such as travel time, access time, cost, accident risk for scooter–sharing, and rainy condition. After reaching a stable model, user–specific variables like demographics were then added. The model that performed best is presented in this section. The utility equations for the different alternatives are grouped under Eq. 1.

$$\begin{aligned}
U_{Scooter} &= ASC_{Scooter} + \beta_{\mathrm{Time}_{Scooter}} \times \mathrm{Time}_{Scooter} + \beta_{\mathrm{Cost}_{Scooter}} \times \mathrm{Cost}_{Scooter} \\
+ \quad & \beta_{\mathrm{Rain}_{Scooter}} \times \mathrm{Rain} + \beta_{\mathrm{Accident}_4} \times \mathrm{Accident}_4 + \beta_{\mathrm{Female}_{Scooter}} \times \mathrm{Female} \\
U_{Carsharing} &= \beta_{\mathrm{Time}_{Carsharing}} \times \mathrm{Time}_{Carsharing} + \beta_{\mathrm{Cost}_{Carsharing}} \times \mathrm{Cost}_{Carsharing} \\
+ \quad & \beta_{\mathrm{Rain}_{Carsharing}} \times \mathrm{Rain} + \beta_{\mathrm{Female}_{Carsharing}} \times \mathrm{Female} \\
U_{None} &= ASC_{None}
\end{aligned} \tag{1}$$

In the above equations, alternative–specific coefficients were estimated for each of the attributes. For carsharing, travel time values include as well access and egress times; for scooters, access and egress were not significant attributes and travel time values refer only to in–vehicle travel times. Moreover, alternative–specific constants (ASC) were estimated for scooter and "none" alternatives; for carsharing, no ASC was estimated since it was the reference alternative. Rain variable is a dummy variable referring to whether the given choice was a rainy day or not. Similarly, female is a dummy variable and is the only demographic attribute that was found to be significant. Finally, the "accident" variable is also a dummy variable, referring to the level of scooter accident compared to carsharing, where the accident risk of scooter sharing was four times higher compared to carsharing; accident risk which was twice as high was

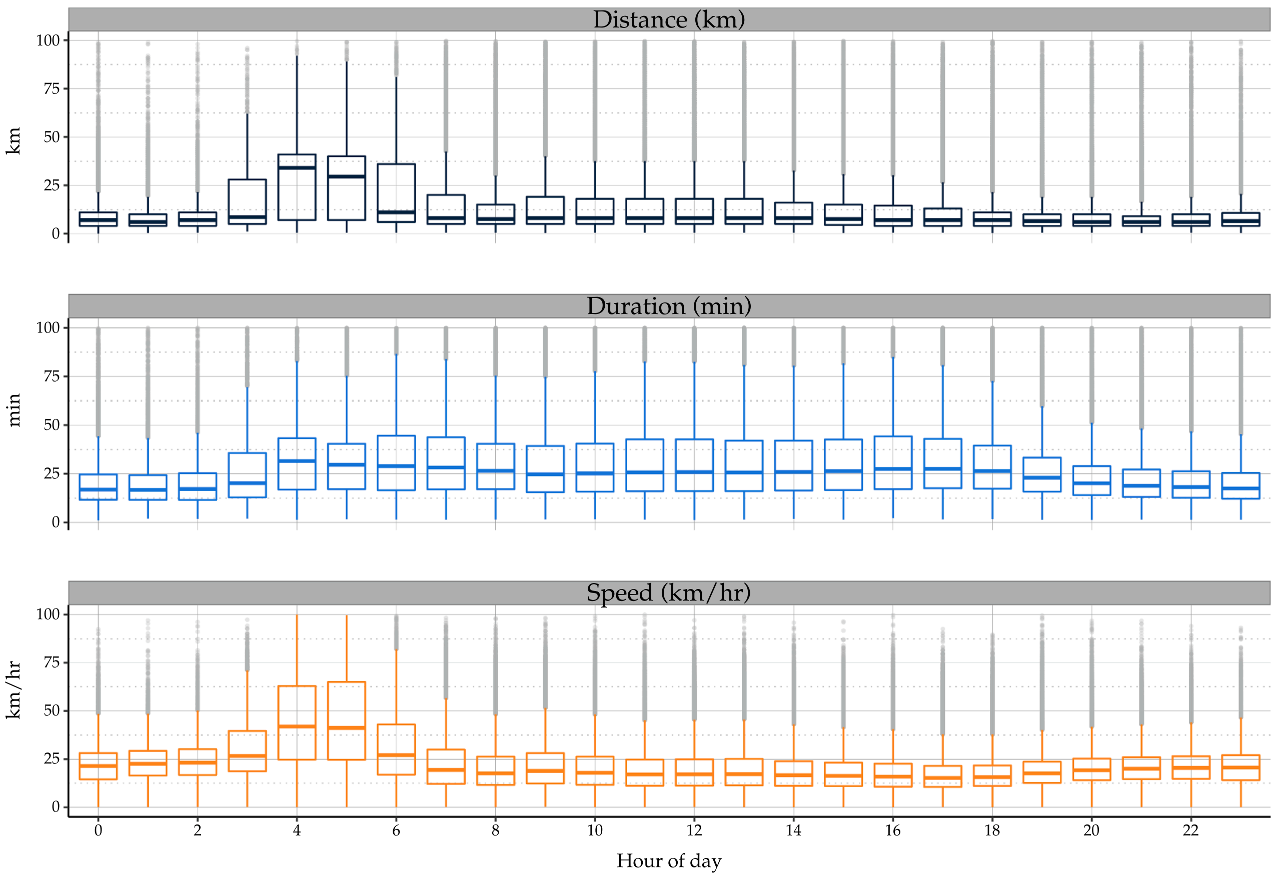


Fig. 4. Carsharing trip data analysis by hour of day.

removed as it was highly insignificant to the model.

The estimated model reflects findings that are consistent with prior expectations. Estimated coefficients for travel time (in–vehicle and total) and travel cost are significant and negative in sign, for both carsharing and scooters, with a higher magnitude for scooter–sharing. In particular, travel cost estimates were found to be extremely significant for both scooter and carsharing (levels of significance of 99% and 98%, respectively), whereas travel time estimates were only found to be significant for scooter–sharing (90% significance level). Still, the travel time coefficient for carsharing was retained, as the aim is to use the model estimates to predict the shift from carsharing, to scooter–sharing. Based on the model estimates, the calculated values of time for scooter–sharing and carsharing: around 6.7 and 7.9 €/hour respectively.

Rain as a condition was also found to be significant and to negatively impact scooter use, compared to carsharing, or none; the rain coefficient estimate was extremely significant for scooters (the highest attribute in terms of magnitude and significance for scooters, with a 99% level of significance), whereas for carsharing this estimate was positive in magnitude (meaning that rain would most likely increase the utility of carsharing with respect to other modes) and significance (level of 90%). Moreover, scooter accident risks was also found to negatively impact the choice of scooters, particularly when the risk is four times higher than that of carsharing, for which the coefficient estimated was highly significant (99% level). Finally, the coefficient for gender reflected a general lower affinity of females, compared to males, to use either scooter or carsharing; this affinity was even lower for scooters, in terms of both magnitude, and significance (99% for scooters, compared to almost 90% for carsharing.).

4.3. Scenario prediction

The developed scenarios were used to predict carsharing trip percentage, by applying the parameters of the estimated mode choice models. After running the 1620 scenarios for each of the dataset trips, an analysis was performed by changing different input parameters, such as trip distance, or scooter–sharing accident risk. Fig. 5 presents the findings on the shift of carsharing trips to scooter–sharing, by trip distance and scooter risk.

However, as previous literature indicated that for distances above 4 km, the share of e–scooters is practically zero (Reck et al., 2020), only scenarios with trip distances ranging to 4 km were taken into account, as presented in Fig. 6.

For scenarios where scooters have the same risk as carsharing, scooters have the potential to shift carsharing to 77%, or in other words to attract 23% of the carsharing trips; in this case, optimal scooter conditions are as follows: base fare of 0.15€, route diversion of 0.7, speed of 22 km/h), whereas carsharing has less advantageous conditions (base fare of 0.36€/min, and access time of 5 min). For the worst case scenarios, where scooter–sharing have four times more risk compared to carsharing, the share of carsharing drops to

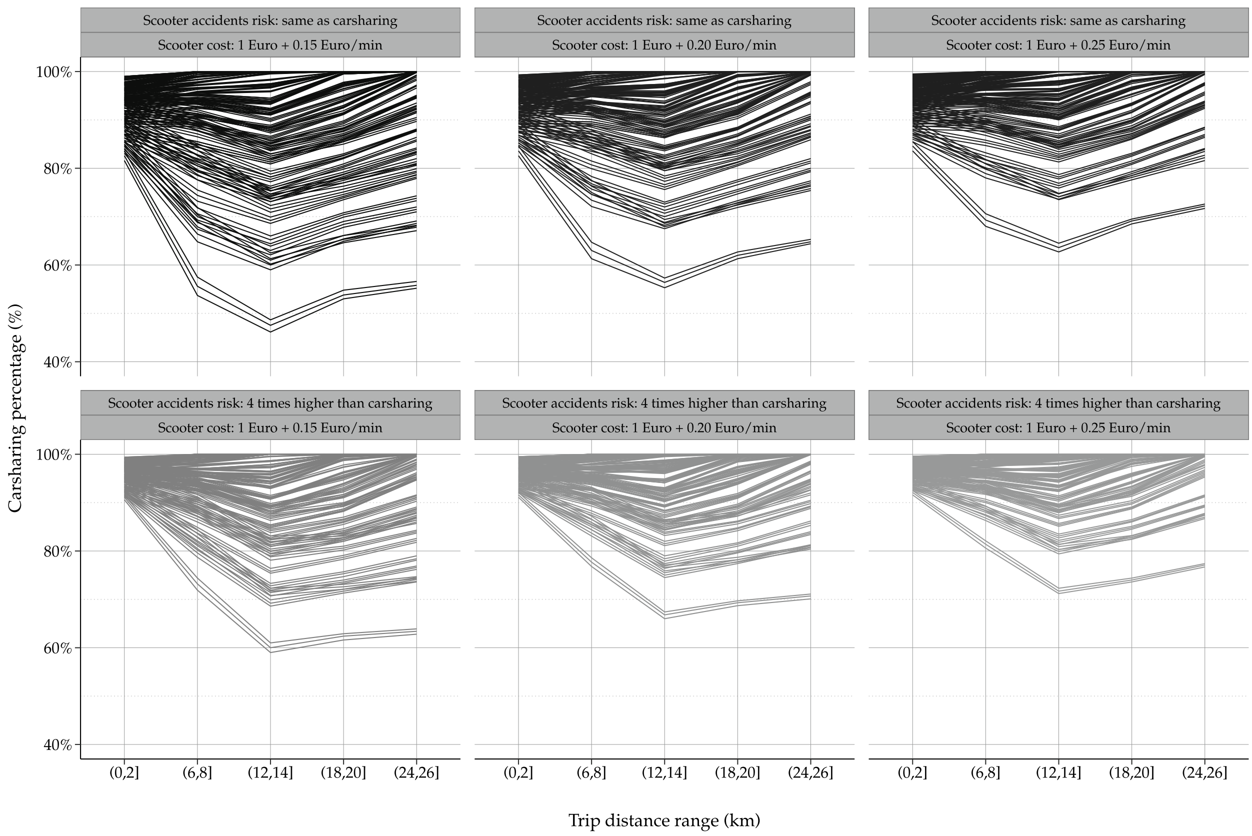


Fig. 5. Sensitivity analysis of scenario prediction of carsharing penetration up to 24 km: by trip distance, scooter price and scooter accident risk. Multiple curves per subfigure indicate different combination of scenario parameters: car sharing speed, cost, access and egress times and scooter speed.*Note: y-axis is truncated to 40% and not all x–axis labels are shown for readability.*.

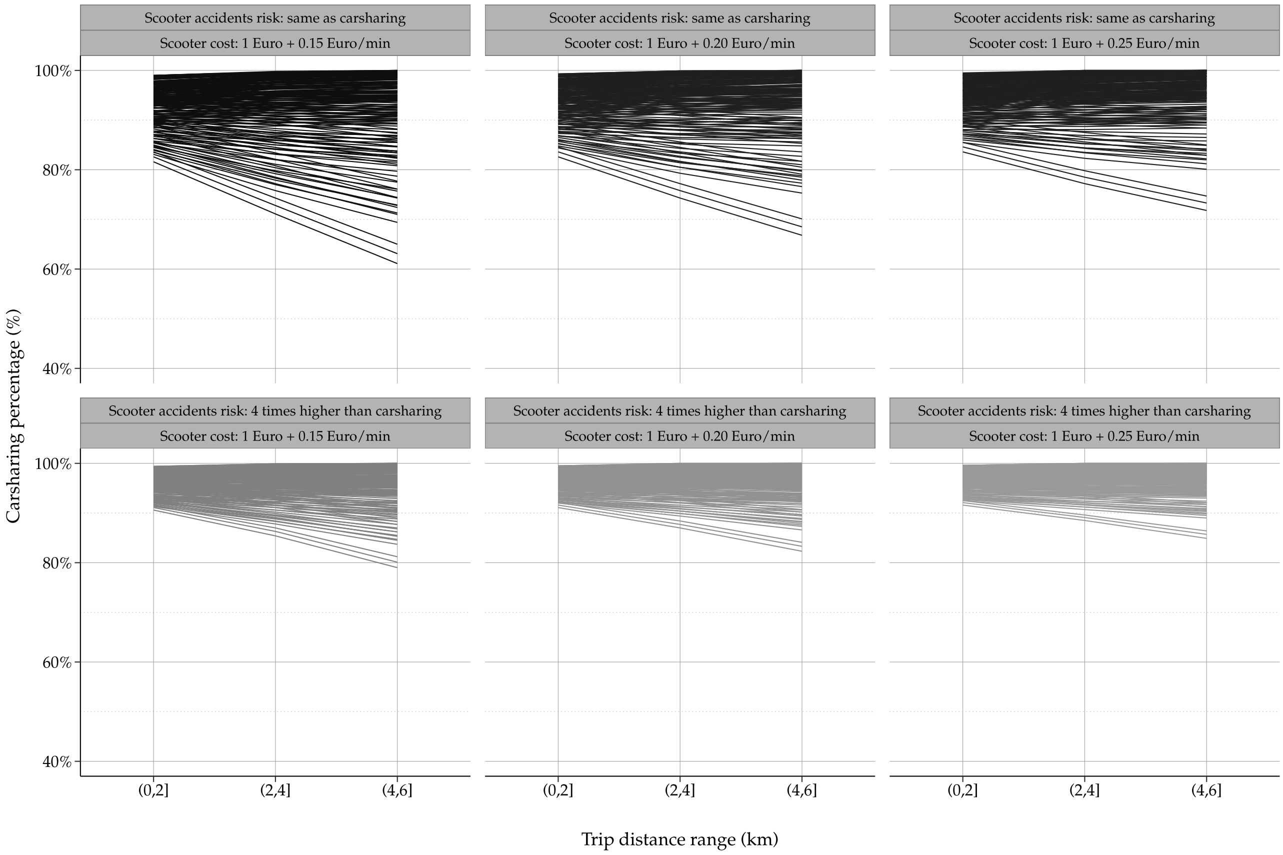


Fig. 6. Sensitivity analysis of scenario prediction of carsharing penetration up to 4 km: by trip distance, scooter price and scooter accident risk. Multiple curves per subfigure indicate different combination of scenario parameters: car sharing speed, cost, access and egress times and scooter speed.*Note: y-axis is truncated to 50% and not all x–axis labels are shown for readability.*.

87% for a range between 0 and 4 km), or the equivalent of a 13% attraction of carsharing trips.

5. Discussion

The estimated choice model for carsharing and scooter preferences revealed findings consistent with prior expectations as well as the literature. The model in Table 4 highlighted the significance of travel time, travel cost, rain, scooter accident risk, and gender on the choice between scooter–sharing and carsharing (with different levels of significance, but mostly above 90%, as elaborated in Section 4). Travel time and travel cost were often cited as significant factors influencing the use of both carsharing and scooter–sharing (De Luca and Di Pace, 2015; 6-t, Bureau de recherche, 2019); for carsharing, travel times also included access and egress times into account as mentioned by De Luca and Di Pace (2015). Obtained values of time for scooter–sharing and carsharing (6.7 and 7.9 €/min) are rather low (possibly due to the high student percentage and the domination of low income classes); they indicate that people are willing to pay roughly 1.2€more per hour for carsharing compared to scooter–sharing. It is important however to note that a comparison between these values of time is subject to limitations, since in the final model specification, the coefficient estimate for carsharing time is that of the total time (including access and egress), whereas for scooter–sharing, it refers to the in–vehicle travel time. This is due to the model significance and implies that these are not directly one–to–one comparable.

Rain and accident risk attributes were also highly significant and higher in magnitude for scooter compared to carsharing; again, this makes sense since scooter is more likely to be impacted by bad weather and higher accident risks. These as well are consistent with previous findings pertaining to weather conditions impact on scooters (Noland, 2019; 6-t, Bureau de recherche, 2019); accident risks or safety in general was often mentioned as a reason for not using scooters (SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019; Portland Bureau of Transportation, 2019). Finally, gender impact, females being less likely to use either scooter and carsharing, was often mentioned in the literature; in this model estimate, the gender attribute has an even higher magnitude for the scooter utility. This is consistent with city reports indicating that the majority of scooter users were males (SPC on Transportation and Transit, 2019; 6-t, Bureau de recherche, 2019; SFMTA, 2020).

The model application indicated that scooters have the potential to attract up to 23% of carsharing trips in the best case scenario, for a range between 0 and 4 km; this would drop to about 13% in the worst case scenario; these represent different scooter risks (equal and four times higher than carsharing, respectively).

This being said, in the best case scenario, for optimal scooter conditions (speed, cost, risk), and comparatively less advantageous carsharing attributes (speed, cost), the introduction of scooters has the potential to attract about 23% of carsharing trips, considering

Table 4
Mode choice model for carsharing and scooter preferences.

	Scooter		Carsharing		None	
	Estimate	Rob.t.ratio	Estimate	Rob.t.ratio	Estimate	Rob.t.ratio
ASC	−0.585	−1.44	-	-	−2.52	−9.26
In–vehicle travel time (min)	−0.0297	−1.70				
Total travel time (min)			−0.0161	−1.47		
Travel cost (€)	−0.266	−2.82	−0.123	−2.33		
Rain (no-rain as reference)	−0.977	−7.68	0.159	1.68		
Scooter accident (4*higher)	−0.369	−3.57				
Female (male as reference)	−0.344	−3.55	−0.195	−1.63		
Model summary						
LL(0)	−4973.418					
LL(final)	−3438.472					
Rho-square (0)	0.3086					
Adj.Rho-square (0)	0.3064					
AIC	6898.94					
BIC	6969.54					

Only highly significant attributes (> 90%) are presented in Bold.

short distances; for trips between 0 and 4 km, scooter–sharing could replace about 44,624 trips, or the equivalent of 118,060 km without taking into account the kilometer-travel produced from scooters' distribution, recharging, and maintenance.

This shift in number of trips and the equivalent distance (in kilometers) inevitably poses the question of the environmental impact this might induce. From a life cycle assessment perspective, a dockless shared scooter system produces more CO_2-equivalent per passenger-kilometer, than the modes they replace Moreau et al. (2020); in other words scooters attracting users from environmentally friendly modes, such as walking and biking, generate empty vehicle kilometers traveled (redistribution and maintenance). On the other hand, benefits from scooters can be noted every time an e-scooter substitutes for a personal automobile; it thus saves a significant amount of end-use energy. One-kilowatt hour of energy could propel a scooter 100 km compared to 2 km for a passenger vehicle using the same amount of energy[2] (Agora Verkehrswende, 2019). In the case study presented, this would amount to a saving of roughly 57,850 kWh.

Of course, this is based on the assumptions made, and not taking into account the entire vehicle life-cycle. Energy efficiency and power plant emissions are only a first step in assessing e-scooter impacts. Modal shift, fleet management, manufacturing, and durability impacts are all key elements in assessing the overall sustainability of e-scooters. Therefore, it is difficult to really know the exact savings in energy, but it would be fair to say that a replacement of personalized vehicles with e-scooters is likely to save considerable amounts of energy. The equivalent reduction also depends on durability, the use, and other assumptions. Moreover, it is worthy to note that while scooter trips are mostly for one passenger, carsharing trips are not exclusively for one person. In the presented case study, if the occupancy of each trip was known, we could calculate the equivalent person trips, in which case it would be interesting to see whether or not group trips can be shifted to scooter trips (a priori not expected), and what is the replacement of person trips resulting from the introduction of scooters. However, this information is not available from the carsharing dataset, and the SP study did not have an input variable for the number of passengers, meaning that it assumed a one person trip. These, of course, are part of the study limitations.

Still, the highlight of the study is that scooters have the potential to reduce motorized trips, and their introduction could disrupt the existing patters of transport. Shaheen and Cohen (2019) highlighted the need for an operational model with an emphasis on infrastructure (curb space and rights–of–way), but also guidelines to take into account stakeholder interests, equity policies, enforcement procedures, data sharing guidelines. Gössling (2020) discussed problems like space, speed, and safety management; the authors advise urban planners to introduce policies regarding speeds, mandatory use of bicycle infrastructure, and dedicated parking, and a limited number of licensed operators. In the case of Munich, responsible policy-making is of utmost importance to ensure a smooth integration of scooter–sharing within the existing transport systems, but also to account for the very needed infrastructure requirements, parking policies, and guidelines facilitating operation.

6. Conclusions

The developed methodology in this paper allowed to develop a choice model for preferences between carsharing and scooter–-sharing. The model estimate was then applied to a set of developed scenarios, with different parameter inputs, to predict the shift from carsharing demand to scooter–sharing, according to different inputs. The estimated model findings on the one hand revealed the importance of travel time, travel cost, weather, scooter accident risk, and gender. On the other hand, calculated values of time showed a higher willingness to pay for one minute of carsharing compared to scooter–sharing. For the case study in Munich, in the best case scenario, scooter–sharing was found to potentially shift the demand from carsharing by about 23%. This implies a reduction in total

[2] The comparison is between a VW Golf 1.0 TSI (4.8 L Gasoline per 100 KM), and 0.47 kWh battery Bird scooter

kilometers travelled in motorized travel and the corresponding energy consumption and CO_2 emissions. Yet, this study has its own limitations, such as the survey data representativeness of Munich, which led to lower than expected values of time, and could have impacted the model prediction. Moreover, stated preference studies are subject to their own biases and might not help capturing realistic decision scenarios. For the case study of Munich, a revealed preference study would be highly beneficial to validate and calibrate the estimated models. This could be done by using pilot data similarly to what was done in other cities. It is also worth noting that the substitution shares from carsharing to scooter–sharing are only valid under the assumption that travelers can only choose between carsharing and scooter–sharing.

Finally, while the study targeted young users as the ones most probably using shared mobility systems, as suggested by previous research (Efthymiou et al., 2013), it would be interesting for future research to further enrich the findings and policy insights, by collecting additional datasets and compare the obtained values of time, but also by extending the current work to take into account age differences, as indicated by Herrenkind e al. (2019b). Further approaches considering machine learning methods could also be considered for self–learning systems (Herrenkind e al., 2019a) or even to enhance discrete choice models (Sifringer et al., 2020).

The increasing demand in scooters is not only an indication of the potentials of this emerging mode, but also that guidelines for responsible scooter operations is essential for the smooth integration of scooters in existing transport modes.

CRediT authorship contribution statement

Mohamed Abouelela: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Visualization. **Christelle Al Haddad:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft. **Constantinos Antoniou:** Conceptualization, Methodology, Writing - review & editing, Supervision, Funding acquisition.

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Psychological Factors Impacts on Carsharing Use

Mohamed Abouelela[a,*], Christelle Al Haddad[a], Constantinos Antoniou[a]

[a] *Chair of Transportation Systems Engineering, Technical University of Munich, Munich, Germany*

Abstract

Carsharing services have a significant potential for improving urban mobility by increasing the independence and freedom of travel and reducing traffic externalities. Although carsharing has been used for over a decade, several aspects need further investigation, such as the impact of user's psychological factors on service use, as well as the factors impacting users' choices between different carsharing operators, in particular their preferences for different payment schemes, and their perceptions of the operators' application rating. Accordingly, four hybrid choice models (HCM) were estimated to investigate factors impacting (i) the knowledge about carsharing services, ii) carsharing adoption, (iii) the shift from other modes to carsharing, (iv) the choice between carsharing operators with different payment schemes, using a large survey sample (N =1044 responses 9,469 SP observation) from Munich, Germany. The models showed the significance of sociodemographics, such as income level, education level, household size, employment status, ownership of a bike, access to a car, the availability of a driving license, and public transport subscription-based tickets on the carsharing use directly and indirectly, and four psychological factors encompassing different personality traits (i.e., adventurous), travel behavior, and attitudes were found to be significant in the various models; the latter covered service–related attitudes (perceived carsharing app importance) and travel behavior attitudes or profiles (frequent public transport user and frequent shared micromobility user). This research raises questions regarding the inequitable use of carsharing, the impacts of mobile applications on using the service, and the potential of integrating carsharing in mobility as a Service (Maas) platforms to increase the potential for multimodality.

Keywords: Shared mobility, carsharing, choice model, attitudes, personality

1. Introduction

In the past ten years, there has been a significant increase in the acceptance, utilization, development, and improvement of app-based shared mobility services. This growth has been made possible by revolutionary advancements in information and communication technologies (ICT). Shared mobility services encompass various options, including schemes, services, vehicles, and business models. Examples of these services include ridesharing and carpooling, in which people share or split a ride, as well as carsharing and shared micromobility options such as bikesharing and e-scooter-sharing, in which vehicles can be rented based on time or distance (Narayanan & Antoniou, 2022; Gilibert & Ribas, 2019). These new mobility services have changed the landscape of urban mobility by introducing the concepts of on-demand services and pay-per-use, which increases the attractiveness of such services for users due to their ease of use, ease of payment, convenience, but also as they are perceived to be convenient, safe, and environmentally friendly (Arteaga-Sánchez et al., 2020; Tirachini & del Río, 2019; Watanabe et al., 2017; Rayle et al., 2016).

The benefits of shared mobility services are not only limited to the individual level but could also be beneficial for cities and could be an attractive solution for various transportation problems as they do not need large infrastructure investments and are quick to implement in most of the cases (Abouelela et al.,

*Corresponding author at Technical University of Munich, Arcisstrasse 21, Munich, Germany E-mail address: Mohamed.abouelela@tum.de

2022). Maintaining, upgrading, and constructing transportation infrastructure generally needs significant investments and a long time to materialize, which is not always a viable solution; one example is extending the transportation system's accessibility to suburban areas with inefficient public transportation's access (Burghard & Dütschke, 2019; Abouelela et al., 2022). Shared mobility services could reduce the demand and congestion on roads, as well as the vehicle kilometer traveled (VKT), such as in the case of pooled rides; this would, however, require specific conditions to be maintained, such as not replacing public transportation trips and replacing low occupancy vehicles (Tirachini et al., 2020). Alonso-Mora et al. (2017) concluded that shared rides could as well reduce the number of cars on city roads. The same promises of reducing the number of vehicles on the streets could be achieved using carsharing services, as private cars are idly parked for around 90% of the time (Zhang et al., 2015). Transport for London (TfL) sees carsharing services as complementary to public transportation services (Akyelken et al., 2018). Carsharing use could even be correlated with the increase in public transportation use (Aguilera-García et al., 2022). Overall, the system is attractive to implement as establishing its infrastructure is considered relatively quick, and its market has the potential to grow in the future; however, its economic viability is rather challenging, , as the North American experience has already demonstrated (Nansubuga & Kowalkowski, 2021; Golalikhani et al., 2021; Poltimäe et al., 2022).

Carsharing is a form of shared mobility that provides easy access to on-demand car use without the burden of car ownership responsibilities, the need to process paperwork such as for car rental services, or even the need to return the vehicle to the pickup points as in free-floating systems or one-way trips (Liao & Correia, 2022). Carsharing services and other shared mobility services are not only changing the landscape of urban mobility, but also the traditional idea of a car manufacturer producing, buying, and selling vehicles. Currently, some leading car manufacturers are promoting themselves as mobility providers (Akyelken et al., 2018), including Daimler, BMW, Volkswagen, Toyota, and General Motors. Daimler has two carsharing services (Car2go[1], and Croove), acquired two taxi services (myTaxi[2], and Hailo), is investing in two ride-hailing services (Via[3], and Blacklane[4]), and starting its own mobility platform moovel[5] (Akyelken et al., 2018). Therefore, there is an essential need to understand in–depth the different aspects of these services for better operation and integration within the urban environment.

Some of the main aspects of shared mobility that are important for the different stakeholders are the socio–demographic characteristics of the users and their general travel behavior, as well as their impacts in deriving the demand and identifying user target groups (Jochem et al., 2020). Moreover, psychological factors such as attitudes, perceptions, and personality traits play a significant role in individual travel behavior and mode choices (Kroesen & Chorus, 2020). The importance of understanding the impact of psychological factors on travel behavior and mode choice lies in their ability to facilitate encouraging the use of the modes of interest, as they could be described as the underlying motivation for specific mode use (Bhagat-Conway et al., 2024). Previous research has shown that attitudes were found to have a significantly higher impact on the use of shared mobility as compared to sociodemographics, such as in the case of pooled rides (Abouelela et al., 2022). Still, there is a gap in terms of existing research on attitudes and personality traits in the scope of carsharing and shared mobility in general, mostly when comparing it to studies focusing on sociodemographics, which have been well examined and explored in the literature (Monteiro et al., 2023; Efthymiou & Antoniou, 2016; Efthymiou et al., 2013). Several of these psychological factors are still under exploration and their roles in the mode choice travel decision (Rahimi et al., 2020a) in general, and shared mobility use in particular, are being assessed. Moreover, and to the best of the authors' knowledge, many aspects of carsharing services have not yet been studied, such as the perceived service and feature offerings by different carsharing operators, including digital operator aspects (often reflected in the operator rating on the app store), as well as their impact on service adoption and use frequency (Monteiro et al., 2022). The digital dimension of the carsharing services has also not been investigated in–depth, and includes the mobile

[1]share-now.com, car2go is now unified with BMW service DriveNow under the new name ShareNow
[2]free-now.com, now the service is a joint venture between Daimler and BMW
[3]info.ridewithvia.com
[4]blacklane.com
[5]moovelus.com, the platform is one of the Mobility as a Service (MaaS) providers

application friendliness and ease of use, the service provider's website landing page, the digital marketing of the service, the online marketing campaigns, and the business–to–business offers (Janasz & Schneidewind, 2017). Another service feature to consider is the operator payment schemes (per minute or kilometer as recently introduced by some operators). The impact of the above–mentioned features on the operator choice still needs to be investigated. Finally, carsharing research on adoption and use has not yet been totally understood due to the novelty of the services; a large number of the carsharing studies have been completed before the services were even launched or during the early operational and adoption stages, during which users might have a different use behavior as they are getting familiar with the service. Another motivation of this paper is therefore to contribute to the existing body of research with more timely study in which the operation of carsharing services is ongoing at the time the research is done (Le Vine & Polak, 2019a; Hjorteset & Böcker, 2020).

We therefore contribute to the current literature by updating the knowledge regarding carsharing use, using user-level information through a large online survey, and answering the following two research questions (RQ) investigating the roles of users' psychological factors: personal attitudes, travel behaviour, and carsharing–related features on the different aspects of carsharing services.

- RQ1) How do users' psychological factors impact carsharing adoption and use?
- RQ2) What factors impact the choice between different carsharing operators?

The rest of the article is organized as follows; section 2 summarizes some of the selected studies related to user factors and attitudes impacting carsharing use and the different service-related characteristics that impact user's choices. Section 3 explains the methods used in the research and the case study setup used for the analysis and modeling. Section 4 spans across two parts that answer the research questions (RQ1 and RQ2); first, we analyze the collected data, second, we model the different factors that impact carsharing adoption and use, with a special focus on personality traits and attitudes. We also model and extract the factors impacting users' choices between different carsharing operators. Finally, section 6 discusses the study findings, highlights the policy implications, and summarizes the conclusion.

2. Literature review

2.1. The benefits of carsharing

Sustainability is one of the many benefits associated with carsharing; it is considered a sustainable mode of transportation that has a wide array of positive impacts on the urban environment, such as the reduction in household car ownership and, subsequently a reduction in Greenhouse Gas (GHG) emissions that could reach up to 30%-54% as a consequence of reduced Vehicle Miles/Kilometers Travelled (VMT/VKT) (Shaheen et al., 2019; Nijland & van Meerkerk, 2017; Martin & Shaheen, 2011a). Also, electrification of the carsharing fleet was proven to be environmentally advantageous (Luna et al., 2020) and was able to yield more than 30% reduction on carsharing users' GHG even if there was no change in VKT (Namazu & Dowlatabadi, 2015). Several examples of the previous positive potentials of carsharing use were observed; in Germany, evidence associated with the reduction of car ownership and the number of station-based carsharing in the same area were present (Kolleck, 2021); in China, in 2017, carsharing has caused a significant reduction of energy used, and CO_2 emissions, with the expectation of higher savings by 2025 (Te & Lianghua, 2020). Shaheen et al. (2019) and Martin & Shaheen (2016) observed a decline in the average VKT of carsharing users ranging from 6% to 63% in North America, considering several conditions such as giving up car ownership, and the type of the service one-way or round trip. These tendencies were further corroborated by studies in Palermo, Italy (Migliore et al., 2020), the Netherlands (Nijland & van Meerkerk, 2017), and London, UK (Wu et al., 2020). Also, Wu et al. (2020) noted that in London, higher satisfaction with the proximity to carsharing vehicles contributed to a larger reduction in VKT. Interestingly, carsharing users who live in suburban areas tend to drive fewer kilometers than their counterparts in dense urban areas (Clewlow, 2016), which could be attributed to the lower density of available vehicles in the suburbs, resulting in carsharing users canceling the non-essential trips. Other environmental-related positive impacts, such as saving materials and reducing wastes, were observed (Harris et al., 2021). However, the environmental impacts of carsharing and their total magnitudes are heavily dependent on the occupancy rate, the used vehicle and fuel type of the fleet, the modal share of carsharing, the modes replaced by carsharing, and the vehicle's lifespan (Poltimäe et al., 2022; Harris et al., 2021; Jung & Koo, 2018). On the other hand, adverse environmental impacts of carsharing were observed; in Palermo, Italy, the fleet only contains diesel and natural gas vehicles, and it was found to increase the CH_4 and NO_x emissions of the city (Migliore et al., 2020).

Impact related to infrastructure and built-environment were also observed, as carsharing use can help in reducing car ownership rates, which promotes more positive impacts on curb-side management, minimizing the space uptake for car parking (Golalikhani et al., 2021). A study among students in Ithaca, New York by Stasko et al. (2013) found that since the introduction of carsharing in the area, student parking permit sales had declined despite a continuous increase in enrollment. The causality of these occurrences, however, was not investigated or verified. Another survey in France investigated carsharing use impact on parking derived that for every carsharing vehicle on the street, between 1.6 to 4.2 on-street parking spaces, 0.3 to 0.6 public parking spaces, and 2.1 to 4.2 private parking spaces could be eliminated (6t-Bureau de recherche & ADEME, 2016). Diana & Chicco (2022) analyzed the spatial distribution of changes in parking demand related to carsharing and found that more relieved parking spaces could be anticipated for central areas, while more negative impacts might be imposed on the parking in peripheral areas.

Integrating carsharing with public transportation would yield more benefits by extending the spatiotemporal accessibility of public transportation. Some examples of this integration are the decentralized mobility hub (Czarnetzki & Siek, 2022), implementation of dedicated carsharing facilities (Engel-Yan & Passmore, 2013) and unbundled parking (Schure et al., 2012) in residential buildings, and appropriate financial and policy backing from the authorities in forms of aids to the low income-groups (Rabbitt & Ghosh, 2013; Bocken et al., 2020). Note that the extent of carsharing impacts could highly vary depending on the region, built environment (Clewlow, 2016; Jain et al., 2022), accessibility of public transportation, and the carsharing replaced modes (Shaheen et al., 2019; Jain et al., 2022; Kolleck, 2021; Duncan, 2011). Other positive potentials for carsharing use were observed. However, they were less explored, such as benefits associated with the B2B carsharing model capabilities of reducing work trip cost as the car can be used without bearing ownership–related costs and duties, increasing thereby not only trip sustainability, but also the workplace attractiveness, which could now subsidize carsharing trips for their employees (von Wieding et al., 2022). Moreover, carsharing trips were found to encourage multimodality, physical activities, and a healthier lifestyle (Kent, 2014; Shaheen et al., 2019; Harris et al., 2021). Also, carsharing was found to increase access to cars for car-less households (who do not own private vehicles), providing them thereby with more independence and equitable access to opportunities (Stasko et al., 2013; Kent, 2014; Shaheen et al., 2019). This in turn improves the mobility of lower-income groups by increasing the number of available travel options (Kumar Mitra, 2021), and strengthening the sense of community among users (Hartl & Hofmann, 2022; Harris et al., 2021).

2.2. Factors impacting the adoption and use of carsharing

Several factors impact the adoption and use of carsharing services; these factors could be categorized into three main groups; i) service-related factors, ii) exogenous factors, and iii) user-related factors. The first group of factors included the number of available vehicles in the stations, and vehicle age; in a study by (De Lorimier & El-Geneidy, 2013), this encouraged carsharing use in Quebec, Canada. In metropolitan Vancouver, lowering the membership fees was found to attract more users (Namazu et al., 2018). The difference between the trip cost, and the mode carsharing replaced was found to be the most significant factor impacting carsharing use in Beijing, China (Yoon et al., 2017). Personalized use incentives were also found to attract more users (Feng et al., 2023). In Shanghai city, electrical vehicle battery charging level and the number of available vehicles in stations impact the user choice for the vehicles (Hu et al., 2018b). Secondly, exogenous factors are also key such as adverse weather conditions (Yoon et al., 2017), availability, accessibility of public transportation station (Balac et al., 2015; Hu et al., 2018a; Khan & Machemehl, 2017), land–use (Kim et al., 2012; Stillwater et al., 2009), intersection and road density, and the availability of parking (Chen et al., 2018; Yoon et al., 2017; Hu et al., 2018a).

Thirdly, several studies focused on investigating the sociodemographic characteristics influencing carsharing use. The findings of these studies have identified users as young, male, well-educated, with high-income, and full-time employment (Le Vine & Polak, 2019b; Martin & Shaheen, 2011a; Alemi et al., 2018; Ahmed et al., 2021; Luo et al., 2019). However, the role of other important personal drivers to the service is less known, and here we mean the personal attitudes and personality traits, despite the fact that there is evidence suggesting the significance of attitudes on the use and adoption of carsharing services, noting that understanding personal attitudes is claimed to enhance the models predictability (Pronello & Gaborieau, 2018). For instance, carsharing users are more likely to own "greener" vehicles (Clewlow, 2016) and exhibit more eco-friendly behavior (Jung & Koo, 2018), hinting at higher concerns towards environmental issues. Li & Kamargianni (2020) found that carsharing advocacy attitude increased the adoption of carsharing compared to other modes. In the realm of carsharing, research on the role of personal attitudes has yielded mixed conclusions. Zhang & Li (2020) and Li & Zhang (2021) discovered that subjective/social norms had the biggest influence on the intention to use carsharing, and attitudinal variables, including environmental concerns, imposed a much more limited impact, while a study in Taiwan (Buschmann et al., 2020) reported the complete opposite. Varieties also exist within the range of behavioral constructs that were found to be significant in carsharing familiarity and adoption. Aguilera-García et al. (2022) found that high sharing propensity, variety-seeking lifestyle, and preference for driving positively impacted familiarity, and that pro-environmental behaviors reduced carsharing usage. On the other hand, Thurner et al. (2022) concluded that people who were believers of science and technology, who were generally early adopters of novel technology, and those with self-expressive social values tended to be carsharing adopters. The previous discrepancies are unsurprising, considering the virtually unlimited spectrum of attitudes that humans might have. Yet, researchers are constrained to investigate only a select few, along with behavioral indicators which vary across the board. Furthermore, cultural context might play a role in moderating the effects of other sociodemographic variables. For instance, society could be more concerned about conforming to the norms than their individual expressions, leading to subjective norms being more influential in their decisions. Moreover, there is a complex interrelation between these attitudinal constructs, which is hard to interpret. This is well demonstrated by Zhang & Li (2020); Burghard & Scherrer (2022); Li & Zhang (2021); Acheampong & Siiba (2020) in which environmental attitudes imposed no direct impact or even negative impact on carsharing intentions, while simultaneously being positively correlated with another construct which in turn positively impacted the carsharing intention (i.e., positive indirect impact). This shows how the role of attitudes in human decision is a complex topic and requires further research with a possibly wider range of attitude constructs. For example, Hjorteset & Böcker (2020) further differentiated the resulting attitude towards carsharing into general interest, anticipated intention, and actual decision to utilize the service. Another part of human attitudes is personality traits, which are the main drivers of travel demand (Mokhtarian et al., 2001). Different personality traits are hypothesized to impact travel behavior differently; while the adventure-seeker personality was found to be likely to travel and drive faster than other personalities, are prone to have and create more elements of danger (Furnham & Saipe, 1993). Redmond (2000) concluded that people with adventure-seeking personalities are more likely to enjoy leisure trips over work trips and may also prioritize them. Another personality associated with the preference for using private cars over public transport is the organizer personality (Redmond, 2000). A summary of the factors impacting carsharing use is presented in Figure 1 below.

2.3. *Synergies between carsharing use and travel behavior*

Carsharing might play a significant impact on travel behavior and users' long and short-term travel decisions. It can impact the decision to give–up a car and forego/delay the decision to acquire a new one (Ko et al., 2019; Seo & Lee, 2021). Although varying conclusions exist across case studies, the general consensus suggests a decline in the level of car ownership, with studies quoting four (Migliore et al., 2020; Shaheen et al., 2018) to twenty-three (Lane, 2005) private vehicles being replaced for every carsharing vehicle in operation. This conclusion is consistent with Le Vine & Polak (2019b) findings, which highlighted, based on a survey in London (N = 347 responses), that as much as 37% of respondents had their car ownership decisions impacted by using carsharing, as users opted to drop the decision of buying a car or dispose of their currently owned car. Factors affecting a user to dispose or forego buying a car include income level, age, housing type, satisfaction towards the carsharing service, access time to carsharing station, fuel type, and the price or cost of the service(Jung & Koo, 2018; Ko et al., 2019). However, simultaneity bias can also be a concern as Jain et al. (2020) found within their case study; carsharing mostly acted as an enabler

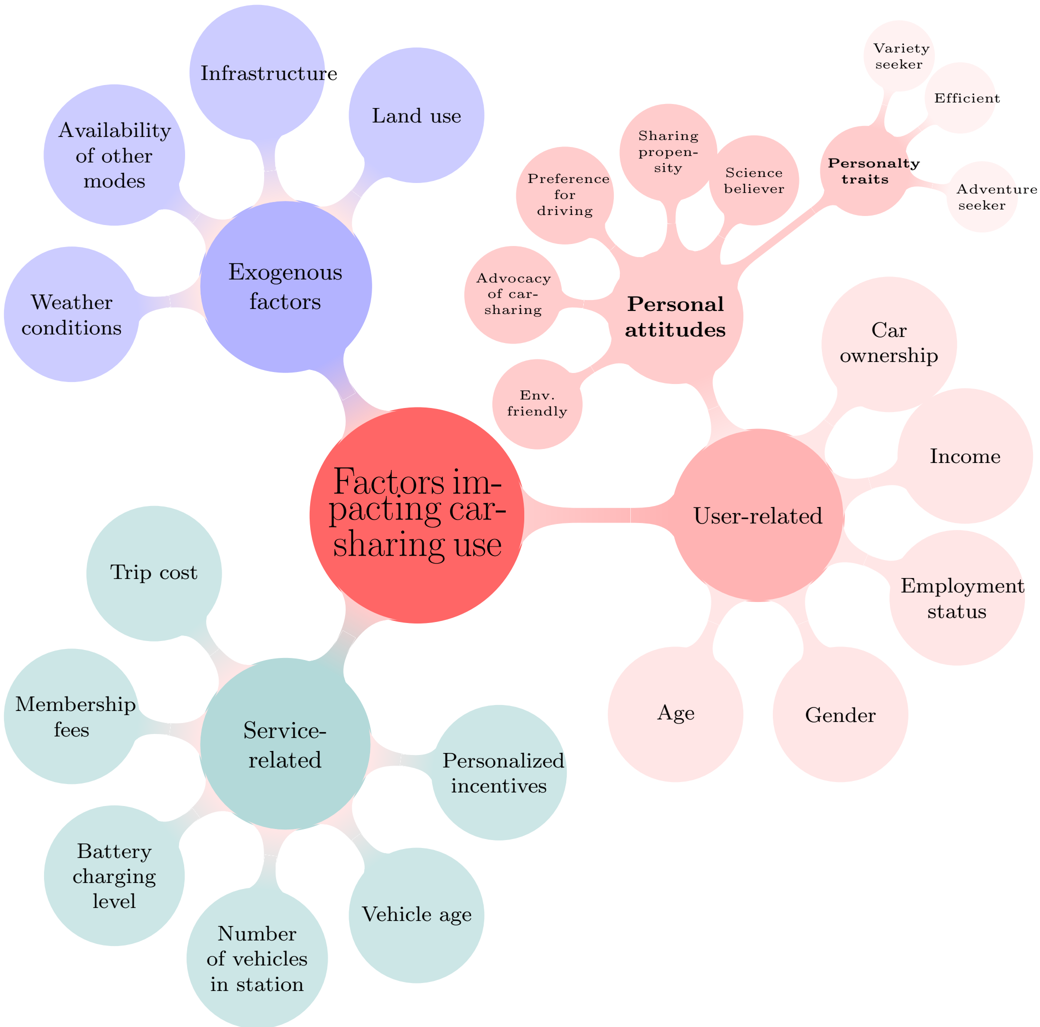

Figure 1: Summary of factors impacting carsharing adoption and use *(own illustration)*

of mobility lifestyle change but was not the primary cause of households shedding their private cars, as life events had a stronger influence.

Furthermore, carsharing's overall impact on sustainability depends on the modes it replaces, whether they are "greener" and more active modes such as walking, cycling, and public transportation (Chicco & Diana, 2021). The impact of carsharing on the general car use is less conclusive as some studies reported that the majority of carsharing users drove less frequently (than before carsharing adoption) (Martin & Shaheen, 2011b; Shaheen et al., 2018), while others studies claimed the contrary (Stasko et al., 2013; Martin & Shaheen, 2016). This is due to the fact that the effect of those who dispose of private cars is counterbalanced by the impact of those who gain access to cars through carsharing (Lane, 2005). While such studies often relied on user surveys, the latter have often been criticized as they focus on carsharing users and therefore create self-selection biases, which might impact the conclusions.

2.4. Modeling techniques

Attitudes are often treated as latent variables derived from stated behavioral statements. To capture these latent attitudes and determine the indicating constructs, several methods have been used in the past, including Structural Equation Models (SEMs) (Yazdanpanah & Hosseinlou, 2016; Aguilera-García et al., 2022; Rahimi et al., 2020b; Zhang & Li, 2020), Principal Component Analysis (PCA) (Queiroz et al., 2020; Thurner et al., 2022), and Latent Class Analysis (LCA) (Olaru et al., 2021). Subsequent regression analysis (e.g., Bivariate Logit (Queiroz et al., 2020), and Hybrid Choice Model (HCM), or Integrated Choice and Latent Variable models (ICLV) (Sun et al., 2021)) incorporating the latent attitudinal variables in models is frequently conducted to assess the causality between attitudes and other variables in question (e.g., acceptance of carsharing). The main objective of this integration is to enhance the model's ability to understand the choice process by incorporating the user's cognitive behavior, attitude, and psychological factors into the choice model. This integration also aims to improve the model's goodness of fit where applicable (Vij & Walker, 2016; Temme et al., 2007; Ben-Akiva et al., 1999). ICLV models were, for instance, used to quantify the factors impacting the frequency of pooled-rides uses in Mexico City, Mexico (Abouelela et al., 2022). Moreover, the Theory of Planned Behavior (Jain et al., 2021; Zhang & Li, 2020; Li & Zhang, 2021), Rogers et al. (2014)'s Theory of Innovation Diffusion (Jain et al., 2021; Burghard & Scherrer, 2022), and the Theory of Reasoned Action (TRA) along with its extensions (Buschmann et al., 2020) are often incorporated in assessing the role of personal attitudes. Further scientific frameworks that are prevalent in this research topic are the Technology Acceptance Model (TAM) (Al Haddad et al., 2020; Schlüter & Weyer, 2019; Buschmann et al., 2020) and its modifications, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) (Fleury et al., 2017).

2.5. Gap analysis

The review of the current research shows that a significant portion of carsharing-related studies was developed before the implementation of the service or during the early deployment stages, and accordingly there is a pressing need to update the current literature with more recent case studies, especially for users who are already familiar with the service and used it for a long period of time (Hjorteset & Böcker, 2020; Le Vine & Polak, 2019a). Moreover, studies investigating the impact of carsharing-related features, such as operator offering and the used mobile app, on service use, adoption, and choice between different operators are still scarce in the existing body of the literature (Monteiro et al., 2022). Finally, the impacts of personal attitudes and personality traits on the use and adoption of carsharing services are not well established (Aguilera-García et al., 2022), despite their importance in deciding on our travel behavior in general and carsharing in particular. This study aims, therefore, to address the above–mentioned gaps, by testing the impacts of the different personality traits and latent variables, as well as the importance of service–related features, on carsharing, answering thereby the research questions formulated in Section 1.

3. Methods and study set–up

3.1. Methods

3.1.1. Survey design

The main goal of this research is to understand the impacts of attitudes, travel behavior, and personality traits on the use of carsharing services; therefore, we designed a survey in four parts, which was implemented online using Limesurvey platform (`Limesurvey.com`), and disseminated to different users group in Munich, Germany, during the period of 20 of January to 25 of March 2022. We opted to deploy the survey online as it was deployed during the COVID-19 pandemic, and we wanted to eliminate the chances of infection during the data collection process. As carsharing users are likely young, we targeted them in our data collection process. Young users are commonly adopters of shared mobility in general and carsharing in particular, as highlighted in studies in different locations, such as in Munich and Madrid (Aguilera-García et al., 2022), in Vancouver, Canada (Namazu et al., 2018), in Puget Sound region in the state of Washington, USA Dias et al. (2017), and all over Germany (Burghard & Dütschke, 2019). Moreover, we collected data from non-users to check the different reasons for not adopting the service, as well as to evaluate the differences between the two groups. Overall, we collected 1170 completed responses, and the average survey completion time was 12 minutes. The survey consisted of four main parts;

- In the first part, general travel behavior was investigated, where users were asked to specify their usage frequency for different urban modes of transport, whether they had a public transportation subscription ticket (such as a monthly ticket), whether they owned bikes, e-bikes, a private car, and whether or not they had a valid driver's license in Germany. The modes that their use frequency was investigated are:

  1. Bus
  2. Car as a passenger
  3. Car as a driver
  4. E-hailing
  5. Personal bike
  6. Shared bike/E-bike
  7. Shared E-scooter
  8. Suburban train
  9. Taxi
  10. Tram
  11. Underground metro
  12. Walking

- In the second part, we investigated user familiarity with and usage of carsharing services; we focused on usage frequency, willingness to walk to the vehicle pickup location, trip purpose. Respondents were also asked about the modes they would have used instead of carsharing for their last carsharing trip. Finally, respondents were asked to evaluate the importance of different aspects of carsharing services, such as mobile-application rating on the digital store, application ease of use, service availability in different cities, service availability in EV, service availability in the airport, service availability in different size vehicles (SUV, trucks, etc.), and the availability of offers bundles (discounts, e.g., for all-day rental, and long-distance rentals).

- The third part of the survey was the stated preference experiment; refer to Figure 2. In this experiment, respondents had to choose one carsharing service to perform an 11-kilometer trip; the choice was between operator A, where the user pays a fixed cost per kilometer. The other choice was operator B, where the trip cost would vary between a minimum cost, an average cost, and a maximum cost based on congestion conditions. The latter (cost range) would vary based on speeds (maximum, average, and minimum, respectively) of previous trips (previous trip distribution).

Carsharing services are gaining popularity for their ease of use, and their increased availability in our cities, especially among the young population. The service was initially priced by the minute of use, but now there are new schemes of paying a fixed price per kilometer. The main difference between the two schemes is the certainty regarding travel time, as users might encounter delays that would increase the trip cost if users are paying per minute of use and not by kilometer traveled. In the following scenarios, we ask you to choose the most convenient option to use based on your evaluation of the available options based on a hypothetical 11 km long leisure trip in Munich, Germany noting the following:

- ***Travel cost***; fixed if you choose to pay per kilometer and could fluctuate if you pay per minute based on the unknown road conditions and unexpected delays.
    - **Min cost**: The minimum expected cost based on fastest speed of previous trips
    - **Avg cost**: The average expected cost based on the average speed of previous trips
    - **Max cost**: the maximum expected cost based on the slowest speed of previous trips
- ***Access distance in meters***: the distance you will need to walk to pick up the carsharing vehicle
- ***Application rating in store***: the used operator app users' rating on the digital store you use

	Operator A Payment by KM Fixed cost	Operator B Payment by Minute
		cost depends on congestion conditions
Travel cost in €	7.34 €	Min 5.6 €
		Avg 8.1 €
		Max 12.1 €
Access distance in meter	150 m	150 m
Application rating on digital stores (stars)	4 Stars	3 Stars
Engine type: Electric	Yes	No

Certainly A | Probably A | Indifferent | Certainly B | Probably B | **None**

Figure 2: Scenario details and one block example

Table 1 shows the attributes and their corresponding levels that were used for the experiment. We opted to use travel cost, as it is a decisive factor in travel mode choice, and we wanted to investigate two new factors that were not investigated previously, which are the access distance users needed to walk to the nearest available vehicle and the service rating on the digital application store. The attribute levels were calculated as follows:

- Travel cost:
    - **Operator A**, payment by km scheme, the average cost per km is 0.89 € /km, obtained from the operator's online website and is similar to values used by Abouelela et al. (2021). A variation of this level (-0.25%, 0%, +25%) would result in a range of (0.66, 0.89, and 1.11) € /km.
    - **Operator B**, based on actual carsharing speed distribution. Essentially, minimum, average, and maximum costs were calculated using the same carsharing trips in Munich, Germany, for 2016, as described in Abouelela et al. (2021). The trip cost was calculated based on the speed distribution and multiplied by the cost per minute. The minimum cost was calculated based on the average speed for the first speed quartile distribution. The average speed was calculated based on the average speed, and the maximum cost was calculated based on the third-speed quartile average speed. For each speed, subsequent cost (-0.25%, 0%, +25%) values were calculated.

    * **Operator B**, costs per minute were obtained from operators' online websites and similar to the values used by (Abouelela et al., 2021).

- The levels of access distance calculated for this experience considered that the walking speeds are around 4-6 km/hr (Bohannon & Andrews, 2011), and that more than 50% of pooled ride users opted to walk less than ten minutes for the ride pick up location (Abouelela et al., 2022).
- Application rating on the digital application store was created specifically for this experiment, as no similar attributes were not investigated before.
- Engine type was used to check the impact of the electric engine type on the user's choice, and it was a binary attribute with two levels: yes, and no. A similar attribute was used by Monteiro et al. (2022).

Table 1: Stated preference attributes and levels

	Levels	
Variable (unit)	**Operator A** (payment by km)	**Operator B** (payment by minutes)
Travel cost €	[7.3, 9.8, 12.2]	Minimum cost [5.6, 7.1, 9.2] Average cost [8.1, 10.3, 13.2] Maximum cost[12.1, 15.4, 19.8]
Access distance (meter)	[50, 100, 150]	[50, 100, 150]
Application rating (⋆)	[3, 4, 5]	[3, 4, 5]
Engine type: electric	Yes / No	Yes / No

The fourth part of the survey investigated the sociodemographic characteristics of the users, where we asked users to specify their age, gender, education level, occupation, number of people and children in the household, and average monthly income. Also, in this part, we asked users to specify their agreement on a five-points-scale (totally disagree, disagree, neutral, agree, totally agree) on how much they identify with each of the 18 personality traits below, as used by (Queiroz et al., 2020; Mokhtarian et al., 2001; Redmond, 2000):

1. Optimist
2. Adventurous
3. Like routines
4. Spontaneous
5. Like being outdoor
6. Risk taker
7. Like to stay close to home
8. Efficient
9. Variety seeking
10. Punctual
11. Like to be alone
12. Independent
13. Creative
14. Calm
15. Anxious
16. Like being in charge
17. Participating
18. Lazy.

3.1.2. Modeling framework

The main target of this research is to model the impact of attitudes and personality traits on carsharing use, using the collected survey data. The survey consists of answers to attitudinal and personality evaluation, revealed preference, and stated preference questions. The different parts of the survey were used to answer the research question related to investigating factors impacting adoption, the shift from other modes, the choice between operators, and finally, the knowledge or awareness level regarding carsharing service (essentially the research questions RQ1 and RQ2). In investigating the examined factors, Hybrid Choice Models (HCM) were estimated. The main purpose of estimating HCM models was to integrate and investigate the impacts of user cognitive behavior, personality, and attitudes on the service adoption (Abouelela et al., 2022; Bolduc & Alvarez-Daziano, 2010; Ben-Akiva et al., 2002), but also to get a more realistic choice behavior, as pointed out in Raveau et al. (2010); Bolduc & Alvarez-Daziano (2010).

The first step in HCM is to estimate the latent constructs of the data (namely attitudes, travel behavior, and personality) using Exploratory Factor Analysis (EFA). We started the analysis by performing a scree test (Cattell, 1966) to decide on the optimum number of factors. The test showed two factors as the desired number, and we kept attributes with factor loading 0.4 or larger, based on the sample size and following

Hair et al. (1998). Varimax rotation was applied to obtain an orthogonal structure between the different factors, and the polychoric correlation was used as it suits the ordered nature of the data better than other correlation methods (Holgado-Tello et al., 2010). After deciding on the estimated factors for each of the question groups, the corresponding discrete outcome model was first estimated, and the latent variable model was added afterward. Four HCM models were estimated using Apollo package (Hess & Palma, 2019) under the statistical software R (R Core Team, 2023).

3.2. Study setup

Munich is the third largest city in Germany, with a population of around one and a half million and six million inhabitants in the metropolitan area (Aguilera-García et al., 2022). The city has a strong transportation infrastructure network reflected in many aspects of the inhabitants' daily travel behavior, where 80% of the population owns at least one bike, served by a 1,200 km long bike lanes network and 28,000 bike parking spaces. Also, the overall city modal shift reflects the solid public transportation culture, where 33% of the trips are made by cars, 23% by public transportation, and 44% of daily trips are done by active mobility, walking and biking[6]. The city-shared mobility landscape is vibrant, with different options for carsharing, bikesharing, shared e-scooters, moped scooters, and e-hailing. Munich City demonstrates an excellent example of a case study for carsharing use city, with the free-floating carsharing service starting in 2011. In 2019, there were around 2,100 shared cars on the city streets. Different operators adopt different pricing schemes, such as pay per minute, hour, and day, and lately, some operators are calculating trip prices based on trip length (Aguilera-García et al., 2022).

4. Analysis results

4.1. Summary of sociodemographic and travel behavior characteristics

The survey resulted in 1170 valid and complete responses. Table 2 shows the collected sample demographic characteristics compared to the city of Munich. The collected data is skewed in comparison to the city population in terms of age, education, occupation, and income; however, this is a direct result of the sampling strategy targeting young users. In general, the sociodemographic characteristics of the shared mobility users, are different from the ones of the average population as discussed in Section 2.

In terms of age, 89% of the sample is younger than 36 years old, compared to 40% of the average city residents age; also, users are highly educated, with 85% of the sample having at least a bachelor's degree compared to 26% of the city's residents. The number of students in the sample is over-representative in comparison to the city, as 43% of the sample respondents are students compared to only 4.5% of the city population. Therefore, the age and occupation of the respondents are reflected in other aspects, such as income being lower than the city average and the low number of children in the households. As the focus target group of this research are users younger than 35 years old, we only considered them in the following analysis, excluding all the other users (N = 1044). When comparing carsharing users with non-users, using a Perason's Chi-square test (χ_2) (Pearson, 1900), the differences were found to be significant in terms of users being males, more educated, with higher income, compared to the average population, full-time occupation, having access to a car, and owning a driving license that is valid in Germany. This profile of the carsharing user is similar to other shared mobility services in other locations, such as the United States, Canada, Great Britain, and Australia (Howe & Bock, 2018; Degele et al., 2018; Raux et al., 2017; Shaheen & Martin, 2015; Kim et al., 2015)

Travel behavior is an important factor that impacts users' adoption of shared mobility services (Abouelela et al., 2022); therefore, we asked respondents about the frequency of their use of twelve modes of transport. The majority of the sample can be described as active PT users, with at least 40% of the sample using PT more than once a week, which is reflected in their subscription to PT weekly and monthly tickets. The subscription to PT services reflects various aspects, such as the users' loyalty to the service or the high

[6](civitaS.E.u/cities/munich, last accessed 30/05/2023

quality of the PT system. Also, younger respondents more actively using PT than their older counterparts, who tend to use more private cars, was observed in other locations as well (Chaisomboon et al., 2020). A considerable percentage of users have access to private car use, as reflected in their car usage. Active travel is evident in the sample, mainly in the form of walking and personal bike, and not much use of shared micromobility modes. We further analyzed the modes used by users vs. non-users and also made an assessment by gender; see Figure 3, Table A.2 and Table A.3. The differences in travel behavior between the genders are well established, where women generally tend to utilize slower transportation modes like public transport and walk more frequently than men. They generally travel shorter distances and have more complex trip arrangements. Moreover, women are more likely to travel accompanied by children or dependents, facing more challenges related to physical accessibility, safety, and security (Pourhashem et al., 2022; Xu, 2020; Tilley & Houston, 2016). Moreover, gender is a decisive factor in shared mobility use, and specifically in the case of carsharing, as discussed in Section 2. Therefore, we considered the travel behaviour analysis per gender to further investigate these differences and test their impacts on the carsharing use.

Figure 3 shows the frequency of using the different urban modes for users and non-users; to assess the significance of these differences, we performed a chi-square test. From the twelve compared modes, nine were found to have significant differences, and only three modes did not have significant differences, namely walking, tram, and the underground metro. Carsharing users were, on average, more frequent users of all other modes than non–users (of carsharing services), except for bus(es). In terms of gender, differences in mode frequency were limited and were significant in the case of car use as a passenger and as a driver, shared bike, and taxi; in particular, males used, on average more bikesharing systems and were more often car drivers, as compared to their female counterparts.

Table 2: Summary of sample demographics and travel behavior and comparison with the Munich Census (2011)

Variable	Subgroup	n (pct%)	User	Non-User	Munich Census
Age	18-24	415 (35%)	175 (30%)	240 (40%)	(18-29) 27.2%
	25-30	521 (44%)	272 (47%)	249 (42%)	
	31-35	108 (9.2%)	68 (12%)	40 (7%)	(30-39) 16.7%
	36-40	46 (3.9%)	29 (5%)	17 (3%)	
	41+	81 (6.9%)	34 (6%)	47 (8%)	(40+) 51.5%
Gender	Female	523 (45%)	241 (42%)	282 (48%)	51.70%
	Male	648 (55%)	337 (58%)	311 (52%)	48.30%
Education level	Masters & PhD	386 (33%)	219 (38%)	167 (28%)	(PhD 2.5%)
	Bachelor	657 (56%)	309 (53%)	348 (59%)	Bachelor/MS: 22.7%
	High school or less	128 (11%)	50 (9%)	78 (13%)	66.90%
Monthly income	500€ or Less	140 (12%)	40 (6.9%)	100 (17%)	Avg: 4220 AC /household
	500€ - 2000€	580 (50%)	259 (45%)	321 (54%)	
	2000€ - 4000€	259 (22%)	159 (28%)	100 (17%)	
	4000€ and more	192 (16%)	120 (21%)	72 (12%)	
Occupation	Full time	405 (34.6%)	258 (45%)	147 (25%)	full/part-time 87.1%
	Part-time	165 (14.1%)	81 (14%)	84 (14%)	
	Self employed	43 (3.7%)	14 (2.4%)	29 (4.9%)	
	Student	510 (43.6%)	208 (36%)	302 (51%)	4.50%
	Other	48 (4.0%)	17 (3%)	31 (5%)	8.40%
Children	No	1,019 (87%)	491 (85%)	528 (89%)	
	Yes	152 (13%)	87 (15%)	65 (11%)	
Household size	1	441 (38%)	200 (35%)	241 (41%)	50.30%
	2	296 (25%)	174 (30%)	122 (21%)	28.80%
	3 and more	434 (37%)	204 (35%)	230 (38%)	20.90%
PT ticket*	Yes	859 (73%)	407 (70%)	452 (76%)	
	No	311 (27%)	171 (30%)	141 (24%)	
Own bike or E-bike	Yes	595 (51%)	335 (58%)	260 (44%)	
	No	575 (49%)	243 (42%)	333 (56%)	
Car access	Yes	451 (39%)	243 (42%)	208 (35%)	44%
	No	719 (61%)	335 (58%)	385 (65%)	56%
Driving license**	Yes	523 (45%)	343 (59%)	180 (30%)	88.90%
	No	647 (55%)	235 (41%)	413 (70%)	11.10%
$N_{Total} = 1,170$		$N_{User} = 578$	$N_{Non-User} = 593$		

*Subscription-based tickets; **Valid in Germany

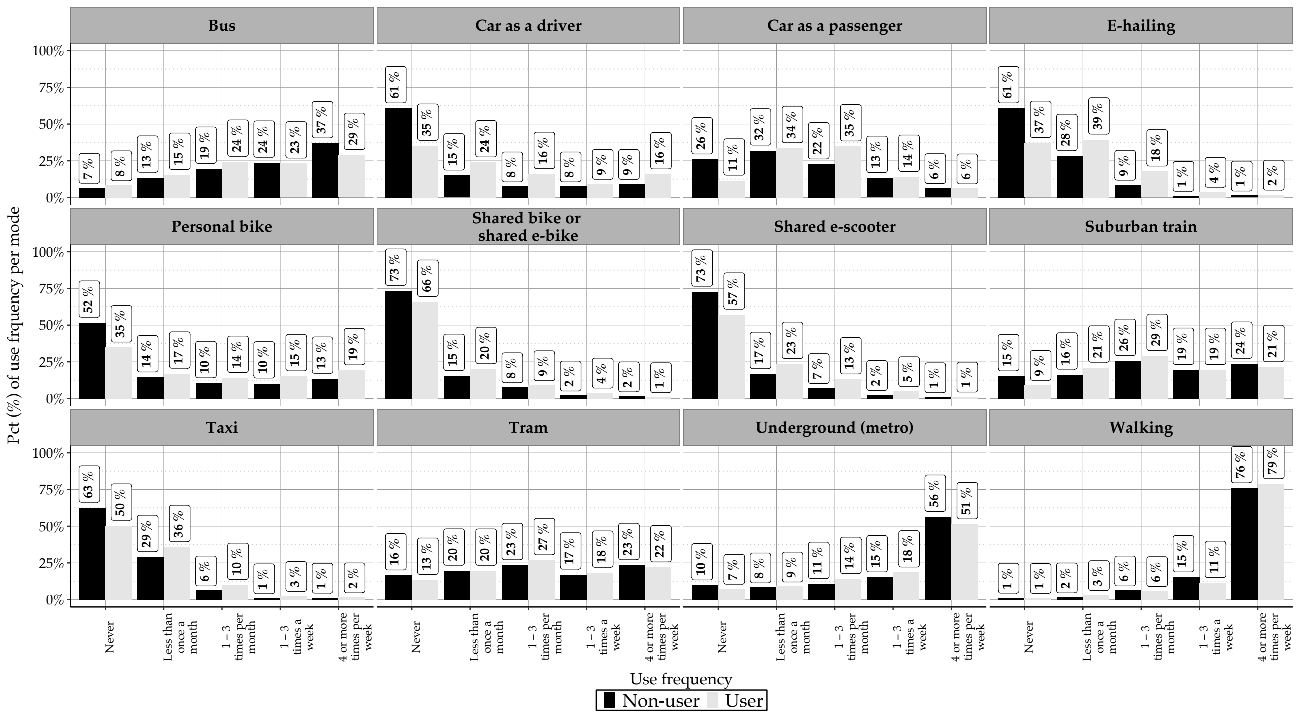

Figure 3: Urban modes use frequency for users and non-users of carsharing services

4.2. Familiarity with carsharing and carsharing use

In this section, we explore the respondent familiarity with carsharing services, and the way they use the service. We asked the users to rank their familiarity with the carsharing service on a four-point scale ranging from: "I do not know about them" to " Very familiar, I know almost everything about them." Most users (65%) knew about the service, and around one-fifth were very familiar with the service. We asked this question as we believed carsharing use is correlated with user familiarity with them, and we wanted to test the familiarity impact on the different service use aspects as explained in detail in section 4. Table A.1 shows the summary statistics for the familiarity with carsharing services for each user and non-users, per gender. Results indicated that users generally had a higher level of familiarity with the service compared to non-users; 88% of users were familiar with the service as compared to 43% of non-users. It is important to highlight that the 12% of the users who were unfamiliar with the service reported that they had used carsharing mainly as passengers. When assessing by gender, there was no significant difference in terms of knowledge, except that males were very familiar with the service, as compared to females.

Table A.1 shows the summary statistics of the different aspects of use and familiarity of carsharing services for the different groups; Chi-square tests were used to test the significance of the differences between the different subgroups. The majority of users used the service as passengers, and they used it mainly less than once per week. The major trip purposes are leisure, visits, work, and shopping. Users were asked about the modes they replaced the last carsharing trip with, and the top five modes were the underground, car as a passenger, suburban train, e-hailing service, and car as a driver. These results show potential for negative impacts, as carsharing trips replace mainly PT trips which might increase the vehicle kilometer traveled (VKT) on the roads and, subsequently GHG emissions. We also asked the users to express their willingness to walk to the nearest carsharing vehicle locations, for which 75% of the users specified that they would walk up to seven minutes to the pickup location. We also tested the impact of frequency of use on the willingness to walk, for which no significant results were found. Users' willingness to walk was uniformly distributed among the different use frequencies. Similar results were observed in fixed-route commercially organized pooled rides (Abouelela et al., 2022).

5. Modeling results

In this section, we first present the exploratory factor analysis results, after which we present the findings extracted from the four developed hybrid choice models. The aim was to first extract the latent constructs on both user and service–related aspects to carsharing, to then incorporate them and assess their impact on carsharing. In particular, the impact of personality traits and attitudes on knowledge about carsharing, carsharing adoption, and use, was assessed. Moreover, the importance of service–related attributes on the choice between carsharing operators with different payment schemes was also explored.

5.1. Exploratory factor analysis

In this sub–section, the exploratory factor analysis (EFA) results are presented, based on which the latent constructs have been extracted, notably for user attitudes; the impact of the extracted factors on carsharing use was then studied. In particular, the factor analysis was conducted for three question groups relating to carsharing operator–related features (Section-5.1.1), personality traits (Section-5.1.2), and travel behavior (Section-5.1.3).

5.1.1. Carsharing operator–related features

For the first questions group, we asked respondents to rate how important different aspects of carsharing services were to them, on a five–point Likert (Likert, 1932) scale that ranges from (1 = not important at all, 2 = not important, 3 = neutral, 4 = important, 5 = very important). Table A.2 presents the summary statistics for the ratings of the seven examined aspects of the carsharing service characteristics. The rating summary shows no significant difference between gender groups in the evaluation rate; however, a slight difference in the ranking of the importance of each aspect was observed. Application ease of use was selected as the most critical aspect, while the availability of EVs in the carsharing fleet was rated as the least important factor as per the evaluation order for both genders; the latter was found to be less than neutral for male users with an average evaluation score being less than 3. The rest of the operator–related features were almost the same for both gender groups, with women's evaluation scores (in terms of importance) generally consistently higher than males; however, without any statistically significant difference.

When comparing user and non-user groups, interestingly, non-users had, on average higher evaluation scores for the different aspects, except for the availability of different size vehicles, which was the second to last least important aspect based on their rating. Also, application ease of use was the most important service aspect, with a significant difference in rating compared to the next important aspect, app rating. The differences between users and non-users were significant and evident in all aspects, except for service availability in different cities and for app ease of use.

The top part in Table 3 shows the factor analysis results with two main factors representing the main latent constructs and explaining 46% of the total data variability. Factor one can be described as the physical offers, and the second factor as the application-related factors. The results of the EFA for the carsharing operator–related features could possibly reflect on the important dimensions of the service that operators need to focus on to achieve a high level of satisfaction among users.

5.1.2. Personality traits

Understanding personality traits is essential for understanding human travel behavior; however, the impact of such traits on travel behavior is still not well comprehended (Jani, 2014). Also, personality might not be a direct influence on travel behavior, but it dictates a certain pattern of behavior (Revelle, 2007), and it is more likely to be associated with different levels of mobility; for example, having an adventurous personality might be associated with a higher level of mobility (Redmond, 2000). The middle part in Table A.2 presents the summary statistics for the answers pertaining to personality traits for different respondent groups (users, non–users, males, and females). In particular, respondents were asked to specify their agreement with different personality types on a five–point Likert scale (ranging from "Totally disagree", "Disagree", "Neutral", "Agree", "Totally agree"). After conducting Chii–square tests for assessing the statistical significance in personality traits between different respondent groups (see Table A.3 middle part), we found significant differences in personality traits between users and non-users than between the different gender groups (i.e., males and females).

Our initial hypothesis for the EFA was that we would estimate five factors representing the five major personalities, namely risk-taking, loner, ambitious, organized, and lazy. The middle part in Table 3 presents the estimated EFA results for the personality–related questions, for which two main factors were extracted, interpreted as "adventurous" and "organized". The two factors explain 39% of the data variability. The results of these factors were further used to estimate the impact of these two types of personalities on carsharing use.

5.1.3. Travel behavior

The final set of questions that were analyzed using EFA techniques focused on the frequency of use of the different available modes. For this question, we hypothesized three types of users: PT users, private mode users, and finally, shared mobility users. The bottom part in Table 3 bottom part presents the results of the EFA for the mode use frequency. Two factors were extracted and found to be significant, one for PT users and the other for shared micromobility users; the two factors explained 51% of the variance of the data, and the initial hypothesis was partially correct.

Table 3: Factor analysis model results

I–Carsharing operator–related features	Physical offerings	Application
App ease of use		0.92
App rating		0.60
Availability in airport	0.71	
Availability of different size vehicles	0.62	
Service offers bundles	0.56	
Availability in other cities	0.53	
Availability of electric vehicles	0.51	
Model diagnostics		
Factor loadings	1.82	1.38
Proportion variance	0.26	0.20
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.80		
Cronbach's alpha = 0.73		
II–Personality traits	Adventurous	Organized
Adventurous	0.82	
Being outdoor	0.51	
Spontaneous	0.61	
Risk taker	0.58	
Variety seeking	0.50	
Efficient		0.70
Punctual		0.46
Model diagnostics		
Factor loadings	1.93	0.76
Proportion variance	0.28	0.11
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.75		
Cronbach's alpha = 0.6		
III–Travel behavior	Frequent PT user	Frequent micromobility user
Bikesharing		0.75
Shared E-scooter		0.70
Tram	0.68	
Underground	0.85	
Suburban Train	0.73	
Bus	0.69	
Model diagnostics		
Factor loadings	2.43	1.10
Proportion variance	0.35	0.16
Kaiser-Meyer-Olkin factor adequacy: MSA= 0.78		
Cronbach's alpha = 0.72		

5.2. Factors impacting knowledge about carsharing

This model investigates the factors impacting user's knowledge regarding carsharing. The answer to the question investigating the knowledge about carsharing was set as the dependent variable, which is ordered in nature. The answers to this question were "I do not know about them "; "I have heard about them"; " know about them, but not much details"; "Very familiar, I know almost everything about them". Ordered HCM model was estimated, and Figure 4, and Table 4 show the full path diagram and the estimated model results.

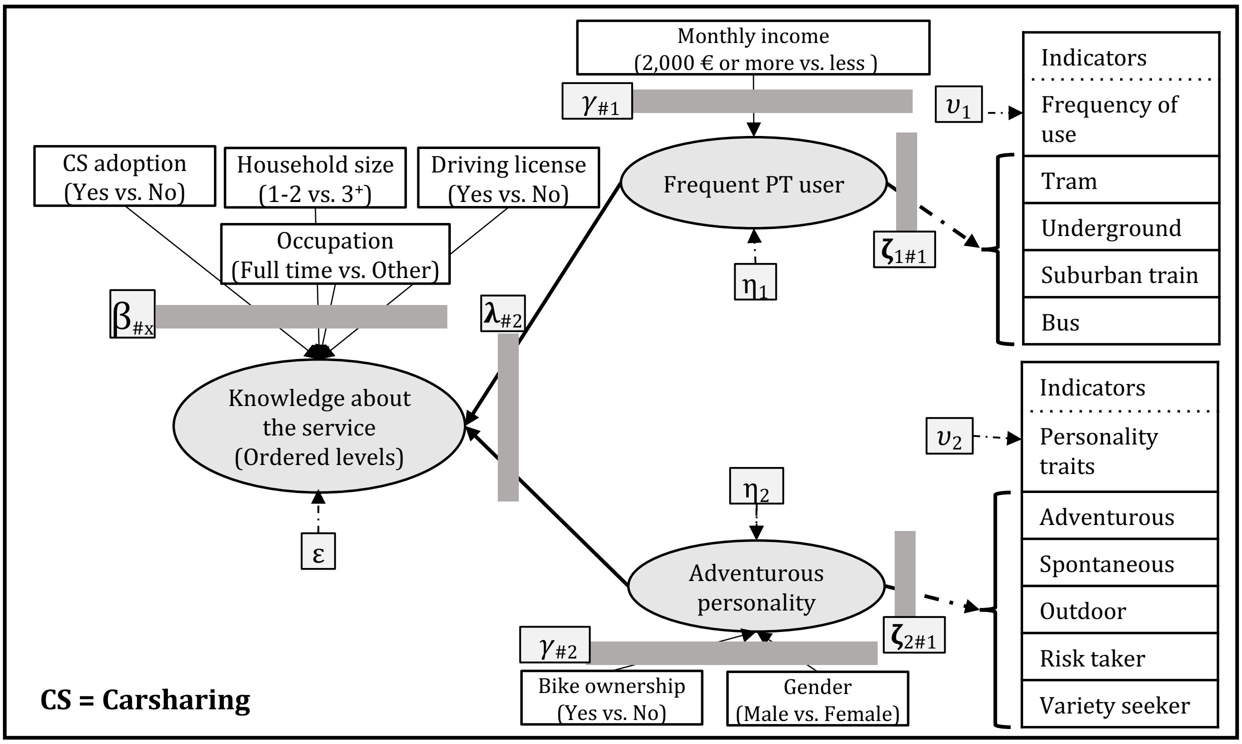

Figure 4: Full path diagram for the ordered HCM for knowledge about carsharing

532 Four variables and two latent variables were significant with positive estimated coefficients ($+\beta$), which show that these variables are associated with a higher likelihood regarding higher knowledge about carsharing
534 services: previous use of carsharing, ownership of a driving license, full-time workers, people who live in small households, adventurous persons, and frequent PT users. The thresholds between the different knowledge
536 levels are significant, showing that people understand the difference between the different levels.

The latent variable models can be interpreted as follows: for the measurement model adventurous per-
538 sonality, the positive sign for the estimated coefficient (ζ) for the measurement model part shows that the more the person agrees with the statement, the more likely is this personality type, and the more likely he
540 is to be an adventurous person. The signs of the coefficients of the Structure model part (γ) for males and bike owners show that these variables increase the probability of being an adventurous person compared
542 to the other population group. The other latent variable is the PT frequent user, and the measurement model positive coefficient (ζ) sign shows that the higher the answer the more frequently the person uses PT,
544 and the negative sign for the high-income coefficient (γ) shows that high-income people are less likely to be frequent PT users. The estimated model partially answers the first research question (RQ1).

Table 4: ordered HCM results for knowledge about carsharing (ordinal variable)

Variable	β	S.E.	P-value
Carsharing use (yes vs. no)	2.09	0.15	0.00
Driving license (yes vs. no)	0.68	0.14	0.00
Occupation (full–time vs. other)	0.34	0.14	0.01
Household size (1-2 vs. 3 and more)	0.21	0.13	0.10
LV1: PT user (λ_1)	0.20	0.08	0.01
LV2: Adventurous (λ_2)	0.29	0.08	0.00
Threshold			
I do not know about them – I have heard about them	-0.93	0.13	0.00
I have heard about them – I know about them, but not details	0.63	0.12	0.00
I know about them, but not details – very familiar with them	3.73	0.17	0.00
Number of observations = 1044			
Latent variable Model			
Structure model (Frequent PT user)	γ	S.E..	P-value
Income (2,000 € or more vs. less than 2,000 €)	-0.44	0.08	0.00
Measurement model (Frequent PT user)	ζ	S.E..	P-value
Tram	1.68	0.12	0.00
Underground	2.68	0.25	0.00
Suburban train	2.00	0.15	0.00
Bus	1.62	0.13	0.00
Latent variable Model			
Structure model (Adventurous personality)	γ	S.E..	P-value
Gender (male vs female)	0.14	0.07	0.06
Bike or E-Bike ownership (yes vs. no)	0.12	0.07	0.10
Measurement model (Adventurous personality)	ζ	S.E..	P-value
Adventurous	2.61	0.24	0.00
Spontaneous	1.37	0.11	0.00
Outdoor	1.13	0.11	0.00
Risk taker	1.43	0.11	0.00
Variety seeker	1.03	0.10	0.00

5.3. Factors impacting carsharing adoption

This section presents the model results for the model investigating the factors that impact the adoption of carsharing services, and partially answers RQ1. A binary choice and latent variable HCM was estimated to investigate the examined factors. For the subject model, the dependent variable was coded as a binary variable considering responses indicating that they never used carsharing as zero, with the rest of users being coded as 1.

Figure 5 and Table 5 present the full path diagram and the estimation results for the hybrid choice model for carsharing adoption. The estimated model shows that people familiar with carsharing services, with a driving license, who are full-time workers, owners of bikes, with a high-income level, and with a higher education level are more likely to adopt carsharing services compared to other population groups. These significant variables are aligned with the hypothesized profile of shared mobility users, who are in general, wealthier and more educated than the average population. On the other hand, people who have access to a car, live in a small household, and have a subscription to PT tickets are less likely to adopt carsharing services. The two latent variables, frequent shared micromobility users (λ_1) and adventurous personality (λ_2), were found to be significant predictors impacting the adoption of carsharing. This model shows that

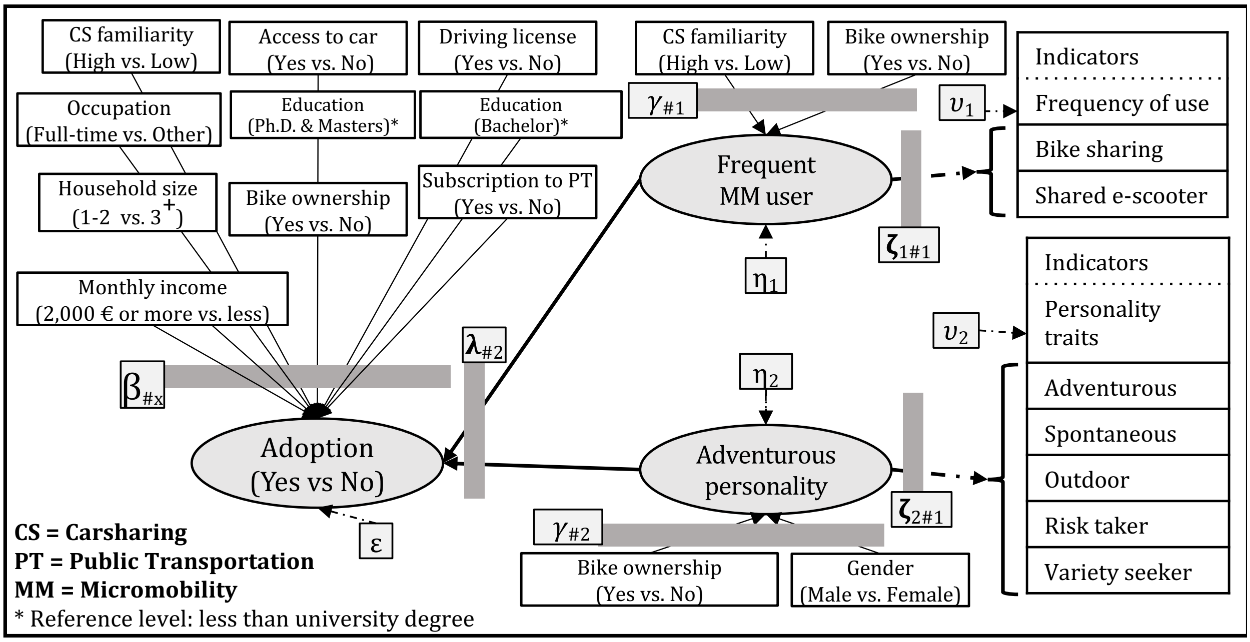

Figure 5: Full path diagram for the binary HCM for carsharing adoption

users with adventurous personality have a higher probability of adopting carsharing; such personality was previously (in previous studies) associated with a preference for higher levels of mobility, being outdoor, and disliking routine (Gao et al., 2017; Redmond, 2000), which might be the utility provided by carsharing. The other latent variable shows that frequent micromobility users are more likely to adopt carsharing services in comparison to other population groups. This behavior was also observed in the adoption of other shared mobility services, such as in the case of pooled rides (Abouelela et al., 2022).

The lower part of Table 5 shows the structural equation model of the HCM. The estimation of the latent variable model for the personality part shows that the coefficients of the measurement model part (ζ) is positive, which indicates that the higher the level of agreement with the personality statement questions, the more likely the person to be adventurous. Coefficients of the Structure model (γ) are positive, showing that each of males and bike owners (as opposed to females and non–bike owners) are more likely to be adventurous. The estimation of the second latent variable model shows that the coefficients of measurement models (ζ) are positive, indicating that the higher the frequency of using bike–sharing and/or shared e–scooters, the higher the likelihood to be a frequent shared micromobility user. Finally, the (γ) coefficient for the Structure model part shows that users who are familiar with carsharing use are more likely to be users of shared micromobility, and car owners are more likely to use micromobility in comparison to other population groups, which matches the general profile of shared mobility users. For both latent models, we did not show the estimation results of the thresholds between the different indicators, as they have no meaning by themselves and only indicate the order of the thresholds.

Table 5: Binary HCM results for carsharing adoption

Variables	(β)	S.E.	P-value
Intercept	-2.40	0.36	0.00
Carsharing familiarity (high vs. low)	2.03	0.17	0.00
Access to car (yes vs. no)	-0.46	0.20	0.01
Driving license (yes vs. no)	1.10	0.17	0.00
Occupation (full-time vs. other)	0.47	0.20	0.01
Education (Ph.D. & Masters vs. less than uni degree)	0.60	0.29	0.02
Education (bachelor vs. less than uni degree)	0.49	0.27	0.04
Household size (1-2 vs. 3 and more)	-0.21	0.16	0.10
Bike or e-Bike ownership (yes vs. no)	0.25	0.16	0.06
PT subscription (yes vs. no)	-0.27	0.21	0.10
Income (2,000 € or more vs. less than 2,000 €)	0.32	0.20	0.05
LV1: Frequent micromobility user (λ_1)	0.28	0.11	0.00
LV2: Adventurous (λ_2)	0.10	0.09	0.13
$\rho^2 = 0.291$	$\rho^2_{Adjusted} = 0.287$		
Number of observations = 1044			
Latent variable model			
Structure model (adventurous personality)	γ	S.E..	P-value
Gender (male vs. female)	0.15	0.07	0.02
Bike or E-Bike ownership (yes vs. no)	0.10	0.07	0.08
Measurement model (adventurous personality)	ζ	S.E..	P-value
Adventurous	2.67	0.25	0.00
Spontaneous	1.34	0.11	0.00
Outdoor	1.11	0.10	0.00
Risk taker	1.42	0.11	0.00
Variety seeker	1.02	0.1	0.00
Latent variable model			
Structure model (Frequent micromobility user)	γ	S.E..	P-value
Carsharing familiarity (high vs. low)	0.34	0.09	0.00
Bike or e-Bike ownership (yes vs. no)	0.35	0.08	0.00
Measurement model (Frequent micromobility user)	ζ	S.E..	P-value
Shared E-scooter	3.76	1.28	0.00
Bike sharing	1.30	0.16	0.00

P-values are based on the robust standard errors used to control for heteroscedasticity that might exist.

5.4. Factors impacting the shift to carsharing

This model investigated factors impacting the shift from different modes to carsharing. We grouped the modes replaced by carsharing into two groups; the first one being the low-capacity vehicles groups (including cars as a driver, cars as passengers, E-hailing, and Taxis) and the second group being the PT group (with bus, tram, underground, and suburban trains). These observations amounted to 478 users who shifted from the previous specific modes, representing 93% of the total number of carsharing users (515 users). The rest of the observations (37) were removed from the sample used to estimate this model. The dependent variable of the model was coded as a binary variable with the value of one in the case of the shift taking place from a low capacity vehicle (cars as a driver, cars as passengers, E-hailing, and Taxis), the first group, and zero otherwise, similar to the approach adpoted by Abouelela et al. (2022). Table 6 shows the model estimation results, and Figure 6 shows the model's full path diagram.

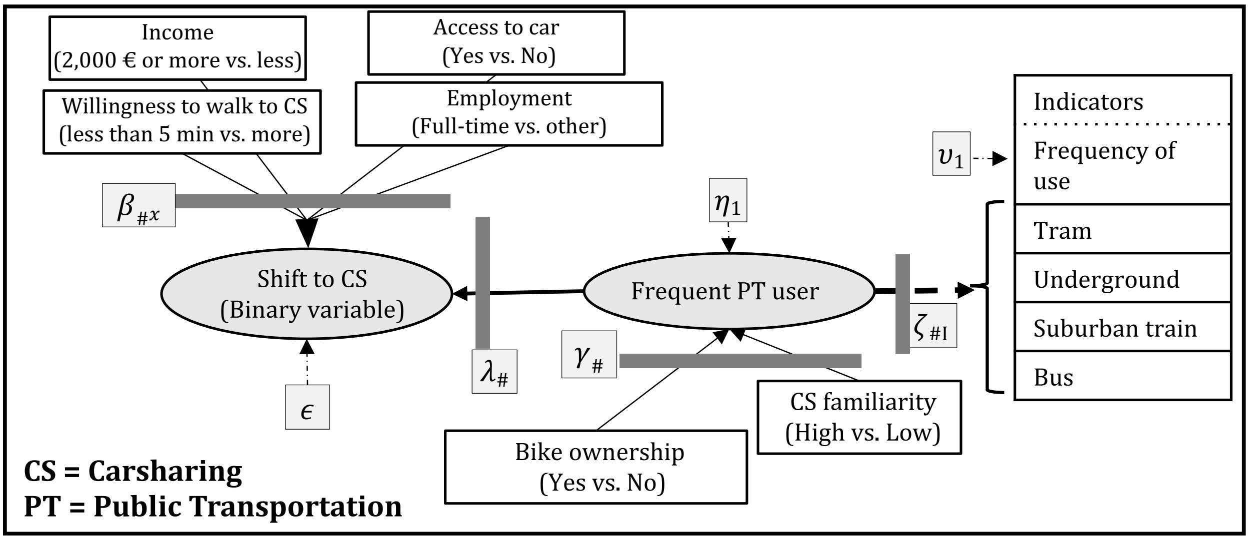

Figure 6: Full path diagram for the binary HCM for shift to carsharing

Table 6: Binary HCM results for the shift from different modes to carsharing

Variable	β	S.E.	P-value
ASC	1.04	0.27	0.00
Willingness to walk to carsharing (less than 5 min vs. more than 5 min)	0.32	0.19	0.06
Income (2,000 € or more vs. less)	0.45	0.24	0.05
Access to car (yes vs. no)	0.66	0.21	0.00
Occupation (Full–time vs. other)	0.46	0.23	0.05
LV1: Frequent PT user (λ_1)	-0.30	0.12	0.01
$\rho^2 = 0.155$	$\rho^2_{Adjusted} = 0.147$		
Number of observations = 478			
Latent variable Model			
Structure model (Frequent PT user)	γ	S.E..	P-value
Bike or E-Bike ownership (yes vs. no)	-0.21	0.11	0.05
Carsharing familiarity (high vs. low)	0.27	0.17	0.09
Measurement model (Frequent PT user)	ζ	S.E..	P-value
Tram	2.06	0.21	0.00
Underground	2.57	0.32	0.00
Suburban train	2.26	0.25	0.00
Bus	1.76	0.20	0.00

P-values are based on the robust standard errors used to control for heteroscedasticity that might exist.

The estimated model results show that high-income individuals, who are full-time employed, have access to a car, and are willing to walk less than five minutes to carsharing pick-up locations, are more likely to shift to carsharing from low–occupancy vehicles as compared to the rest of the population, which are in line with the profile of shared mobility users. Only one latent variable was significant in this model, namely the frequent PT users. The negative sign for the latent variable, LV1 (λ), showed that PT frequent users are less likely to shift from low-capacity vehicle trips to carsharing. Similar results were found in the case of pooled rides, where PT frequent users were less likely to adopt shared mobility in the form of pooled rides

(Abouelela et al., 2022). The latent variable model shows that for the measurement model part, all the coefficients (ζ) are positive, showing that the higher the use frequency, the more likely it is to be a frequent PT user, which is intuitive. The Structure model part shows that people who are familiar with carsharing services are more likely to be frequent PT users, and people who own bikes are more likely to use PT in comparison with those who do not own bikes. The estimated model answers the the remaining part of RQ1.

5.5. Factors impacting the choice between carsharing operators

This model targeted factors impacting the choice between the different operators with different payment schemes, namely payment per minute or payment per kilometer, which answers the second research question (RQ2). As shown in Figure 2, six options were available; certainly-A and probably-A, indifferent, probably-B, certainly-B, and "None". Options certainly-A and probably-A were aggregated to A, the same aggregation was done for options B, the indifferent option was deleted, and option "None" was kept as the third option, following similar procedures to Abouelela et al. (2021); Fu et al. (2019); Vermeulen et al. (2008).

The indifferent options represented 9.3% of the total answers, and the choices of the remaining aggregated scenarios were distributed as 53.1% for option A, 33.6% for option B, and 4% for the none option. Our hypotheses for the model-building process were that males and people who have adventurous personalities might opt for operator B for its possibility to have cost savings; also, we believe that adventurous users would opt for option B as they were expected to drive faster for cost saving.

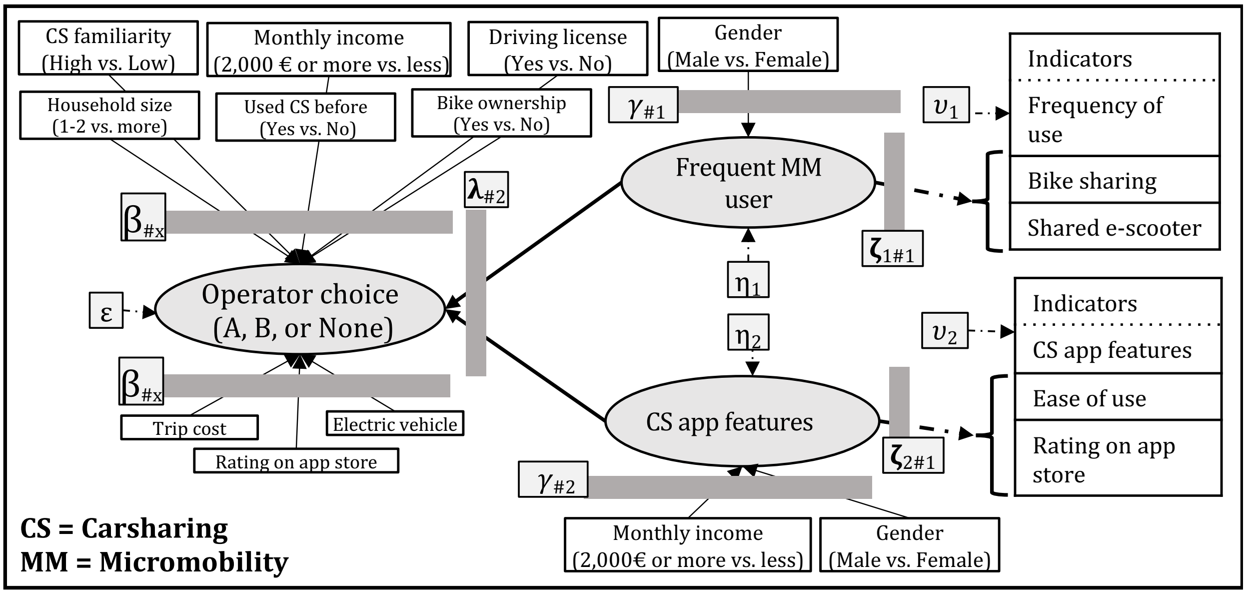

Figure 7: Full path diagram for the multinomial HCM for carsharing operator choice

Figure 7 shows the full path diagram and Table 7 and Table 8 show the estimated model coefficients and parameters for the HCM of the payment schemes. The interpretation of the model results considers the "non-trip" option as the reference level for comparison with other options. The choice experiment tested the significance of four carsharing-related attributes on the choice between the payment schemes; trip cost, access distance, rating on the app, and vehicle engine type, electric or not. All the variables were significant except the access distance. The cost coefficient for option B (pay-per-minute option) was based on the average cost shown in the experiment, and the coefficient of the vehicle being electric or not was generic for both options. Interestingly, app rating was the variable with the highest absolute coefficient value for this group of variables.

The cost coefficient shows that users value the cost of paying per minute to be cheaper than paying per km; we believe that this is most likely due to the fact that there is a chance to pay a lower cost when choosing to pay per minute. Other factors show that app rating is more effective in the choice of option

A, compared to option B. Six user characteristics were significant, showing that users with high-income levels, familiarity with carsharing services, valid driving licenses, and who have used carsharing before, were more likely to adopt carsharing compared to other population groups. On the other hand, people who live in small size households and who own bikes were less likely to choose car sharing in comparison to other groups. Finally, the two latent variables were only significant for option B, and they indicated that shared micromobility users were more likely to choose option B, and people who value the importance of the app were more likely to choose option B. We believe that the main reasons for this are that shared micromobility trips are paid per minute of use; besides, people who value the importance of the app in the service users are more likely to be used to the scheme of paying per minute, which was the original offer for all the shared vehicle services.

Table 7: MNL model results for the choice between different carsharing operators

Variable	**Operator A** (per km)			**Operator B** (per min.)			**None**		
	β	S.E.	P-value	β	S.E.	P-value	β	S.E.	P-value
ASC							-4.77	0.20	0.00
Cost (€)	-0.37	0.01	0.00	-0.32	0.01	0.00			
Access distance (Meter)									
Rating on the app. store (★)	0.41	0.02	0.00	0.30	0.02	0.00			
Electric Vehicle (yes vs no)*	0.16	0.03	0.00	0.16	0.03	0.00			
Income 2,000€ or more (vs. less)	0.34	0.13	0.01	0.41	0.13	0.00			
Driving license (yes vs. no)	0.57	0.13	0.00	0.43	0.13	0.00			
Carsharing familiarity (high vs. low)	0.64	0.11	0.00	0.38	0.11	0.00			
Carsharing use (yes vs. no)	0.79	0.13	0.00	0.83	0.13	0.00			
Household size = 1-2 (vs. 3^+)	-0.19	0.12	0.10	-0.26	0.12	0.03			
Bike ownership (yes vs. no)	-0.38	0.11	0.01	-0.46	0.11	0.00			
LV1: Frequent micromobility user (λ_1)				0.13	0.03	0.00			
LV2: Carsharing app feature (λ_2)				0.14	0.03	0.00			
$\rho^2 = 0.344$	$\rho^2_{Adjusted} = 0.343$								
Number of observations = 9469									

P-values are based on the robust standard errors used to control for heteroscedasticity that might exist.
* Generic coefficient for both options

Table 8 shows the latent variable models. The first latent variable model, the importance of app-rating, can be interpreted as the coefficient (ζ) for the measurement model being positive, showing that the higher the rating for the importance of app ease of use and the higher the rating on the app store, the more likely the person is to be in this user group. The structural part of the model shows that males and high-income individuals are less likely to be in this group in comparison with the rest of the population. In the second latent variable model, frequent shared micromobility users, the measurement model part coefficients (ζ) shows that the more frequently shared micromobility used, the more likely to be in this group. The structural model part shows that male users are more likely to increase the use of shared micromobility in comparison to female users, which is usually observed in the case of shared mobility services.

It is important to highlight that our initial hypotheses were not significant and personality traits did not impact the choice for the payment scheme; however, gender indirectly impacted the choice between payment schemes through the latent variable.

Table 8: Latent variable model results for the choice between different carsharing operators

Latent variable Model			
Structure model (Frequent micromobility user)	γ	S.E..	P-value
Gender Male (vs female)	0.291	0.032	0.000
Measurement model (Frequent micromobility user)	ζ	S.E..	P-value
Shared E-scooter	1.973	0.131	0.000
Bike–sharing	1.825	0.093	0.000
Latent variable Model			
Structure model (Perceived app importance)	γ	S.E..	P-value
Gender: male (vs. female)	-0.112	0.025	0.000
Income: 2,000 € or more (vs less than 2,000 €)	-0.056	0.027	0.041
Measurement model (Perceived app importance)	ζ	S.E..	P-value
App ease of use	4.052	0.377	0.000
App rating on app store	1.471	0.046	0.000

P-values are based on the robust standard errors used to control for heteroscedasticity that might exist.

6. Discussion, limitations, and conclusions

6.1. Discussion

In this research, we collected user and carsharing–related data to understand the impact of psychological factors including personality traits, travel behaviour, and attitudes on the knowledge about carsharing, its adoption, and use on the one hand, as well as examine the factors impacting the choice between different carsharing operators.The research was applied to a case study in Munich, Germany, focusing on young users. The collected data shows that carsharing users are young, highly educated males with high-income levels, with full-time jobs, living in small size households, and with a valid driving license, which is aligned with the general profile of shared mobility services and specifically carsharing users (Liao et al., 2020; Namazu et al., 2018). Obviously, the characteristics of carsharing users show the potential for inequitable use problems, wherein population groups, such as low-income and low-education groups, are not frequent carsharing users, which was evident in the collected sample, and revealed by the analysis process and the estimated models. Shared mobility needs a smartphone, digital banking options, and knowledge about the app use to use the service. Such conditions are not always available and add to the inequitable use situation that might result from other conditions, such as service unavailability within reach and service unaffordability (Abouelela et al., 2024). Digitalization therefore becomes a concern as it is often highlighted as a key enabler to sustainable development of cities (Balogun et al., 2020) in general, and to shared mobility in particular Goehlich et al. (2020). Several strategies could help mitigate this, such as subsidizing the service and offering an alternative to digital access and digital banking options; however, these solutions do not always guarantee success. For example, in Chicago, IL, only 0.05% of shared e-scooter trips were made with non-digital banking options that were provided to help solve the inequitable use problem for shared e-scooter use (Abouelela et al., 2023). While providing alternatives to digital solutions might be plausible in the short–term, addressing concerns of digital literacy and access might be the only viable long–term solution, so that all population groups can have access to the service and its digital platform.

The collected data analysis showed that users and non-users have distinguished travel behavior with significant differences, which indicates the need for further investigation into how to adjust carsharing service operations to cater to the different travel behaviors and to attract non-users, if possible. Moreover, most users (40%) indicated that their last carsharing trip replaced PT (underground, suburban train), showing that there is a potential that carsharing might increase the VKT, as it replaces large occupancy vehicles (PT). On the other hand, 35% of users reported carsharing as a replacement for low–occupancy vehicles, including private cars as passengers or drivers and e-hailing, which may reduce the total VKT. The latter could have positive impacts such as reducing energy consumption and resulting CO_2 emissions, and required parking spaces (6t-Bureau de recherche & ADEME, 2016; Baptista et al., 2014). However, more information is required, including the access and egress modes, and the vehicle capacity and occupancy, to better quantify the impacts of carsharing on the VKT; this, however, was not investigated, as it was not the focus of this research. The responses to the questions regarding familiarity with carsharing services show that there is a proportional relation between carsharing use and knowledge about the service, indicating that to increase the use of such services, more marketing and reach-out plans should be conducted by providers to increase people's knowledge and awareness regarding the service, mainly to target non-users. The EFA was conducted on the three main question groups (service aspect rating, personality traits, and travel behavior), and each of these groups showed two factors. The first question group related to the carsharing service's important aspects showed two factors: I) the app-related attributes and II) physical offers. These estimated factors show the importance of the app-related attributes, which were not examined in previous research, up to the best of our knowledge, and which need more investigation to reach the recommended design by users, as it has a role in impacting service use, as shown in the estimated models. App-related attributes were significant in the preference of paying per minute; however, physical attributes were not significant in any of the estimated models, confirming the importance of the app-related aspects of the service. The second question group is the personality trait group, which showed two distinctive personality traits, III) an adventurous personality and IV) an organized personality. Our hypothesis was that an adventurous personality would be more likely to use carsharing services than other types of personality due to the higher levels of mobility and independence provided by carsharing, which fits the characteristics of the adventurous personality (Redmond, 2000). The estimated model showed the significance of the adventurous personality in adopting carsharing services and the higher level of knowledge regarding the service. For the last question group, travel behavior, two estimated attitudes were related to travel behavior; V) PT frequent user and VI) shared micromobility user. Both factors indicate a distinguished travel pattern that shapes the adoption and use of carsharing services. Shared micromobility users are likelier to adopt the service and prefer to pay per minute of use, while frequent PT users are less likely to shift from low-capacity vehicles to carsharing. The impacts of the travel behavior latent construct on the use of shared mobility use were evident in the case of pooled rides (Abouelela et al., 2022), showing the importance of accounting for the different travel preferences when planning new services or even integrating them with current services such as PT, and other shared services that could increase the potential of multimodality. Moreover, frequent shared micromobility users, in this case, shared e-scooter and bikesharing, are more likely to adopt other shared mobility services, which highlights the question of the impacts of shared mobility frequent use on Mobility as a Service (MaaS) platforms adoption or would the availability of all the shared service within one platform increase the use of these services, and increase the possibilities of multimodality, which could be a sustainable outcome. Multimodality is one of the expected positive potential outcome of MaaS, and subsequently increasing the sustainability of the transport system (Ho & Tirachini, 2024). It is also to be noticed that carsharing service plays a significant role in MaaS use and utilization, which was observed in the aces of the Augsburg, Germany MaaS trial, where customers of the Maas bundle utilized their full carsharing allowance and subsequently increase their carsharing use showing the pivotal role for carsharing in MaaS use and utilization (Reck et al., 2021). Also, Keller et al. (2018) observed that carsharing user have higher intention to use MaaS platforms then the rest of the population.

The estimated models showed that sociodemographics attributes, knowledge about carsharing, and personal attitudes and personality traits play significant roles in carsharing use. The estimated model showed that the attributes that increase the probability of carsharing service adoption are: high familiarity with carsharing service, having a valid driving license, full-time employment, a high education level, high-income level, owning a bike, having an adventurous personality, and being a frequent micromobility user. The results of this model are in line with the general profile of shared mobility users (Le Vine & Polak, 2019b; Martin & Shaheen, 2011a; Alemi et al., 2018; Ahmed et al., 2021; Luo et al., 2019). It is to be noted that the variable with the highest estimated coefficient is familiarity with carsharing services, followed by the availability of a driving license and the (high) level of education. It is clear that knowledge about the service is very important in impacting its adoption, which highlights the role of marketing in service use. Also, shared mobility users are more likely to use such services in different forms. On the other hand, users who have access to a car, users with PT subscription-based tickets, and living in small size households are more likely not to use the service, showing that there is a need to investigate the potential of integrating carsharing services in the PT subscription to increase the service use.

Again, sociodemographic characteristics and attitudes play a significant factor in the shift from different modes to carsharing, where high-income people who are full-time employed, willing to walk for a short period (less than 5 minutes) and have access to a car have a higher likelihood to shift from low occupancy vehicles to carsharing, while PT frequent users are less likely to do so. This model also shows the significance of sociodemographics and travel behavior in replacing different modes with carsharing services, and it is also in line with the profile of shared mobility users.

When looking at factors impacting the choice between operators with different payment schemes, trip cost, rating on the app store, and availability of electric vehicles were found to be quite significant. App rating was the coefficient with the highest reported value, showing its importance in the choice between different payment schemes. Also, people perceive the payment per minute as cheaper than the payment per km, which is an interesting result showing the preference of users for the payment scheme per minute (the oldest, more common scheme for carsharing payment) over the payment per km with all the other factors being constant. Also, sociodemographics are crucial in choosing between operators, such as high income, driving license, familiarity, and previous use of carsharing services. On the other hand, having a bike and living in a small size household reduce the likelihood of carsharing use. The highest estimated coefficient in this model related to user characteristics is the previous use of carsharing, showing that people who have experience with the service are more likely to choose to pay per minute if all other factors are kept constant. Attitudes also played a significant role, wherein respondents who valued the importance of the app and shared micromobility frequent users are more likely to use the service and choose to pay per minute of use. These findings highlight the preference for the payment per minute and could be used by operators to increase their demand by focusing on app development and rating.

The answer to the final research question regarding the knowledge about carsharing services emphasized again the importance of sociodemographics and attitudes on the level of knowledge; in particular, previous use of carsharing, availability of a driving license, living in small size households, and full-time employees were more likely to have a higher level of knowledge regarding carsharing service. Service adoption and knowledge about the service were found to be significant in increasing the probability of each other, showing the need to advertise the service to attract more users and to focus on the other social groups that do not have enough knowledge regarding the service and subsequently who do not adopt it. Also, frequent PT users and people with adventurous personalities were more likely to have a higher knowledge regarding the service. Two highlights from these findings are that frequent PT user knowledge about the service should be coupled with encouraging carsharing use as a first-last mile solution that could increase multimodality.

6.2. Study limitations and future research needs

This research tries to update the current knowledge regarding carsharing services, using a mix of revealed answer questions and a stated preference experiment. However, the study comes with limitations, which we believe do not impact the overall research integrity. The main objectives of appraising the limitations are to have a transparent outcome and to help similar studies avoid or consider them in the future. The collected sample was balanced in terms of users vs. non-users of carsharing services and in gender; however, it was unbalanced for other sociodemographic characteristics, such as income level and education level. On the other hand, shared mobility users are likely to be young and highly educated compared to the average population, which makes the sample acceptable for the purpose of the study. Moreover, the sample was not representative of the city's population; the findings should, therefore, not be directly interpolated or carried out on other social groups. Different attitudes were examined, along with their impacts on the different aspects of carsharing use; however, attitude and personality traits are hard to quantify and measure. They are essential to understand user preferences for the different aspects of shared mobility use, and they might be more significant and influential in deciding travel behavior in general and shared mobility use.

The used stated preference experience examined only a number of attitudes, travel cost, app rating, electrification of the vehicle, and access distance to the nearest vehicle; other attributes could have been used as well. However, this was done on purpose, not to overload the respondents with information that might distract their attention, and to have a simpler experience. The stated preference experiment assumed that the payment by KM is a fixed cost, although this can slightly change in reality, such as in the case of congestion; users could alternate from the original route, the shortest path, causing extra travel distance that would increase the trip cost. However, the variation of the travel cost ($\pm$25%) around the average trip value would cover this possibility. The survey was deployed online, which can create a response bias, as groups with no access to the internet and older populations might not be represented in the sample. However, as shown in previous studies, this would not be the case for younger groups, shared mobility users, and highly educated individuals with access to the internet. The hybrid choice models are not the only way to implement attitudes into discrete models, but we believe that in this research, they fit the required methodology to answer the main research questions. The personality traits that were estimated via EFA were what the people report, their self-perception on their own personality, but might not be how they are if they had done real psychometric tests. Finally, the assessment of the impact of modal shift (to carsharing) on VKT was not conclusive (see Section 6.1), as in most cases carsharing trips replaced PT (likely increasing VKT), however they also often replaced small occupancy vehicles such as cars (possibly reducing thereby VKT). To further investigate this and better quantify the impact, more information would be needed regarding the trips replaced, such as trip distance, vehicle occupancy, but also the modes used to access and egress the carsharing services. Moreover, to project the findings on a larger scale, additional travel behavior data would be essential, so that the modal shift analysis does not only rely on the last trip made, but rather go beyond it to take into account a longer time frame which would encompass the frequency at which such modal shift would occur. As the above was not part of this study, a further in-depth exploration for the VKT analysis is recommended for future research.

As currently carsharing only accounts for a small portion of the total modal share compared to private cars, the magnitude of its impacts is limited (Migliore et al., 2020). Future research could also focus on how extending the service coverage areas, fleet size, and ideally electrifying the fleet could help cities reap the optimum benefits of carsharing (Migliore et al., 2020; Harris et al., 2021; Ye et al., 2021).

It is important to highlight that the survey data was collected during the last waves of the COVID-19 pandemic, and it should be noted that the pandemic conditions inevitably impacted carsharing use and safety perception on different levels. However, lessons from previous studies on the pandemic impact on carsharing use has been inconclusive. For instance, in Madrid, Spain, carsharing has been perceived by some users as a means to avoid public transport (and therefore as a safer mode), while for others less so, as they replaced it with walking and biking (Alonso-Almeida, 2022). A study in Poland showed other findings, in which the pandemic was not a challenge for carsharing users, as it did not hinder their overall use (Gorzelańczyk et al., 2022).

6.3. Conclusions

This research investigated the impacts of personality traits and attitudes on the different aspects of carsharing use: adoption, the shift from other modes, the choice between different operators, and finally, the knowledge about the carsharing services. A large sample (N = 1044) of young user data was used in the analysis collected from Munich, Germany. The results continue to highlight the importance of the user sociodemographic characteristics in impacting service use and raise questions regarding inequitable service use and adoption. The findings of the estimated econometric models also show the significance of personality traits, travel behavior, and digital service aspects (such as app ease of use and rating on the app store) on carsharing use. These findings also stress the importance of designing user-friendly apps and maintaining good ratings, which can attract more users. Findings also showed that frequent shared mobility users adopt shared mobility in different forms of the service, showing the potential of MaaS in increasing shared mobility use and increasing the potential of multimodality. Finally, the estimated models could be used as a part of broader travel demand models that could estimate the adoption of carsharing and which might be used to quantify the share of the operators based on their payment methods.

Declarations of interest

None

Acknowledgments

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Appendix A. Additional analysis

Table A.1: Usage and familiarity with carsharing service summary statistics

Familiarity with carsharing services	Male	Female	Non-user	User
I do not know about them	13%	13%	24%	2%
I have heard about them	20%	23%	33%	10%
I know about them, but not much details	49%	50%	39%	60%
Very familiar, I know almost everything about them	18%	13%	4%	28%
Willingness to walk				
Less than 2 minutes	12%	13%	14%	11%
2 minutes – 4 minutes	29%	22%	22%	29%
5 minutes – 7 minutes	34%	35%	34%	36%
8 minutes – 10 minutes	21%	15%	20%	17%
More than 10 minutes	10%	7%	10%	8%
Type of use				
Yes, as a driver	16%	9%		
Yes, as a passenger	24%	31%		
Yes, sometimes as a passenger, and sometimes as a driver	11%	8%		
Never	49%	53%		
Frequency of use				
Never	49%	53%		
Less than once a month	37%	34%		
1 – 3 times per month	12%	11%		
1 – 3 times a week	1%	1%		
4 or more times per week	1%	0%		
Replaced Mode (top 5 modes representing 75% of the users)				
Underground (U-Bahn)	24%	26%		
Suburban train (S-Bahn)	15%	14%		
Car as a driver	14%	11%		
E-hailing (Uber, and similar)	11%	9%		
Car as a passenger	11%	12%		
Trip purpose (top 4 purposes representing 80% of users who used Carsharing				
Leisure (Restaurants, bars, parties)	40%	41%		
Visiting someone	19%	18%		
Work	13%	10%		
Shopping	7%	11%		

Table A.2: Attitudinal questions summary statistics

Service rating	User	Nonuser	Female	Male
App ease of use	4.20±0.94	4.21±0.95	4.25±0.97	4.17±0.91
App rating	3.54±1.03	3.74±1.05	3.68±1.06	3.61±1.03
Service offers bundles	3.65±1.19	3.81±1.03	3.81±1.08	3.67±1.15
Availability in other cities	3.52±1.18	3.7±1.16	3.63±1.19	3.60±1.16
Availability in Airport	3.60±1.29	3.71±1.17	3.82±1.21	3.52±1.23
Availability of different size vehicles	3.50±1.20	3.45±1.12	3.60±1.15	3.37±1.16
Availability of EV	3.02±1.16	3.23±1.15	3.30±1.13	2.98±1.16
Personality traits	**User**	**Non user**	**Female**	**Male**
Adventurous	0.83±0.85	0.61±1.01	0.66±0.97	0.77±0.92
Anxious	-0.05±1.04	0.05±1.08	0.2±1.03	-0.16±1.06
Being in Charge	0.72±0.83	0.57±0.89	0.68±0.86	0.62±0.88
Being outdoor	1.06±0.83	0.84±0.98	0.99±0.89	0.91±0.92
Calm	0.68±0.98	0.71±0.95	0.54±0.98	0.81±0.94
Creative	0.74±0.95	0.74±0.93	0.86±0.88	0.64±0.97
Efficient	0.88±0.85	0.81±0.83	0.91±0.83	0.80±0.85
Independent	1.10±0.75	0.99±0.83	1.03±0.79	1.06±0.8
Lazy	-0.13±1.10	-0.12±1.07	-0.17±1.04	-0.09±1.12
Like to be alone	0.15±0.99	0.16±1.11	0.11±1.02	0.2±1.09
Optimistic	0.91±0.85	0.72±0.95	0.76±0.89	0.86±0.92
Participating	0.92±0.72	0.79±0.81	0.85±0.77	0.86±0.77
Punctual	0.66±1.14	0.78±1.05	0.7±1.09	0.74±1.10
Risk taker	0.14±1.02	0.05±1.08	-0.02±1.02	0.19±1.07
Routines	0.47±0.97	0.45±1.00	0.50±0.98	0.43±0.99
Spontaneous	0.65±0.96	0.54±0.92	0.57±0.94	0.61±0.94
Stay close to home	-0.09±1.04	0.25±1.05	0.11±1.06	0.06±1.06
Variety Seeker	0.78±0.79	0.73±0.86	0.72±0.8	0.78±0.85
Mode use frequency	**User**	**Nonuser**	**Female**	**Male**
Bus	2.49±1.28	2.71±1.27	2.6±1.27	2.6±1.28
Car as driver	1.47±1.44	0.9±1.35	0.98±1.31	1.34±1.49
Car as passenger	1.70±1.05	1.42±1.19	1.71±1.17	1.44±1.08
Personal Bike	1.67±1.54	1.19±1.48	1.3±1.51	1.53±1.54
Suburban train	2.23±1.26	2.2±1.37	2.17±1.32	2.25±1.31
Shared E-Scooter	0.7±0.97	0.42±0.81	0.5±0.87	0.61±0.93
Bike sharing	0.54±0.89	0.43±0.84	0.39±0.8	0.56±0.91
Taxi	0.69±0.87	0.5±0.77	0.68±0.9	0.52±0.75
Tram	2.16±1.33	2.11±1.4	2.13±1.38	2.14±1.35
underground	2.97±1.29	3±1.37	3.01±1.34	2.97±1.33
Walking	3.63±0.82	3.63±0.78	3.62±0.82	3.64±0.78
E-hailing	0.94±0.94	0.54±0.81	0.81±0.94	0.68±0.85

Personality question levels were coded as Totally disagree = -2,Disagree = -1, Neutral = 0, Agree = 1, Totally agree = 2

Mode use frequency levels were coded as Never = 0, Less than once a month = 1, 1 – 3 times per month = 2, 1 – 3 times a week = 3, 4 or more times per week = 4

Table A.3: χ^2 test results for personality traits

	Users vs. Non-User			Male vs. Female		
Service aspect rating	χ^2	'P-value'		χ^2	'P-value'	
Service availability in other cities	6.36	0.17		3.60	0.46	
Offers bundles	15.40	0.00	*	4.81	0.31	
App rating	17.70	0.00	*	6.62	0.16	
Different size vehicles availability	13.4	0.01	*	10.46	0.03	*
EV availability	14.80	0.01	*	22.00	0.00	*
Airport availability	16.40	0.00	*	25.73	0.00	*
App ease of use	1.68	0.80		11.77	0.02	*
Personality	χ^2	'P-value'		χ^2	'P-value'	
Efficient	6.20	0.18		5.54	0.24	
Independent	6.72	0.15		5.57	0.23	
Routines	2.57	0.633		1.94	0.75	
Punctual	7.38	0.11		3.35	0.50	
Variety Seeking	4.62	0.32		4.70	0.32	
Lazy	2.04	0.72		5.01	0.29	
Stay close to home	32.6	0.00	*	3.06	0.55	
Being outdoor	20.00	0.00	*	3.26	0.52	
Spontaneous	8.77	0.06	*	3.72	0.45	
Being in charge	12.6	0.01	*	4.10	0.39	
Participative	10.10	0.03	*	5.46	0.24	
being alone	12.90	0.01	*	6.02	0.20	
Optimistic	12.20	0.01	*	8.29	0.08	
Adventurous	20.90	0.00	*	8.29	0.08	
Creative	1.48	0.83		15.00	0.00	*
Calm	6.89	0.14		21.90	0.00	*
Risk taker	4.60	0.33		22.70	0.00	*
Anxious	5.52	0.23		31.60	0.00	*
Mode use frequency	χ^2	'P-value'		χ^2	'P-value'	
Tram	3.28	0.51		3.37	0.50	
Walking	6.23	0.18		6.2	0.19	
Underground (metro)	7.10	0.13		1.22	0.88	
Bus	9.48	0.05	*	4.98	0.29	
Suburban train	12.00	0.02	*	1.5	0.83	
Shared-e-Scooter	29.90	0.00	*	6.15	0.19	
Personal Bike	31.40	0.00	*	7.38	0.12	
E-hailing	64.00	0.00	*	7.41	0.12	
Shard Bike	9.97	0.04	*	12.7	0.01	*
Taxi	18.90	0.00	*	14.5	0.01	*
Car as a passenger	43.10	0.00	*	16.2	0.00	*
Car as as driver	71.50	0.00	*	18.2	0.00	*

* Significant difference with minimum 95% significance level.

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TRANSPORT FINDINGS

Are e-Scooters Parked Near Bus Stops? Findings from Louisville, Kentucky

Mohamed Abouelela[1] [a], Christelle Al Haddad[1], Constantinos Antoniou[1]

[1] Department of Civil, Geo and Environmental Engineering, Technical University of Munich

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Findings

With the increasing popularity of shared e–scooters, understanding where they are parked becomes crucial, especially for integrating them with existing public transportation services. In this study, we analyzed the relationship between trip origins and the nearest bus stops, using 506,000 shared e-scooter trips from Louisville, Kentucky. We examined this relation temporally for different hours of the day and different weekdays, but also spatially, using three metrics including land use, distance from the city center, and the Local Index of Transit Availability (LITA) accessibility index. The temporal analysis showed a different parking distance pattern during early morning hours (between 2 and 4 a.m.), whereas the spatial analysis showed no impact of spatial features on distances between scooter parking (and therefore trips starting points) and nearest bus stops.

1. Questions

Scooters could arguably replace motorized trips (Abouelela, Al Haddad, and Antoniou 2021), or at least reduce their negative impacts, especially if they are well integrated with existing public transportation. This integration can solve the first and last-mile dilemma (Fearnley, Johnsson, and Berge 2020), increasing accessibility to public transportation (Oeschger, Carroll, and Caulfield 2020), but also leading to more sustainable transportation systems (Kager, Bertolini, and Brömmelstroet 2016). One of the most important, but not yet studied aspects of scooter integration with public transportation, is the distance between the stops and the scooters, as walking distance willingness could be a factor affecting or determining the use of different transportation services. In this study, we assessed the distances between bus stops and parked scooters both temporally and spatially. Temporal analysis considered different hours of the day and different days of the week, while spatial analysis looked at different land uses, distances from the city center, and accessibility to public transportation (bus). This assessment aimed to answer following research questions:

1. What is the average distance between scooter trip starting points (origins) and the nearest public transportation stops, in this case bus stops?

a Corresponding author at: Technical University of Munich, Arcisstrasse 21, Munich, Germany E-mail address: Mohamed.abouelela@tum.de

2. How do different temporal and spatial factors influence the distance between parked scooters and nearest bus stops?

2. Methods

We used the open scooter trips data[1] from Louisville, Kentucky, to analyze the relation between trips starting points and the nearest bus stops, as buses are the only available public transportation services in the city, organized by the Transit Authority of River City (TARC, ridetarc.org). We collected 505,993 trips starting the 9th of August 2018 till the 31st of January 2020.[2] Subsequently, we removed trips outside the operation zones, trips with distances less than 100 meters[3] or more than 50 km, with durations more than 120 minutes, or speeds higher than 25 km/hour, resulting in 379,308 trips (75% of the original trips). The bus stops locations were defined using GTFS files downloaded from the Open Mobility Data platform (transitfeeds.com). We retrieved the city's land use data from the city portal (data.louisvilleky.gov). Finally, the census zones limits used for the Local Index of Transit Availability (LITA) calculation were retrieved from the USA Census Bureau (census.gov).

To answer the first research question, we used the Approximate Nearest Neighbor (ANN) searching algorithm library (Arya et al. 2019) available in the statistical software package R (R Core Team 2021), in order to calculate the euclidean distance between trips' starting points[4] and the nearest bus stops.

To answer the second research question, the distance was calculated and aggregated for different temporal features, meaning different hours of the day, and different days of the week. For assessing the impact of spatial features, three metrics were considered: land use (considering the land use of the trip starting point), distance from city center , and LITA (for the different census zones). Thereafter, parking distances were assessed spatially.

LITA calculations consider three aspects of public transportation service characteristics per census zone:

- Route coverage score: the number of public transportation stops per zone
- Frequency: the daily number of buses traveling the zone
- Capacity: seat–miles per capita

1 data.louisvilleky.gov/dataset/dockless-vehicles, accessed 30/6/2021

2 Noland (2019) analyzed in more details the trip characteristics of a sample of this dataset.

3 The removal of short trips, less than 100 meters, was done to avoid GPS multipath errors, as done in McKenzie (2019) for cleaning shared e–scooters trips.

4 Only starting points or origins were considered to avoid data duplication; each trip origin or starting point is a previous trip destination or ending point.

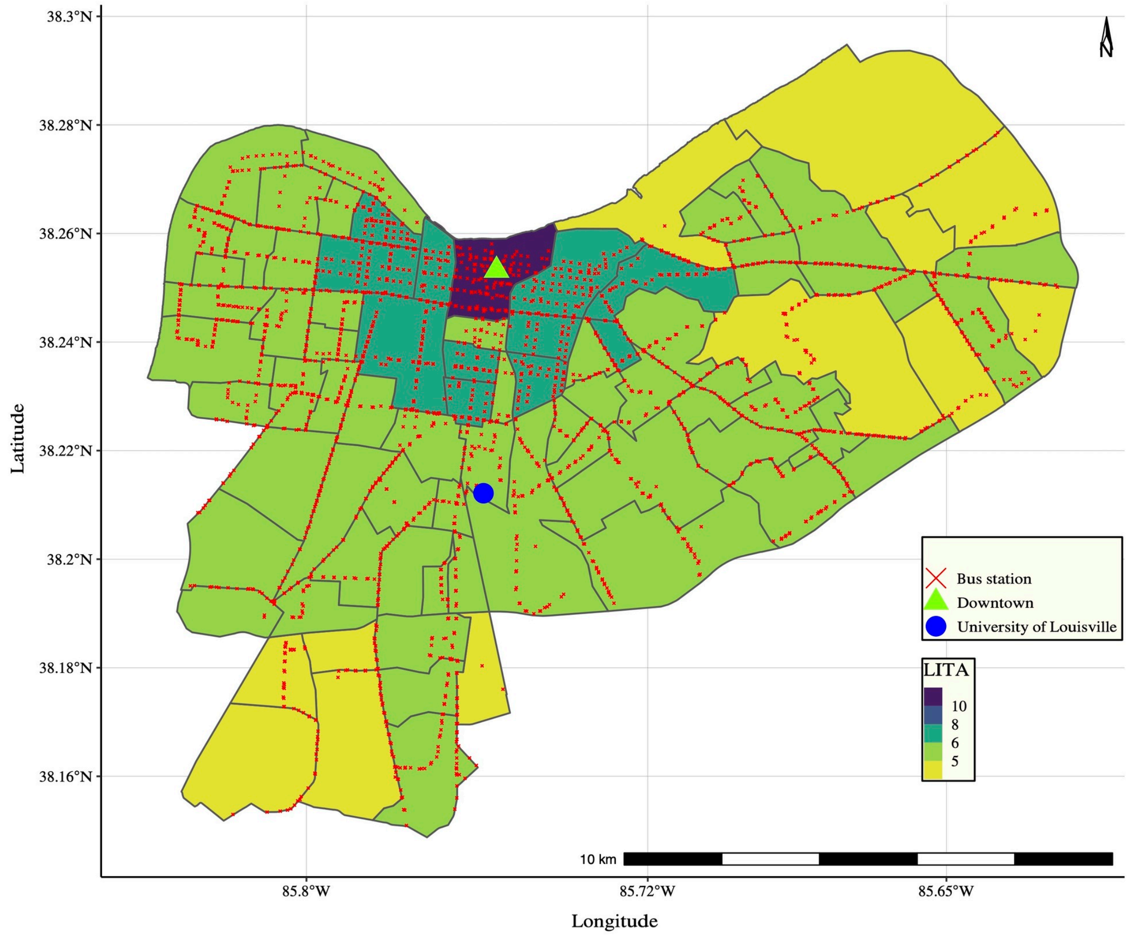

Figure 1. LITA map

> LITA is calculated as the total daily seats on the bus line [bus capacity (assumed 36 seat/bus for TARC buses) multiplied by the number of buses per day] multiplied by the length of the bus route in the zone (in miles), divided by the sum of the total resident and employment population per zone.

Inputs needed for the above metrics, such as the bus stops, number of daily buses, length of bus lines, were all calculated using the GTFS files. The average of the three scores was added to 5.5, to avoid negative numbers resulting in the LITA score (Chen 2018), for which the higher the value, the better the accessibility per zone. Figure 1 shows the calculated LITA per zone for Louisville, Kentucky.

It is to be noted that the trips' geo-locations (latitude and longitude) were rounded to the nearest three decimal numbers for privacy reasons, which on average could affect the scooter location by 30 meters. While this approximation could have affected the distance calculations, the methodology used in this research could be generalized for other datasets with more accurate coordinates.

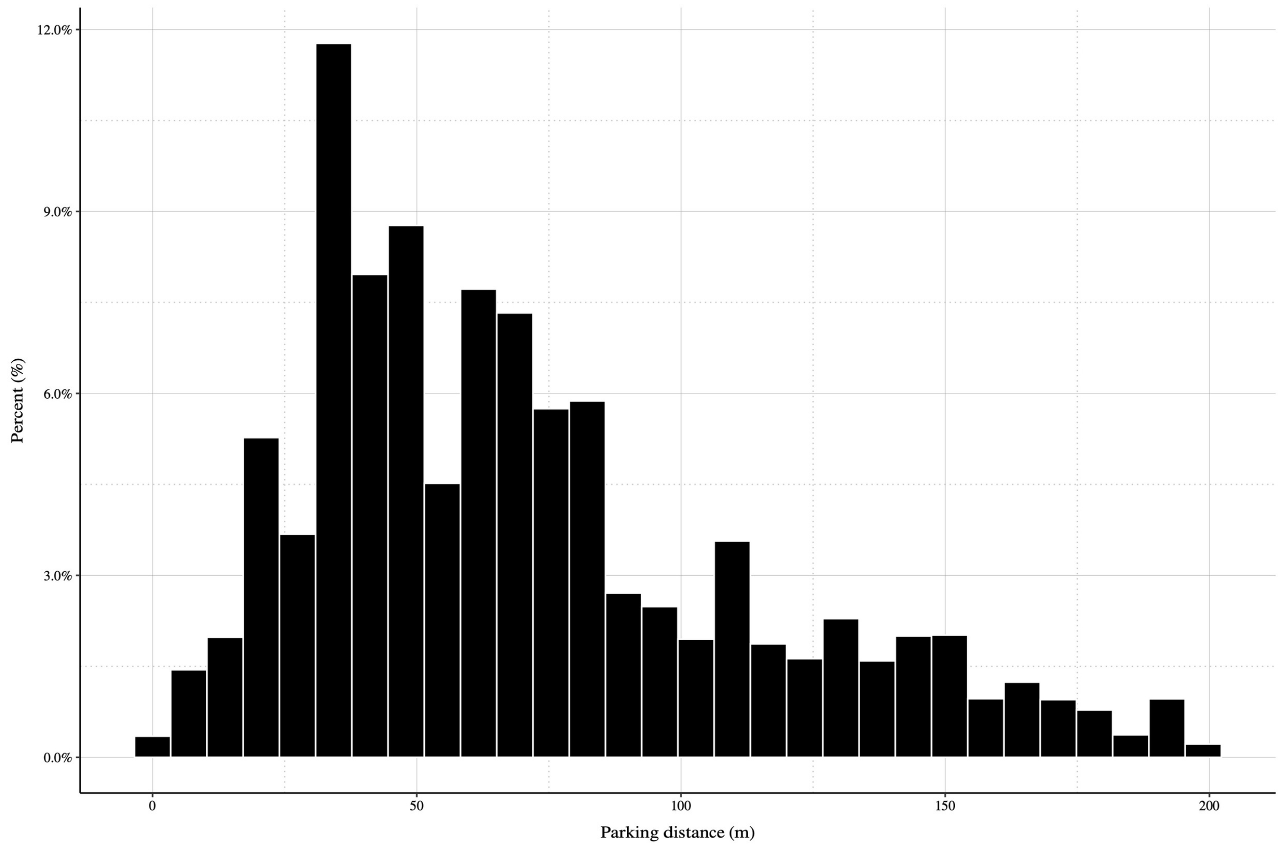

Figure 2. Average hourly distance distribution between parked scooters and nearest bus stops

3. Findings

The euclidean distance calculations, along with the impact assessment of temporal and spatial features on parking distances between scooters and nearest bus stops, are summarized in Table 1. The obtained mean parking distance was found to be $\mu = 115$, with a standard deviation $\sigma = 134$ m, which answers the first research question. The overall parking distance distribution is presented in Figure 2. Findings show that for 50% of the trips, scooters were parked within 70 meters from the nearest bus station, and for 85% of the trips, the parking distance was less than 200 meters.

The hourly distribution of the distances for the different days (Figure 3) shows that the parking distance has a rather similar pattern throughout the day, except between 2 and 4 a.m. Parking distances between 2 and 4 a.m. are statistically different from the rest of the day[5] and tend to be longer, meaning that scooters tend to be further from bus stops. One possible reason could be the very small share of trips originating between 2 and 4 a.m. (about 0.6 % of the total daily trips). To investigate whether this was due to rebalancing and redistribution, distances were calculated between trip starting and ending points and the

5 This was found based on a t−test between the mean parking distances between 2 and 4 a.m. and the mean during the rest of the day.

Table 1. Parking distance to the nearest bus station summary per different temporal and spatial categories in meter

	Min	$1^{st}Q$	mean	Median	$3^{rd}Q$	Max	Std	Trips (N)	Pct (%)
All trips	1	42	115	70	132	2948	134	379,308	100%
Time of the day									
Morning (00:00-06:00)	1	71	116	71	136	1622	135	23,548	6.2%
Before noon (07:00-12:00)	1	70	116	70	133	1731	134	119,665	31.6%
After noon (13:00-18:00)	1	70	115	70	132	2948	133	171,137	45.1%
Night (19:00-23:00)	1	70	115	70	133	2004	133	64,958	17.1%
Day									
Weekdays	1	70	115	70	132	2483	133	256,382	67.6%
Weekend	1	70	115	70	132	2948	134	122,926	32.4%
Land–use									
Right-of-way	1	70	115	70	132	2192	133	112,501	29.7%
Commercial	1	70	115	70	132	1733	133	91,257	24.1%
Public and semi-public	1	71	116	71	135	2004	133	89,925	23.7%
Residential	1	70	115	70	132	2948	136	52,314	13.8%
Industrial	1	70	114	70	132	1323	132	19,586	5.16%
Parks and open space	1	71	117	71	136	1924	138	11,018	2.9%
Vacant	1	71	115	71	136	1013	130	2,707	0.71%
LITA									
4-5	1	72	117	72	135	1193	134	9,256	2.4%
5-6	1	70	115	70	133	2948	134	149,826	39.5%
6-7	1	70	114	70	132	1223	133	27,280	7.2%
7-8	1	70	113	70	132	1731	131	35,006	9.2%
10-11	1	70	115	70	132	2192	134	157,933	41.6%
Distance from downtown (km)									
Less than 0.5km	1	70	115	70	132	2192	133	85,119	22.4%
0.5km - 1.0km	1	70	116	70	132	1731	135	58,130	15.3%
1.0km - 1.5km	1	70	114	70	132	1290	132	39,476	10.4%
1.5km - 2.0km	1	70	114	70	132	1731	131	18,808	5.0%
2.0km - 2.5km	1	70	115	70	132	1223	133	13,304	3.5%
2.5km - 3.0km	1	70	114	70	131	1193	134	12,048	3.2%
3.0km - 3.5km	1	70	115	70	132	2004	134	23,053	6.0%
3.5km - 4.0km	1	70	116	70	135	2483	136	51,009	13.4%
More than 4.0km	1	70	115	70	132	2948	133	78,361	20.7%

Land–use description, retrieved from American Planning Association (planning.org)	
Commercial	Retail and whole sales, business offices
Public and semi-public	Public and private schools, municipal buildings, public property rather than parks, hospital, churches, and golf courses
Residential	Residential uses
Industrial	Light and heavy industrial uses
Parks and open spaces	All public parks, playgrounds, swimming pools, athletic fields
Vacant	Includes undeveloped land

nearest bus stops, and their distribution compared with each other. Yet, as no statistical difference was found between both, there was no evidence to the rebalancing and redistribution effect. Longer distances might indicate that

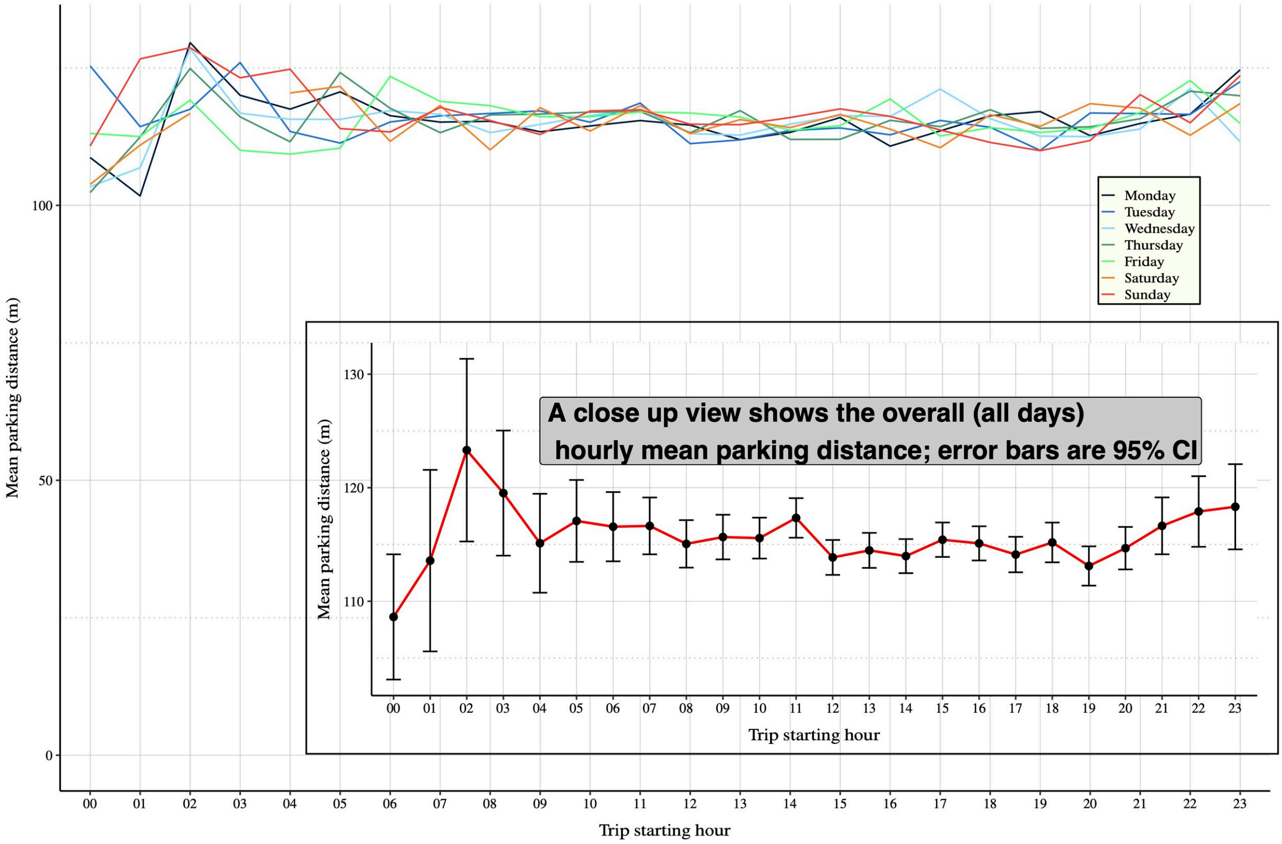

Figure 3. Average hourly distance distribution; error bars in the zoomed view show the hourly standard deviation

people use scooters from bus stops to travel further distances during early day hours (between 2 and 4 a.m.), which have no bus temporal coverage; in Louisville, the service hours for bus is between 5:30 a.m. and 10:30.[6] Also, early morning distances tend to be longer during the weekend compared to weekdays, which could be attributed to an increase in recreational activity during weekends.

Analyzing the distances according to varying land uses did not reveal any significant differences; however, the trip percentages showed that half of the trips started in commercial and public and semi-public land uses; this might indicate that scooters could have been used for recreational trips, as was supported in Noland (2019), and as observed in Washington, D.C. (McKenzie 2019). The distance to the nearest station per each category of LITA values showed no significant differences or relation between the distances and the zonal bus accessibility. However, 40% of the scooters were parked in highly bus–accessible areas (LITA = 10-11), which could indicate that scooters

6 https://moovitapp.com/index/en/public_transit-line-17-Louisville_KY-1442-11408-240824-0, accessed 1/7/2021

complement the use of buses or extend bus accessibility. Also, the distance between scooters and the nearest bus stop was not affected by the scooter's locations away from the city center.

Findings indicated that scooters could be used to extend the temporal accessibility of the bus service. On the contrary, there was not sufficient evidence that distance is impacted by any tested spatial features, including LITA, and land use. Of course, a finer spatial resolution of the data could lead to a more accurate analysis; however, this might come at the price of jeopardizing users' locations, and therefore privacy. Additional data, such as user survey data focusing on trip purpose and multimodality, could undoubtedly help in better understanding whether or not scooters are used as first and last mile access to and from public transport, in the case of Louisville, bus services.

The methodology presented in this paper could be replicated in other cities, in order to better understand scooter parking patterns, and whether the results obtained in Louisville would be comparable in other cities in the US, but also in the world. This could give an insight to service providers on how to better integrate scooters with existing public transportation systems.

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Do we all need shared E-scooters? An accessibility-centered spatial equity evaluation approach

Mohamed Abouelela [a,*], David Durán-Rodas [b], Constantinos Antoniou [a]

[a] Chair of Transportation Systems Engineering, Technical University of Munich, Munich, Germany
[b] Chair of Urban Structure and Transport Planning, Technical University of Munich, Munich, Germany

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ABSTRACT

Shared E-scooters were introduced as a sustainable mode of transport that could help reduce motorized traffic externalities; however, problems, such as inequitable use, emerged shortly after the start of their operations. While existing literature has focused primarily on user and vehicle characteristics as the main drivers of E-scooter inequitable use, it fails to understand or capture other factors that impact travel decisions, such as urban design and activity accessibility. This study proposes a framework to evaluate shared (E-)scooters' equity based on accessibility or lack of accessibility to different activities compared to other existing modes of transportation. To test the proposed framework, a sensitivity analysis tested various scenarios using data from scooter trips in Louisville, Kentucky. In total, 1903 main scenarios and 7612 sub-scenarios were evaluated, focusing on accessibility gains for different social groups, modes of transport that could be replaced by scooters, and different locations within the study area. As a result, scooters have the potential to improve current levels of accessibility in 8% of the examined scenarios, mostly when replacing uni–modal walking, biking, and public transportation trips. Furthermore, disadvantaged groups did not gain significant accessibility advantages compared to the rest of the population. We argue that the observed inequitable use of scooters is inherited from the urban structure and activity density. In areas with fewer activities, where mostly disadvantaged social groups live, people use E-scooters less. In order to make E-scooters a competitive mode of transport in disadvantaged areas, urban structural solutions such as densification of land use and promotion of different activities should be considered first.

1. Introduction

Urban transportation has undergone significant changes in the past decade, thanks to advancements in technology, the emergence of eco-friendly options, and the introduction of shared mobility services (SMS) (Shaheen, 2018). Shared mobility is a pay-per-use system where users are charged based on the time or distance they utilize them (Shaheen et al., 2016; Shared and Digital Mobility Committee, 2018). These services are commonly provided through digital platforms and mobile phone applications and are usually paid using digital banking services (Tirachini, 2020).

SMS can be divided into two main categories. The first category involves users sharing the ride with other passengers or the driver. This group includes ride-hailing, ride-pooling, and alternative transport systems. In the second category, users have direct access to the vehicles for personal use. The modes included in this group are carsharing and micromobility, such as bike-sharing, moped, and shared E-scooter sharing (Hu and Creutzig, 2022). Several reasons have encouraged the use of SMS, driven by the three

* Corresponding author.Correspondence to: Technical University of Munich, Arcisstrasse 21, Munich, Germany.
E-mail address: Mohamed.abouelela@tum.de (M. Abouelela).

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main goals of sustainability, social, economic, and environmental benefits; in principle, SMS are more sustainable transportation options compared to the private passenger car, as they have the potential to reduce the vehicle idle time, have a milder impact on the environment by lowering CO_2 and greenhouse gas (GHG) emissions, reduce energy consumption, travel cost saving, and utilize more compact space (Narayanan et al., 2023; Ruhrort, 2020; Becker et al., 2020; Roukouni and Homem de Almeida Correia, 2020). SMS are gaining popularity and attracting demand from other traditional travel options; the popularity is indicated by the rapid ridership growth, e.g., ride-hailing (Gehrke et al., 2019), bike-sharing (Fishman and Allan, 2019), and shared E-scooters (Abouelela et al., 2023).

While increased mobility and accessibility are expected outcomes of the addition of SMS to the urban environment, this increase in mobility and accessibility should be equally allocated to all the members of society. According to the first Article of the Universal Declaration of Human Rights, all humans have equal rights (United Nations, 1948). These rights cannot be acquired or accessed equally for all the members of the society without the availability of different means of mobility that are accessible to all the society's members regardless of their gender, income, ethnicity, or education level; otherwise, some groups would be excluded from the participation in the daily life activities, creating a so-called social exclusion situation. The equitable use of SMS might not always be achieved and can lead to social exclusion situations for specific user groups (Lucas, 2019). Social exclusion can be defined as people's inability to access different types of opportunities, e.g., economic, political, and social opportunities (Yigitcanlar et al., 2019). Several reasons can lead to the social exclusion situation, such as but not limited to local transport operation, policies, regulations, and infrastructure (Turoń, 2022).

The inequitable use of SMS is widely expected from its unique setup as users, in general, should have digital skills, a smartphone, and digital banking access; otherwise, they will be excluded from using the service by default (Dill and McNeil, 2021). Also, SMS might not be affordable to all population groups, and the spatial coverage of SMS might be limited to areas with high demand, primarily near the downtown, and ignoring areas located in the city's suburbs (Brown et al., 2022). While there are efforts in the literature to identify factors behind the inequitable use of SMS, these efforts, especially in the cases of micromobility and specifically Shared E-scooters, have focused on the user's profile, socioeconomic and demographic characteristics, or availability and proximity of vehicles to the users as the main reasons causing the inequitable use (Javid and Sadeghvaziri, 2023; Aman et al., 2021). SMS are often perceived as oriented primarily toward young males with higher incomes, tourists, and students (Duran-Rodas et al., 2020). However, we believe that the issue of inequitable use is not limited to the user's characteristics or the availability of the vehicles but is extended to the urban forms in terms of land use, neighborhood design, and the availability of opportunities, points of interest (POIs), within an acceptable travel distance and travel cost (Xu et al., 2022; Guo and He, 2020; Levine et al., 2019). Therefore, we hypothesize that the observed inequitable use of shared E-scooters in terms of trip density might have resulted from the fact that the E-scooters' introduction did not add significantly to the population's accessibility to different opportunities (POIs), especially for the transportation-disadvantaged population groups. This research contribution comes from verifying the below hypothesis:

> ***The introduction of shared E-scooters does not increase or poorly increase the accessibility to different opportunities compared to the available modes of transportation, especially for the disadvantaged population groups.***

We propose a methodological framework to assess the equitable use of SMS, specifically shared E-scooters, referred to hereafter in the rest of the manuscript as scooters. To the best of our knowledge, no such approach or hypothesis has been used or evaluated.

The remaining sections of the article are organized as follows: Section 2 reviews the current research, highlighting the methods employed thus far to evaluate the equitable use of shared micromobility and identifying gaps in the existing literature and practices. Section 3 presents the various datasets utilized in the analysis and the methodology used. Section 4 presents the analysis results, while Section 5 offers the final research discussion and conclusion.

2. Literature review

2.1. Mobility, accessibility, social exclusion, and disadvantaged population

Mobility is a crucial part of our daily life; it is essential to fulfill our basic needs (e.g., work, food, health, leisure), i.e., accessibility to activities outside our homes (Vecchio et al., 2020; Stanley et al., 2019). Accessibility and mobility are generally defined as the "ease of reaching" and the "ease of moving", respectively (Moseley, 2023; Vecchio et al., 2020). Mobility is the measure of the efficiency of different modes of transportation, and it is reflected in the level of access to the various opportunities for all the members of society (Martens, 2016). The role of mobility does not stop at increasing commuting levels and the ability to access more essential opportunities. Still, it extends to improving individual well-being and psychological needs, such as interacting with distant family and friends (Rambaldini-Gooding et al., 2021; Tao et al., 2020). Population groups that lack participation in various activities can become socially excluded groups (Luz and Portugal, 2022; Allen and Farber, 2020). Social exclusion from activity participation might result from different factors such as, but not limited to, the absence of an inclusive transport system, availability of opportunities, or both (Lucas, 2022; Yigitcanlar et al., 2019; Hine and Mitchell, 2017).

Social exclusion can be described as the alienation of some individuals from the rest of their society in the form of their lack of participation in everyday normal activities such as jobs and education the other members of the society can do, resulting in insufficient well-being, which makes it a relative relationship with the surrounding society (Luz et al., 2022; Berg and Ihlström, 2019). Social inclusion is necessary to access social capital, gain from civic engagement, and even for well-being (Chikengezha and Thebe, 2022; Stanley et al., 2022). Measuring social exclusion resulting from transportation and mobility-related problems is difficult; therefore, it is tackled by comparing the different social groups as reduced participation, reduced accessibility, or limited welfare for a specific group in reference to the rest of the population (Hidayati et al., 2021; Di Ciommo and Shiftan, 2017). Social exclusion is a relative concept about the place where people live. An example of the concept of the relativity of the exclusion through measuring accessibility is if an individual who lives in a highly accessible area will travel a shorter distance than a person who lives in an inaccessible area and is not mobility-impaired when compared to the rest of the population (Cooper and Vanoutrive, 2022; Luz and Portugal, 2022). Therefore, it is crucial to define the social groups that suffer from inadequate levels of mobility and accessibility and subsequent social exclusion, and we will be labeling such groups under the scope of this article as transportation-disadvantaged groups.

Transport-disadvantaged individuals are people who experience a lack of transport options to access different opportunities (Bardaka et al., 2022; Cochran, 2020); nevertheless, in different situations, a poor transportation system might be coupled with various opportunities within reach (Arellana et al., 2021). Also, people have different preferences for different opportunities and abilities to overcome the barriers to accessing different opportunities (Martens, 2016). So, transportation-disadvantaged groups, or socially excluded groups, are the groups that suffer from a combination of poor transport and urban accessibility issues. A more inclusive definition for transportation disadvantaged groups would identify them as people who live in areas with poor transportation systems and low accessibility to opportunities (Kamruzzaman et al., 2016). Therefore, there is a need to define mobility rights as they are essential to be established as a citizen right, as it might result from distant, poor transport systems and limited ways of communication (Stanley et al., 2019). Transport researchers have underscored the importance of mobility rights and access rights to avoid social exclusion and to make sure that all the members of society can access different opportunities (Allen and Farber, 2020; Barri et al., 2021), and they can overcome different barriers that might hinder their accessibility (Hine and Mitchell, 2017). It is vital to conclude that social exclusion is not the absence of opportunities but the lack of access to opportunities. It is also to be noted that social exclusion is not the product of the different causal factors, such as income, but the interaction between various factors (van Dülmen et al., 2022). Therefore, identifying disadvantaged transport groups and ignoring the interaction between the different factors is an over-simplistic approach, and holistic social inclusion requires better mobility and accessibility (Hine and Mitchell, 2017). Reduced mobility is one aspect of social exclusion; other factors might exist, such as the limited physical or psychological ability to overcome boundaries and access opportunities in more comprehensive spatial content, in addition to depression and anxiety (Shen et al., 2022; Dharmowijoyo et al., 2020).

One of the possible solutions to measure hard-to-quantify social exclusion is measuring accessibility. Accessibility is an essential concept of transport planning, and it must be considered to design fair transport systems; it is a strong predictor of travel behavior and the core of transport-related long-and-short-term travel decisions (De Vos et al., 2023; Martens, 2016). The relationship between commuters, the used modes of transport, and urban forms can be described as residential density, employment density, and neighborhood design representing urban form or physical design impact on human behavior regarding long-term decisions such as location selection of residence and jobs and car ownership, and short-term travel decisions such as mode choice leading to accessibility to the different opportunities and subsequently activity participation (Straatemeier and Bertolini, 2020). Therefore, we can conclude that accessibility is the core of our travel decisions leading to activity participation.

Based on the previous, it is vital to understand how accessibility is measured. Several measures are used to quantify accessibility; these measures can be categorized into two major groups: place-based measures and people-based measures. Place-based accessibility measures depend on quantifying the potential accessibility in a particular location; for example, these measures capture the number of job opportunities that can be accessed using a particular mode of transportation from a specific location (Palacios and El-geneidy, 2022). These measures assume that all people within a specific area have equal abilities, which does not consider individual differences. Also, they can be used to quantify the impact of a new project on the accessibility of specific locations, such as census geographies (Pereira, 2019; Horner and Downs, 2014). Another widely used measure is the gravity model, a location-based model where the distance decay function is applied to discount the accessibility to far opportunities (Wu and Levinson, 2020; Palacios and El-geneidy, 2022). On the other hand, people-based measures account for the unique characteristics of individuals but in an aggregated manner, which opens the door to the question of remapping the individual characteristics to the place, with no solid methodology to date, making this a significant limitation for people-based accessibility measures (Wu and Levinson, 2020; Levinson and King, 2020).

2.2. Micromobility inequitable use

While, in general, introducing new modes of transportation is expected to increase accessibility by increasing the number of modes available to travel, this is not always the case, especially for SMS. The service nature and setup create structural barriers for some population groups to access the service, making its use inequitable (Shaheen, 2018). Different methods were employed to assess the utilization of SMS. Table 1 summarizes several selected studies investigating the (in)equitable use of shared micromobility. The selected studies focus on two main dimensions of the relationship between user and vehicle use: user characteristics and vehicle availability. Although different methodologies were used, they were built on the aforementioned dimensions; e.g., economic indices were used, such as the case of the Lorenzo curve used by Aman et al. (2021) to evaluate equity for bike sharing in Austin, TX, and the use of opportunity index by Bai and Jiao (2021) to evaluate the equity of using the scooter in the same city. Javid and Sadeghvaziri (2023), McQueen and Clifton (2022), McQueen (2020) evaluated the socioeconomic/demographic factors impacting the ridership of bikesharing using regression models for bike sharing in New York and shared scooter in Portland, OR, respectively. Other research used descriptive statistics, causal analysis, stakeholder interviews, and semi-structured interviews to evaluate the equity of shared micromobility, but also these methods considered only the user profile or vehicles' availability or both (Bach et al.,

Table 1
Summary of some selected studies.

Reference	Methodology	Location	Disadvantaged group	Service
Aman et al. (2021)	Lorenzo curve and regression models	Austin Tx	80% of residents have no access to BS and SS. transit-dependent people African American population	SS&BS
Javid and Sadeghvaziri (2023)	Regression models	New York, NY	• Demand is correlated with high income, employment rate, males, and high population density • Racial minorities have fewer trips	BS
Dias et al. (2023)	Descriptive statistics	Braga, Portugal	Access disparities by genders, ages, and income ranges	SS
Su et al. (2022)	Develop an analytical framework	Washington DC	• SS enhances accessibility to SMS for disadvantaged groups • SS increases the access gap in different locations. • BS is more equitable to use for low-income groups compared to SS	SS&BS
Bach et al. (2023)	Semi-structured interviewing approach	Barcelona, Spain		Moped-style scooter
Henriksson et al. (2022)	Stakeholders interviews	Linköping, Sweden	BS attracts users with high levels of accessibility	BS
Desjardins et al. (2022)	A balanced floating catchment area	Ontario, Canada	Enhanced accessibility to BS station for the serviced population; however, the enhancement was not significant for low-income groups	BS
Frias-Martinez et al. (2021)	Causality analysis framework	Chicago (CHI), Los Angeles (LA), New York City (NYC) and Washington D.C. (DC)	Low-income groups	SS
Duran-Rodas et al. (2021)	heuristic and data-mining to weigh both Demand And/oR Equity (DARE)	Munich, Germany		BS
Bai and Jiao (2021)	Opportunity Index	Austin Tx	• Racial minorities • Low income • Physically disabled • Old population	SS
Yan et al. (2021)	Descriptive statistics	Washington DC	SS enhanced access to PT for the under-served neighborhoods	SS
McQueen (2020)	Regression models	Portland	• Racial minorities • Gender disparities	SS
Laa and Leth (2020)	Descriptive statistics	Vienna, Austria	Gender	SS
McQueen and Clifton (2022)	Regression models	Portland	• Racial minorities • Gender disparities	SS
Qian and Jaller (2020)	Regression model	Chicago, USA	• Employment rate • Disadvantaged communities generate fewer trips	BS
Caggiani et al. (2020)	mapping and descriptive statistics	Seattle, Washington		BS
Babagoli et al. (2019)	Statistical analysis, and World Health Organization's Health Economic Assessment Tool (HEAT)	New York, NY	Stations are not distributed spatially inequitable way	BS

BS = Bikesharing, SS = Scooter sharing.

2023; Henriksson et al., 2022; Desjardins et al., 2022; Frias-Martinez et al., 2021; Yan et al., 2021; Laa and Leth, 2020; Dias et al., 2023). The review of the previous research identified the population groups that suffer the most from the inequitable use of shared micromobility: female users, older population, low income, low education, public transportation (PT) dependent users, people with a physical disability, racial minorities, low employment rate, and residents of suburban areas, refer to Table 1.

Brown et al. (2022) analyzed the equity provisions of 239 shared micromobility programs in the USA. The study found that equity programs are more prevalent in the case of shared scooters compared to bikesharing. One possible reason for this difference could be the relative novelty of scooter programs compared to bikesharing programs. Additionally, concerns regarding the equitable use of scooters have emerged more recently; however, most recommendations were not mandatory but preferred or encouraged. A similar situation for the requirement was detected in the case study used in our analysis (Louisville, KY, Section 3.1). Brown et al. (2022), Riggs et al. (2021) summarized the recommendations for equitable use in the program. They examined six main requirements, ordered by the number of times they appeared in the different documents: alternative access for smartphones, cash payment options, reduced fares, geographic distribution requirements, service available in multiple languages, and adaptive vehicles. These recommendations are loose and hard to materialize in beneficial ways, especially for disadvantaged user groups. One example is the reduced fares; how much should the reduction be, and what would be the consequences if the operators did not abide by these rules; are there penalties for operators if they do not follow the equity guidelines?

The analyzed programs and policies indicate that the primary emphasis of these policies is to enhance access to the shared micromobility service rather than maximizing the benefits derived from the service itself. A meticulous approach is necessary. It is evident that the demand for shared services, particularly in the case of free-floating systems, is directly linked to the supply level. Increased supply leads to higher demand; however, this also results in longer vehicle idle time, leading to inefficient utilization of space and resources (Su et al., 2022). The current regulations and policies of shared micromobility programs are unclear on how they are monitoring the equitable use goals, if any. Also, it is essential to underline that most of these programs did not investigate the need for such a service before the implementation, or at least there is no evidence for such a process in the project documentation. It should be mandatory to check whether shared micromobility suits the city from many aspects, such as their impacts on potential user accessibility. We are trying to answer this question by validating this research hypothesis.

Based on the review of the existing literature examining the equitable use of shared micromobility, particularly shared E-scooters, it is evident that the full complexity of the travel decision considering the interaction between the three main elements: commuters, modes, and urban forms following the introduction of shared E-scooters has not been fully captured. Furthermore, to the best of our knowledge, there has been a lack of comprehensive assessment of social exclusion using more sophisticated indicators that evaluate

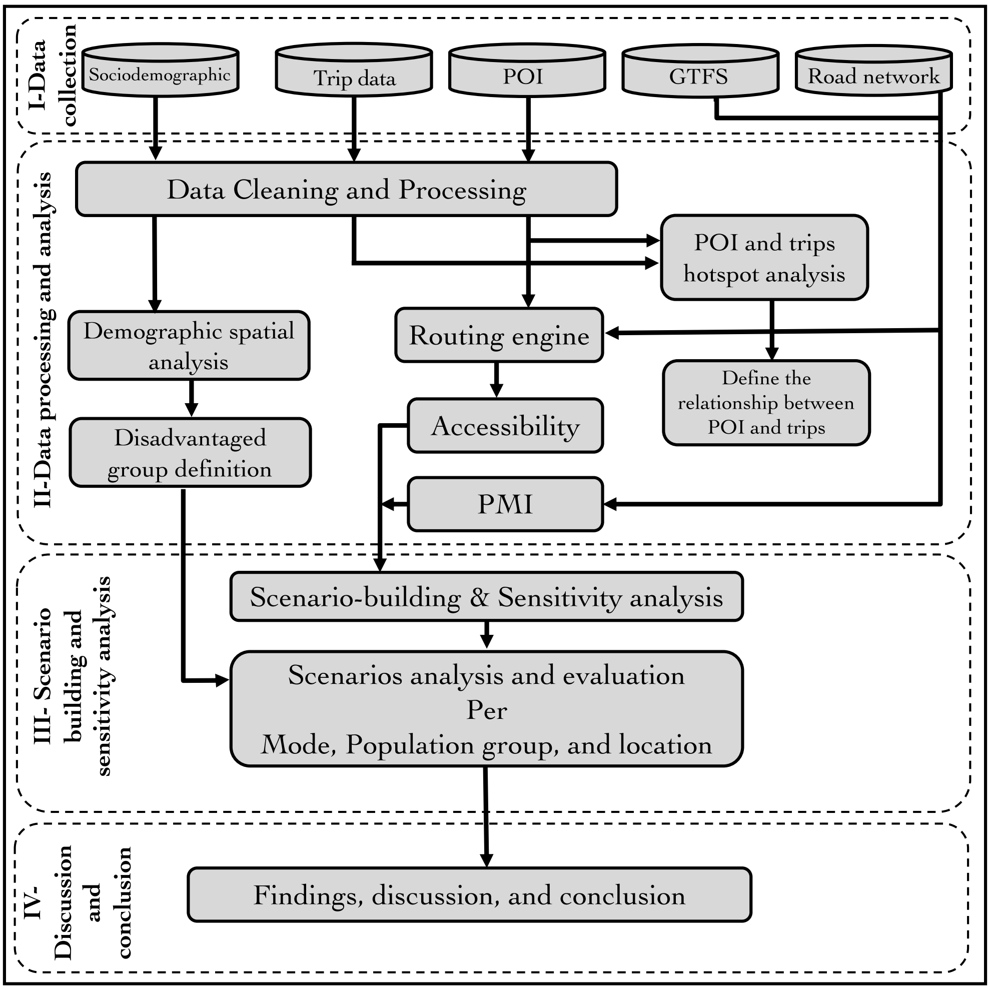


Fig. 1. Research methodology framework.

the enhanced accessibility for different population groups. Therefore, to address this gap, our research hypothesis was examined using the proposed framework, which will be discussed in Section 3.

3. Methods, data, and case study

The prime target of the proposed methodology is to evaluate the equitable use of SMS, using added accessibility as a central measure of SMS equitable use evaluation. Fig. 1 shows the proposed methodology, which consists of three main parts; the first part is the data collection, followed by data processing; next, we used all the collected data, and performed a sensitivity analysis comparing scooter accessibility to the accessibility of the available modes within the city, followed by analyzing the sensitivity analysis results based on replaced modes, population groups, and locations of the different scenarios. Finally, the conclusion and discussion were based on the performed analysis.

Data collection and processing

The proposed methodology was built around using open source data, mainly for creating a transparent methodology that clarifies the concluded decisions and ensures a reproducible methodology. The research hypothesis and methodology depended on assessing the added accessibility to the population after the introduction of scooters, with a close focus on the disadvantaged population groups' gains in comparison to the rest of the population; therefore, we used five primary sources of data:

- Sociodemographic data was used to understand the population characteristics in the study area. We obtained the sociodemographic information for the study area from the US Census Bureau, census.gov, utilizing their API (Application Programming Interface) service through the statistical computing software R (R Core Team, 2023), and the processing package tidycensus (Walker and Herman, 2023). The data contained information regarding the population characteristics. In the analysis, we considered the following population attributes, which are more likely to define the population groups prone to the social exclusion of scooter use: age, income level, education level, race, employment, car ownership, and depending on PT use. The obtained population attributes were aggregated by the smallest geographical unit publicly available, the census block; every census tract contains multiple census blocks. This dataset did not need any cleaning, but it was processed by converting all the aforementioned examined variables into percentages of the total population within each census block, which we used for further analysis.

- Trip data was used to understand the scooter use travel behavior. A dataset containing the trip records between 09-Aug-18 and 31-Jan-20 was retrieved from Louisville city open data portal (data.louisvilleky.gov). The dataset was in long data format; every row represented a trip, and the available information for each trip was the starting and end point geographical coordinates, longitude, and latitude. Also, the data contained trip identification code, trip starting and ending time, and date (trip starting time and ending time were aggregated to the nearest hour quarter by the city authority to protect the user's privacy), trip speed, duration, and the total trip distance. The trip dataset was cleaned using the same procedures followed by Abouelela et al. (2023), Zou et al. (2020). We applied four filtering standards to clean the dataset based on the trip's duration, distance, speed, and spatial location by setting minimum and maximum values for all three criteria. For distance, the minimum considered trip length was 100 m, the maximum was 50 km, the minimum trip duration was one minute, and the maximum was 120 min; one fully charged scooter battery can propel it for two hours. Finally, trips started and ended outside of the scooter operation zones identified by the city were removed from the dataset. After applying the data processing techniques, we had around 390,000 trips for further analysis.
- POIs data was used to verify our hypothesis and to assess the accessibility to the different opportunities. We collected the different points of interest (POIs) geographical locations from Open Street Maps (OSM, openstreetmap.org). The POIs were grouped into six main groups, and each of them had different activities as follows:
  - **Education:**
    - Kindergarten
    - Library
    - School
    - University
  - **Food:**
    - Bakery
    - Bar
    - Beverages
    - Cafe
    - Fast food
    - Food court
    - Greengrocer
    - Pub
    - Restaurant
    - Supermarket
  - **Health:**
    - Clinic
    - Dentist
    - Doctors
    - Hospital
    - Optician
    - Pharmacy
    - Veterinary
  - **Leisure:**
    - Art center
    - Cinema
    - Community center
    - Nightclub
    - Park
    - Picnic site
    - Playground
    - Sports center
    - Stadium
    - Swimming pool
    - Theatre
    - Zoo
    - Artwork
    - Attraction
    - Guesthouse
    - Hotel
    - Memorial
    - Monument
    - Museum
  - **Service:**
    - ATM machine
    - Bank
    - Beauty Shop
    - Fire Station
    - Hairdresser
    - Laundry
    - Police station
    - Post office
  - **Shopping:**
    - Bicycle shop
    - Bookshop
    - Clothes
    - Computer shop
    - Convenience store
    - Department store
    - Do it yourself store
    - Furniture shop
    - Gift shop
    - Jeweller
    - Mall
    - Market place
    - Mobile phone shop
    - Shoe shop
    - Sports shop
    - Stationery
    - Toy shop

  There might be an argument that some of the previous activities could be interchangeably located under different opportunities; the used classification does not impact our results, as we clarify in the methods section.
- Road and local street network (OSM from osm.org), and General Transit feed specifications, GTFS from (transitfeeds.com[1]) were used to calculate the accessibility from the different available modes of transportation to the different opportunities using an online routing engine (conveyal.com).

Data processing

Sociodemographic spatial analysis

The main target of this step was to understand the spatial distribution of the different sociodemographics, especially the variables that are most likely to be attributed to the transport-disadvantaged population in reference to the city structure. Also, we wanted to examine the impacts of the historical segregation and land use policies on the city's population distribution.[2] The first measure that was applied for the sociodemographic characteristics in the scooter distribution zones is the Local Moran I index, or Local Indicator

[1] Last accessed on the 15 of June 2023.

[2] Discussed in more detail in the case study Section 3.1.

of Spatial Association (LISA) (Anselin, 1995; Zhang et al., 2008), which is a spatial measure to measure the autocorrelation for the spatial or the spatial similarity within the study area of one variable in comparison to the surrounding spatial units, in this case, the surrounding spatial blocks. Local Moran's I generates a spatial autocorrelation map, where each location is classified into four categories based on the mean value of the variable: (I) High–High: Locations with high attribute values surrounded by neighboring locations with high values (clustered hotspots); (II)Low–Low: Locations with low attribute values surrounded by neighboring locations with low values (clustered coldspots), (III) High–Low: Locations with high attribute values surrounded by neighboring locations with low values (outliers), and (IV) Low–High: Locations with low attribute values surrounded by neighboring locations with high values (outliers), only significant relation with 90% or more significance level were kept. The queen-case contiguity-based neighbors method was used for calculating the spatial weights.

The next step in the analysis of the sociodemographic characteristics analysis was to define clusters of the disadvantaged population groups. Disadvantaged groups or poor communities are generally defined by their income level. National guidelines define the household's income thresholds; households below them are considered poor. This step used two criteria: household income level, which is a common practice to define the poor population, and car ownership per household, as the main focus of this study was related to travel behavior and one of the most decisive factors of mode choice and daily travel behavior is car ownership (Haque et al., 2019). These criteria were calculated as a percentage of the number of households per census block. The US Census Bureau defines low-income communities as the community (census block group) with 30% or more of its population with household income less than 30,000$ per year; according to the US national equity atlas (nationalequityatlas.org), on average, only 9% of the US households do not have access to cars. Therefore, census blocks were clustered into four quarters using a two-dimensional coordinate system. The horizontal axis represents the percentage of households with income less than 30,000$ per annum per census block, and the vertical axis represents the percentage of households with zero cars per census block. This technique was used to identify the communities with a high probability of being transport-disadvantaged and those with a high probability of forced car ownership (Caulfield et al., 2022). These two population groups should be the prime target for the policy intervention, and they should be served by SMS in general and scooters, as in our case study.

Trips and POI hotspots

The next step was to identify scooter trip patterns spatially and temporally, then the trips and POI significant hot spot using Getis–Ord (G_i^*) (Getis and Ord, 1992). The analysis was based on the number of trips and the number of POI concentration spatial zones. G_i^* statistical significance is evaluated using Z-score. Only spots with Z-scores equal to or more than 90% were kept; we used this analysis step to identify the trip's hot spots in reference to the distribution zones and to see the relation between the trips and the different POI hot spots. This step is targeted to quantify the relationship between trips and POI to understand the impact of POI on trip generation.

Accessibility and PMI calculation

The primary step in the analysis was to compute the accessibility to the different opportunities using the different available modes of transportation: walking, private bikes, PT, and Transport Network Companies TNC (E-hailing), then compare it to the accessibility to the same opportunities using scooters. Accessibility was measured to all the available opportunities combined as people have different preference and subsequently different potential to interact with the different opportunities; measuring accessibility to different opportunities address the multi-dimensional nature of accessibility. Also, it is hard to define which activities are more critical and relevant for the different population groups (Grengs, 2015). A cumulative accessibility measure was used as the number of opportunities reached within a specific trip duration, as it is easy to implement, interpret, and communicate for the different stakeholders (Geurs and Van Wee, 2004). Moreover, the used measure of accessibility depended entirely on publicly available open data sources, making the decision process transparent for the public (Rawls, 1971). Accessibility was calculated for each of the census blocks from the geometric centroid point using a routing engine (conveyal.com), which measured the number of opportunities that can be accessed from the centroid of the block using the specified mode of transportation and for a specific trip duration.

A two-dimensional coordinate system represents the accessibility of the census blocks to the different number of opportunities, and the other axis is the Potential Mobility Index (PMI). PMI is an aerial speed measure from one location to another location, considering the direct distance between the two locations (d) and the network travel time (T) (Martens, 2015). This research calculated PMI as the average aerial speed of each census block's centroid to all the other census block's centroids within the study area using the different modes of transportation.

$$PMI(i) = \frac{1}{N}\sum_{i=1}^{N}\frac{d(i, j...n)}{T(i, j...n)} \tag{1}$$

where:

PMI(i)	= Average aerial speed for zone i
d(i, j...n)	= Aerial distance between i and j
T(i, j...n)	= network travel time between i and j
N	= Total number of census blocks (252)

Table 2
Scenarios summary.

Mode	Access time	Egress time	Speed (km/h)	Total trip duration (min)	
	minute	minute		Min	Max
Walking	–	–	4.4, 4.82	5	15
PT	–	–	Based on GTFS	5	30
Private Bike	0,1,2,3	0,1,2,3	12,14,16	5	15
Car	0,1,2,3,5	0,1,2,3,5	Based on traffic conditions	5	15
TNC[a]	–	–	Based on traffic conditions	5	15
Scooter	–	–	6,9,12	5	15

[a] 5 and 10 min waiting time were considered for TNC.

Scenario-building and sensitivity analysis

There is uncertainty regarding the exact relationship of the modes substituted by scooter; therefore, in order to cover the range of all possible trips substituted by scooter, a sensitivity analysis was considered to cover all the possible combinations of trip duration and trip speeds for the different modes, to ensure that all the possible shifted trips from walking, biking, PT, car, and TNC trips to scooter are captured in this analysis. The following assumptions were used to build the different scenarios, calculate the accessibility of the different modes, and perform the sensitivity analysis:

- All the travel times were considered based on weekday traffic.
- We calculated the accessibility for all the trip durations between five and fifteen minutes with one-minute intervals for all modes except for PT, where the upper bound trip duration was thirty minutes. Longer PT trip durations were considered, as PT trips include access to the station, waiting for the vehicle, and, in some cases, transferring to another line and finally egressing from the service. The accessibility for the different travel times of the different modes was estimated using the "r5r" package (Pereira et al., 2021), as an interface for the (conveyal.com) routing engine.
- Walking: two speeds (4.4 km/h and 4.82 km/h) were considered in the analysis to cover the young and old population groups (Bohannon and Andrews, 2011). Also, based on the US 2017 National Household Travel survey, the average walking trip duration is 11.9 ± 0.2 min (Watson et al., 2021), and 75% of the walking trips are under 15 min (Yang and Diez-Roux, 2012; Agrawal and Schimek, 2007).
- PT: trips included access, egress, and transfer time. Walking was used to access, egress, and transfer between the lines when needed.
- TNC: two waiting times (five and ten minutes) from when the user hailed a car through the application to the pickup time were considered (Rayle et al., 2016; Henao and Marshall, 2019).
- Private car: access, egress, and cruising for parking time were included in the trip duration. It is to be noted that trips only were considered feasible when the in-vehicle time was larger than or equal to the summation of access and egress time. Only the unique combination of access and egress times were considered.
- Private bike: three speeds were considered for the private bike (12 km/h, 14 km/h, and 16 km/h) to cover all range of user expertise and age and their impact on the travel speed. We also considered access and egress times and feasible trips when the in–vehicle time was larger than or equal to the summation of access and egress time, and only the unique combination of access and egress times were considered.
- Shared E-Scooter, the speed, duration, and the scooter trips considered in the analysis were based on the actual trip data. One point to clarify here is that scooter trips might be perceived as slower than bike trips; scooter trip duration is calculated from the time of booking and unlocking of the vehicle from the application till locking the scooter after the trip's end, which reduces the overall trip speed, as the trip time calculation is not only limited to the on-vehicle travel time.

Table 2 shows the summary of the assumptions for the routing and accessibility calculation.

After calculating the accessibility and PMI for all census blocks in the study area using the different modes, 1903 main scenarios were obtained. Four accessibility thresholds, similar to Martens (2016, chapter 8) and Lucas et al. (2019, chapter 3) were calculated for each scenario: the average accessibility of all blocks, 10%, 30%, and 50% of the average accessibility, were defined for each of the 1903 scenarios, Fig. 6. The reason to test the impact of scooters on several accessibility thresholds is that there is no definition for the sufficiency level of accessibility, or a person might have low accessibility to the rest of the community and might still be satisfied with this level. For each scenario, the impact of the scooter replacing the current mode on the level of accessibility and the accessibility threshold is evaluated. Each of these scenarios was evaluated as follows:

- The census block accessibility using the original mode (walk, PT, bike, TNC, car) is evaluated, and if it is under one of the four thresholds, it is identified as problematic.
- For the problematic situations, the scooter accessibility for the same scenario and the same threshold is evaluated, and if it increases the accessibility of the block to cross over the problematic threshold, it is considered to enhance the accessibility, or it has a positive impact.
- If the evaluated scenario scooter accessibility and the original mode accessibility are both below or over a threshold, it is considered to have no impact.
- Finally, if the accessibility of the scooter is lower than a specific threshold and the original mode accessibility is over the same threshold, the scooter is considered as decreasing the accessibility of the block

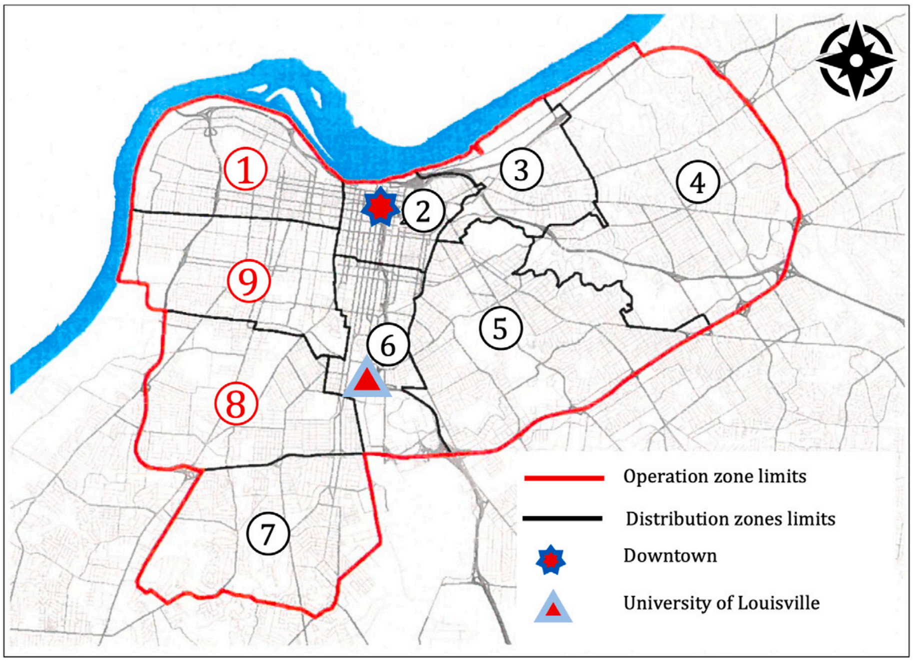


Fig. 2. Study area.

3.1. Case study setup

The data used in this study was obtained from Louisville, KY, a mid-size city on the Ohio River with a population of approximately six hundred thousand. The city has a long historical problem with racial discrimination and population segregation based on the residents' race (Wright, 2004). This segregation still exists, and the city acknowledges the problem that historical land use regulations and policies have unfairly impacted Louisville's residents. Up-to-date land use zoning scheme limits racial and economic diversity and raises housing costs; subsequently, the rising housing cost limits poor communities from accessing opportunities such as schools, parks, or even jobs and extends to limiting the economic growth of local communities. That said, people of low income and people of color might have been pushed to live in areas with deteriorating conditions that increase their chances of being sick.[3]

Historically, the racial segregation ordinance shaped the city's current land use patterns, which granted racial segregation between white and non-white residents. In 1914, the city declared that the black population was not allowed to reside in white majority population neighborhoods, and vice versa; this was followed by the US Supreme Court 1917 racial zoning scheme, which was used to prohibit the sale, lease, and rent of properties for the non-white population. Louisville's comprehensive plan in 1931 depended on the complete separation between the different land uses, e.g., residential and commercial (K'Meyer, 2009). Unfortunately, redlining, or denying loans for people in some geographic regions, was used to discriminate against non-white populations, and previous discriminating policies dragged and continued through the 1937 Housing Act (Benns et al., 2020). The 1958 city plan stressed racial discrimination between residents, and the 1967 and 1970 plans were extensions of the previous plans, keeping the segregation policies in place; however, the 1970 plan started to consider the concept of mixed land use and acknowledged the problem of a shortage of low to middle-income housing, but it did not address the problems that resulted from the previous planning malfunction. The city was planned on a car-centric approach without recommendations for sidewalks or PT and lacking pedestrian networks; however, there is a current effort to eliminate all the previous misconducts in planning that accumulated over the years.[4]

Shared E-scooter was introduced to the city in August 2018 and is still operating; operators follow the city's guidelines for managing and controlling the service within the nine operation zones defined by the municipality, Fig. 2. We focus hereafter on the regulation related to equity. Operators need to deploy a percentage of their fleet in the zones east of the city depending on their fleet size as follows:

- Fleet sizes between 150 and 350 vehicles; 20% of the fleet to be in zones 1 and 9.
- Fleet sizes between 350 and 1050 vehicles; 20% of the fleet to be in zones 1 and 9, and an additional 10% of the fleet in zone number 8.
- Distribution plans for special zones 1, 8, and 9 are to be submitted for approval to the authorities.

[3] Urban.org/zoning, accessed 010/06/2023.

[4] The full details for the historical land use and racial segregation in the city can be accessed from https://storymaps.arcgis.com/stories/8cd986b3c5ab4f1c8bedba85f195662f, accessed on the 01/06/2023.

- Basic education regarding scooter use for the minority groups (low income, non-English speaking, and zero car population) is strongly preferred.
- Operators are encouraged to provide non-smartphone options to access the service.

Several points can be observed from the operation plans. First, the proposed 10%–20% of the proposed fleet in areas with economic hardship are not equivalent to their percentage of area to the total distribution zones area and their population percentage to the total population percentage, 30%, and 35%, respectively. So, the resources and vehicles are already planned not to be equally distributed; moreover, the educational programs and the options for non-smartphone and non-banking access are only recommendations, and nothing is mandatory. It is not clear what would be the case if the operators would not abide by this recommendation; this is not the case for other operation rule violations, such as the case of vehicles parking outside of the distribution zones, where the operators will have to pay monetized fines, and may even lose their license.

4. Analysis results

4.1. Data processing and analysis

4.1.1. Sociodemographic spatial analysis

Scooter's distribution zones comprise 252 census blocks that we used for the sociodemographic analysis. We checked the spatial distribution patterns for the population sociodemographic characteristics that are more likely to impact the inequitable use of scooters as concluded in the literature review, Section 2. Seven variables were considered in this analysis: low-income (households with income less than $30,000 per year), households with zero cars, population older than 45 years old, education level of less than a university degree, non-white population, unemployed, house price less than $50,000, and PT dependent users. Table A.1 shows the summary statistics of the used variables as a percentage of the total census block population. Fig. 3 shows the Moran I for the different variables, and all the examined variables were significantly clustered, except for the old population variable, which showed a random pattern; refer to Fig. A.1 for the numerical correlation matrix for the same variables. It is clear that there is clear segregation between the wealthy population and the low-income population group; however, this has been evident historically from the city planning discriminatory practices; refer to Section 3.1. This step of the analysis shows that the impacts of the historical discriminatory planning laws are still evident to date regardless of the city's effort to end it.[5] We can describe the demographics spatial distribution as low-income, low education, racial minority, no access to a car, depending on PT for work trips, and more likely to reside to the west of the city in a clear separation than the rest of the population.

After identifying the spatial distribution of the sociodemographics, the next step was defining the population blocks more likely to be excluded from using shared scooters. The definition of these blocks was based on two main criteria, low-income and zero car ownership, noting that all the other variables (low education level, racial minority, low price housing units, high rate of unemployment, old population, and PT dependent) were correlated with low income and zero car ownership geographical areas.

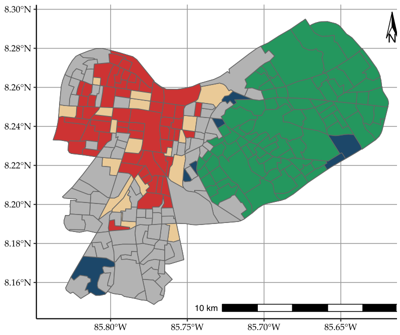
A two-dimensional coordinate system was used to define these groups and to cluster them in a more straightforward way that helps to communicate the results more easily, refer to Fig. 4(a). Hereafter, we will refer to them as quarters. The population was split into four main quarters, where quarter (Q3), 120 census block (47.6%), represents the severely disadvantaged blocks with low-income and zero car ownership, and (Q4), 24 census bloc (9.5%), represents the forced car ownership group, or low-income population with a burden to own a car, mainly for the absence of adequate transportation options, refer to Fig. 4. When quarters were plotted spatially, refer to Fig. 4(b), they were two main clusters; the east of the city contained the wealthy population (Q1), 89 census block (35.3%), and the west of the city contained the poor population Q3; the resultant quarters are in line with the Moran I analysis that was estimated earlier. It is also evident from the analysis that the city is dually polarized as Q1 (wealthy population) and Q4 (disadvantaged population) represent 83% of the total population.

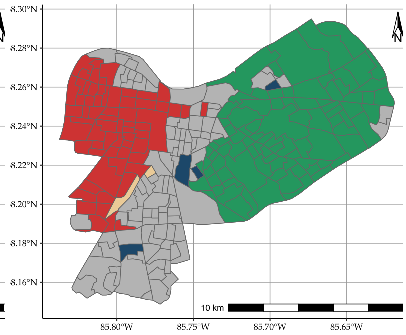
4.1.2. Trips analysis

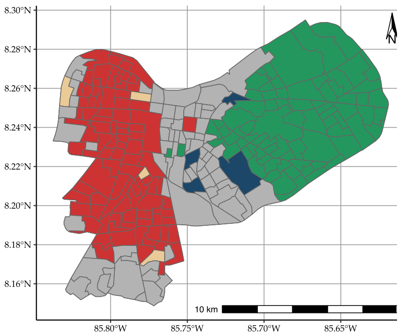
The collected trip data of scooter sharing spanned over 18 months; after applying the data cleaning procedures mentioned before, the cleaned trip was analyzed temporally and spatially. The temporal demand can be described as normally distributed with the peak demand in the afternoon period between 12:00–16:00 during weekdays, and this peak is shifted to late afternoon at 15:00 during weekends; several minor differences exist between the weekends and weekdays demand; in weekends there is an increase in the early day hours demand. This increase in the demand might indicate that scooters used to commute after leisure trips also, during weekdays, there is an increase in the demand compared to weekends at the early hours of the day, with a minor peak of the demand between 5:00 and 6:00 that might indicate scooter use for commuting to school or to work; however, this peak demand is around one-quarter of the maximum daily demand, refer to Fig. 5(d).

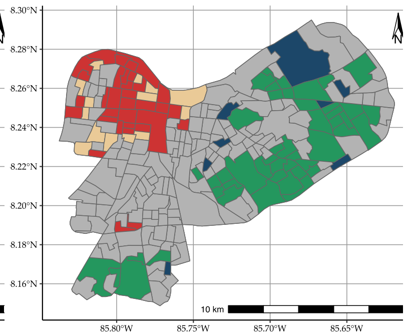
Trips significant hot-spots analysis, considering spots at least 90% significant level, shows distinctive patterns for weekend and weekday trips; refer to Figs. 5(a) and 5(b). Trips spatial patterns can be described as trips concentrated in three prominent locations: the downtown area (zone 2), the north of the distribution zones, the southeast of the downtown (zone 5), or the Baxter Avenue area, where there is a high concentration of leisure activities (restaurants, and bars). The third trip concentration area is in the city's south (zone 6), around the University of Louisville. These patterns stand when comparing weekday trips with weekend trips, but with different magnitudes, where the leisure area (zone 5) and downtown have more weekend trips than weekdays. Also, the university area (zone 6) has more demand during weekdays than weekends.

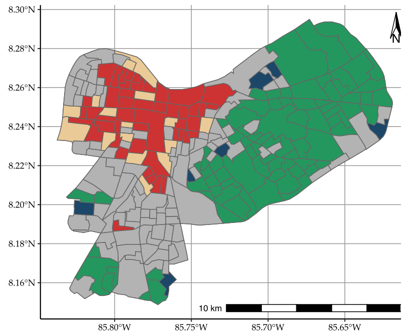
[5] For more details refer to Confronting Racism in City Planning and Zoning Louisville Metro Planning and Design Services https://storymaps.arcgis.com/stories/8cd986b3c5ab4f1c8bedba85f195662f, accessed on 01/06/2023.

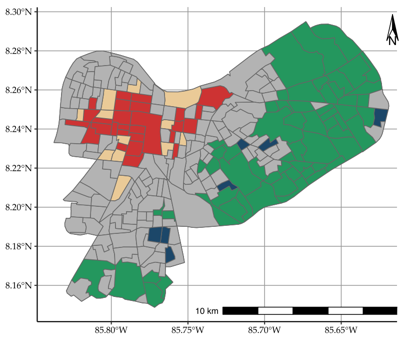

(a) Pct. Household income less than 30,000$/year

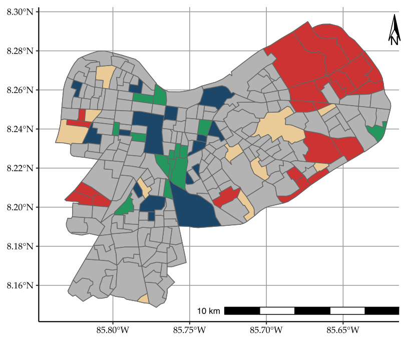

(b) Pct of non-white population

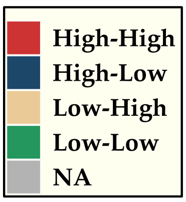

(c) Pct of the population with lower than university degree


(d) Pct of unemployed population


(e) Pct of households with zero car ownership

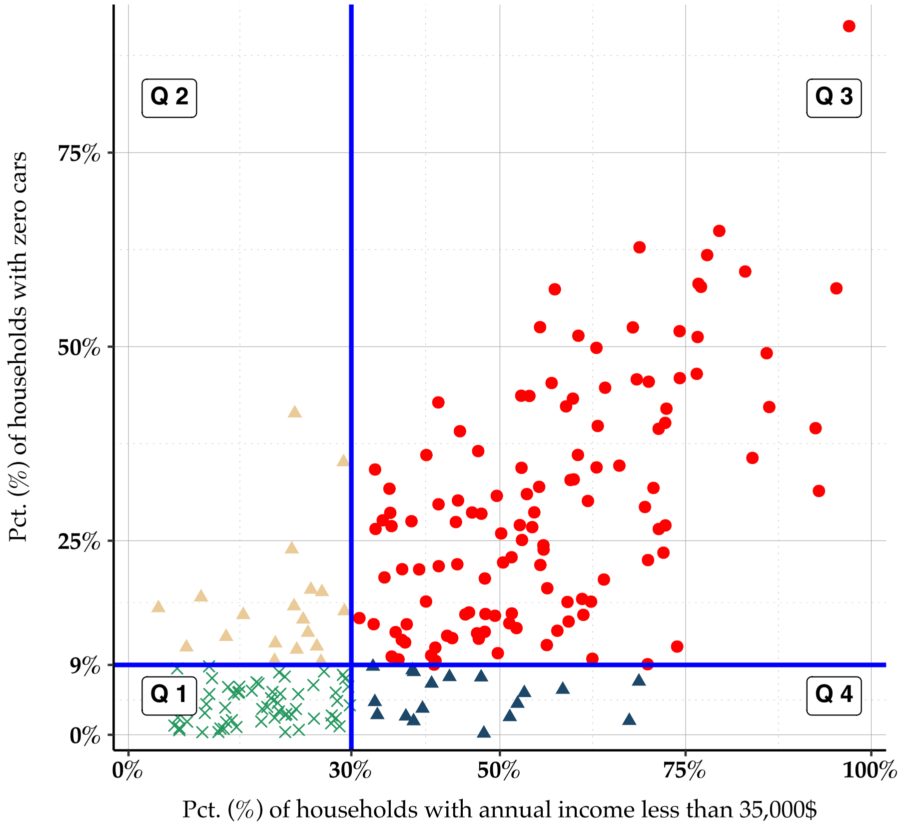

(f) Pct of the population using PT to work


(g) Pct of old population

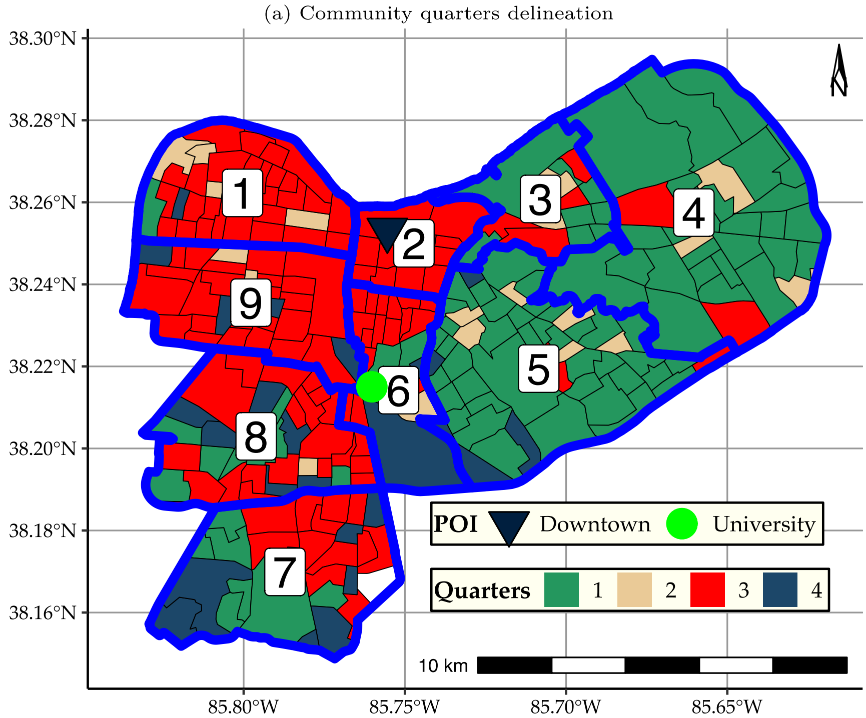


(h) **Legend**

Fig. 3. Local Moran I clusters for the disadvantaged user groups.



(a) Community quarters delineation

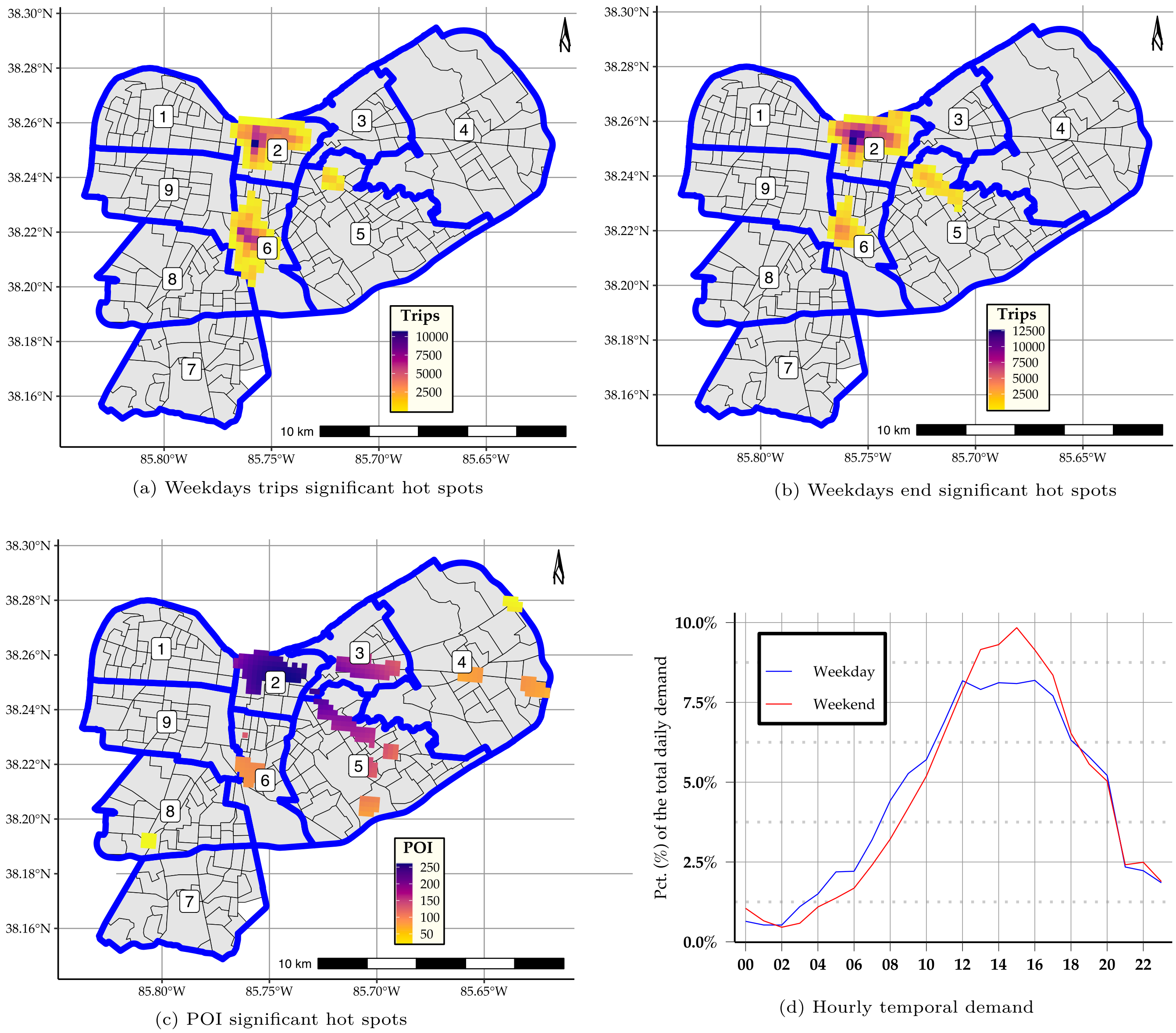


(b) Spatial distribution for disadvantaged quarters

Fig. 4. Disadvantaged quarters definition.

POIs analysis

Fig. 5(c) shows POIs' significant hot-spot locations. POIs are concentrated in four locations: the downtown area (zone 2), where there is a diversity of activities; the University of Louisville area (zone 6), Baxter Avenue (zone 5), and Frankfort Avenue (zone 3); both Baxter avenue and Frankfort avenue are areas with a high concentration of leisure activities. Other smaller hot-spot areas are found in zones 8 and 4. There is a correlation between the trip hot spots and the POI hot spots, which strongly indicates the



(a) Weekdays trips significant hot spots (b) Weekdays end significant hot spots (c) POI significant hot spots (d) Hourly temporal demand

Fig. 5. Trip temporal demand, and trips and POI significant hot-spots.

importance of POI existence on demand generation. We calculated the coefficient of correlation between the number of trips in each significant hot spot and the number of POIs within the same hot spot; Pearson's correlation coefficient was around 0.55 with a 99% significant level, indicating the correlation between the number of POIs and the generated trips.

4.2. Accessibility sensitivity analysis

The last part of the analysis is the central part of the research, where the impact of scooter introduction on the accessibility gains for the different population census blocks compared to the existing modes of transportation was examined. Fig. 6 shows one example of the evaluated scenarios. Each scenario was evaluated on four accessibility thresholds: the average accessibility of the mode and the subsequent 10%, 30%, and 50% of the average accessibility of the original census block accessibility compared to the scooter accessibility on the different thresholds. A total number of (1903 scenarios × 4 thresholds × 252 census block = 1,918,224) scenarios were analyzed comparing the difference in accessibility between the different modes and scooters; from these scenarios, 8% indicated enhancement of the accessibility of the blocks when replacing one of (walking, PT, bike, car, and TNC) trips with scooter trip. In 26% of the scenarios, scooters had less accessibility to the different opportunities than the existing modes. For the rest, there was no impact, or the scooter did not change the level of the accessibility of the block compared to other modes; in other words, if the scooter and the other mode were below the threshold or both of the modes were over the evaluated threshold, we consider it as a no-impact case. To understand the composition of the scenarios, we further analyzed the scenarios that enhanced

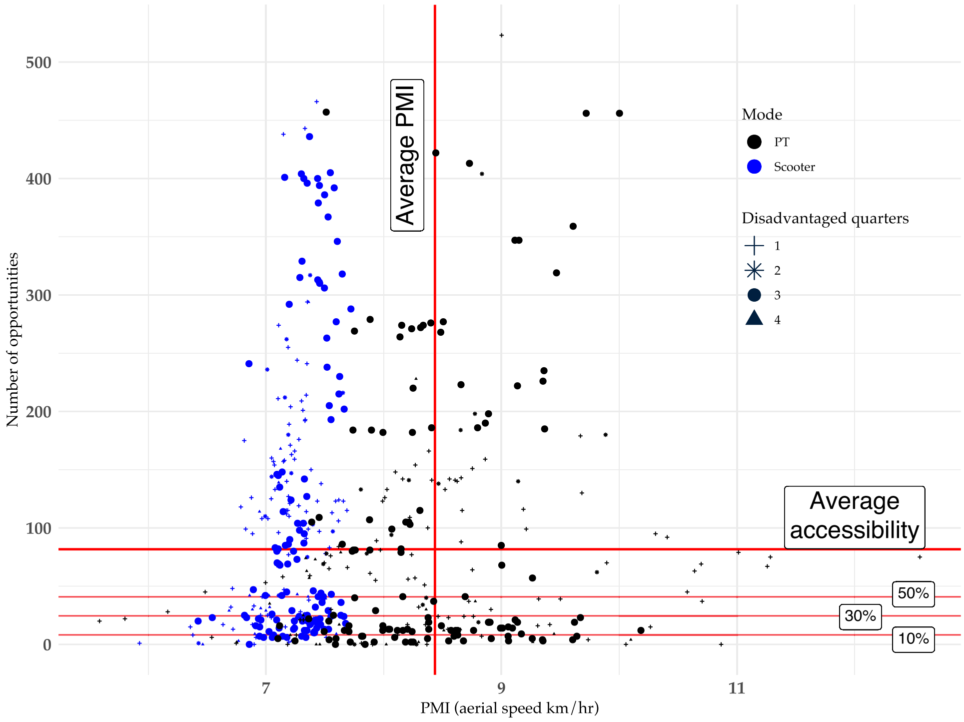


Fig. 6. Example of accessibility and PMI comparison between PT and scooters.

the accessibility of the different census blocks. We divided the scenario analysis into three main parts: the analysis per mode, the spatial analysis, and the impacted population.

Scenarios analysis per mode

In order to understand the nature of the scenarios in terms of their impacts on accessibility for each mode replaced by scooters, we disaggregated the scenarios per mode, Fig. 7. Most accessibility gains scenarios came when scooters replaced walking and PT trips. However, the positive impacts, in terms of increased accessibility, are not always prevailing, as in the case of all the modes except walking. Alternatively, the number of scenarios with positive impacts was less than those with the scooter, which had fewer opportunities reached compared to the other modes. Also, the distribution of the enhanced accessibility within the different modes is somehow analogous to the percentage of modes replaced by scooters revealed in different surveys conducted in different cities; refer to Table A.3. The next question to answer was the distribution of the enhanced accessibility scenarios between the different trip durations to understand the situations where the scooter enhanced the accessibility. Fig. A.3 shows the percentage of the scenarios that experienced enhanced accessibility per the different modes. Most of the enhancement in accessibility was achieved when long scooter trips replaced other modes of shorter trips.

Scenarios impacts on population

We calculated the percentage of the total population that would experience an enhancement of the accessibility level for each scenario; Table A.4 shows the summary statistics per mode. The assessment of the impact on the population was done to quantify the percentage of the benefited population and subsequently evaluate the equitable use of scooters. For the motorized modes, TNC and car, average of (2%–8%) of the population is experiencing enhancement of accessibility level when replacing Car and TNC trips; however, the minimum percentage of population benefiting of the scooter accessibility drops to 0.3%. For walk, bike, and PT, on average, (22%, 12%, and 17%) respectively, of the population would enhance their current accessibility level when using scooters, and the minimum population gains drops to 0.1%.

The disaggregation of the scenarios per population quarter is shown in Fig. 8. There is no significant difference between the accessibility gains in all four quarters when scooters replace walking, private bikes, and PT. The average population percentage that experiences gains in accessibility is around 20%; this percentage drops around 12% when the scooter replaces cars and 7% when replacing TNC trips. Such analysis shows that the gains of accessibility are limited to a small portion of the population, as the percentage of the population gaining accessibility contains all the population groups such as children, older population, and people with physical disabilities who might not be able to use such a service. The disadvantaged groups (Q3 and Q4) had no significant advantage compared to the rest of the population in using scooters regarding enhanced accessibility.

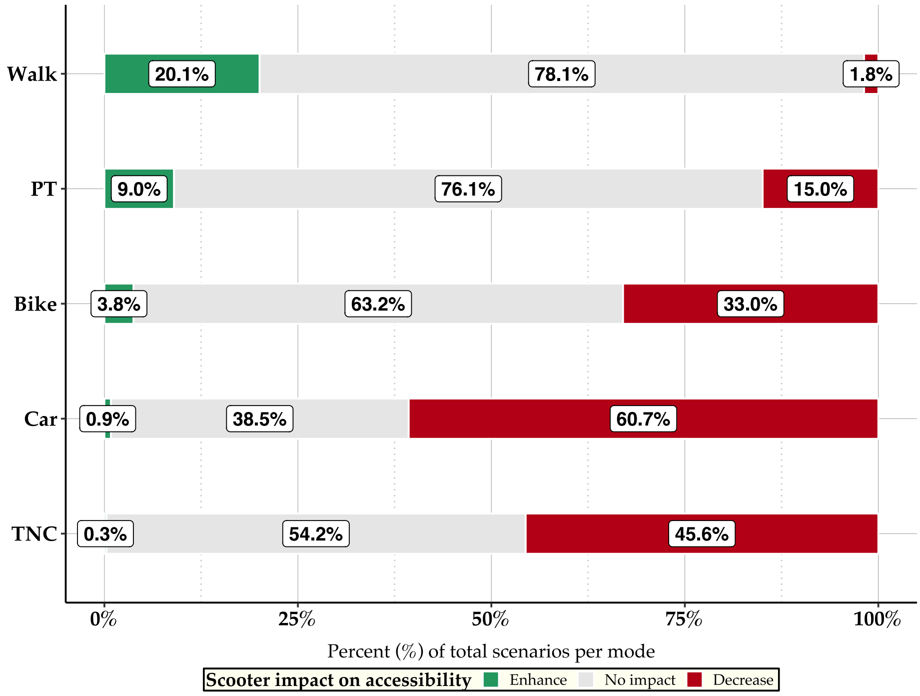


Fig. 7. Breakdown of the enhanced accessibility scenarios per mode.

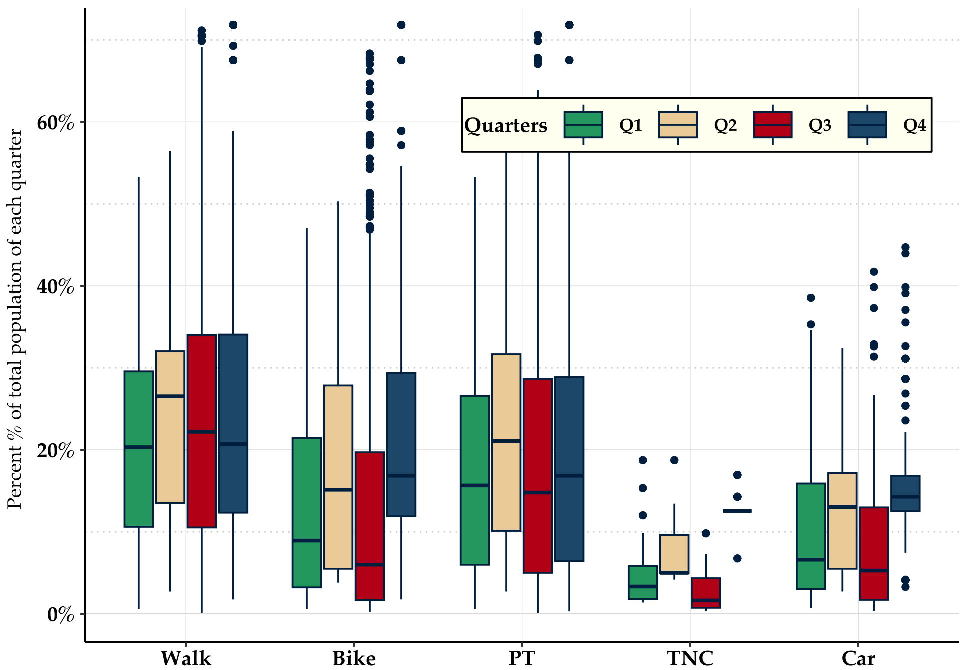


Fig. 8. Distribution of enhanced scenarios per mode per quarter.

Geographical scenarios analysis

Finally, the scenarios were disaggregated by the nine spatial distribution zones, and no significant difference for zones (1, 9, and 8) was found; this disaggregation was done for two reasons: examine the current equity distribution requirement as the operation manual of the city indicates these zones to have a fixed percentage of the fleet distributed in them to ensure equitable use of scooters. The second reason was to test the impact of POI on accessibility gains. This analysis showed that such distribution plans without considering the locations of POI are ineffective. When we further disaggregated the scenarios by each census block, refer to Fig. A.2, intuitively, the areas that had the majority of enhancement in accessibility are the areas further from the POIs, considering that these scenarios considered longer duration scooter trips replacing other short modes trips, refer to Fig. A.3. The spatial scenarios' analysis showed that historical land use patterns discriminating against special population groups are still evident. The reflection of this land use pattern can be seen extending to the SMS deployment, highlighting the seriousness of such a problem in hindering the possible opportunities to develop the current society.

5. Discussion, study limitations

5.1. Results discussion

In this research, we analyzed the changes in accessibility that might occur when shared E-scooter replaces existing modes of transportation, walking, biking, PT, private cars, and TNC, focusing on the impact of scooters on the transport-disadvantaged population groups. The approach of this research was inspired by Martens (2016, chapter 8) and Lucas et al. (2019, chapter 3), where they evaluate accessibility as an indicator for the problems in the transport-land use system. This approach was used to assess the impact of replacing the currently available modes with shared scooters using a two-dimensional coordinate system representing accessibility and PMI. The main advantage of this coordinate system is that it allows us to understand the mobility and accessibility of the examined population group and the difference between modes of transport in terms of accessibility and potential mobility.

In the first step of the analysis, we tried to understand the population distribution in the city by examining the spatial distribution of the disadvantaged groups. This analysis showed a significant pattern that can be described as disadvantaged groups represented by low-income, zero car ownership, education levels lower than a university degree, racial minority, high unemployment rates, and PT-dependent users residing in the areas west of the city. The wealthy population is concentrated in the east of the city.

Moreover, the concentration areas of disadvantaged groups west of the city exhibit low to no opportunities. Therefore, regardless of the scooter use, these areas, in general, are relatively excluding the disadvantaged population from participating in activities compared to the rest of the population, which is mainly a problem of the urban forms in terms of diversity of land use and proximity to opportunities. In continuation of problems of such areas, when the accessibility of the scooter was compared to the original modes, no significant accessibility gains were detected.

We analyzed 1903 scenarios, and from them, 8% had shown enhanced accessibility; when disaggregated by mode, their majority, 53%, materialized when the scooter replaced walking, followed by PT by 28%, and bike by 18%. These analysis results are supported by a similar percentage of the modes displaced by scooters that were stated by users in several surveys (Dibaj et al., 2021); this gives rise to various concerns related to public health and environmental impacts. Shared scooter use increased safety concerns as the number of related accidents and injuries substantially increased (Haworth et al., 2021; Bozzi and Aguilera, 2021). Also, scooter-related accidents are an increased financial burden on society as they impact the labor force in the form of extra sick leaves, increase the burden on health institutions by increased hospitalization cost, and require extra staff (Sikka et al., 2019). Scooter is mainly replacing active mobility and PT modes (99%) of the total enhanced scenarios, which would directly impact several aspects, such as replacing active mobility means reducing the amount of physical effort of the population. Subsequently, inducing more health issues such as obesity and even reducing the quality of life (Markvica et al., 2020; Koszowski et al., 2019), replacing motorized trips with active mobility might help people to achieve the recommended level of physical activities (Long et al., 2021). Huang and Sparks (2023) found that obesity is more evident in low-income groups. As the scope of this study did not include the quantification of the enhance of accessibility and the corresponding impacts on health and safety, there is a need to investigate further if such an enhance in accessibility would overcome the negative possible impacts on health and safety.

Moreover, the displacement of active mobility to scooters might be against the environmentally friendly transport planning practices or the general concept of sustainability (Gargiulo and Sgambati, 2022; Ferretto et al., 2021), scooters on average, increase the emission of CO_{2-eq} per passenger-kilometer by 20% in average in comparison to the displaced modes according to Moreau et al. (2020). Also, the scooters might increase traffic externalities by increasing the overall vehicle kilometer traveled (VKT) due to vehicles' need to perform scooter fleet redistribution and maintenance operations. Several studies have found that income inequality (poor population) is the one that suffers more from traffic externalities, which might even extend to fatalities (Anbarci et al., 2009; Olabarria et al., 2013). Our analysis shows that the gains in accessibility would occur when scooters replace active modes. Several studies (Dibaj et al., 2021) show that Scooters are replacing active modes and PT, which is most likely because they compete with sustainable modes rather than unsustainable modes. Scooter riders use bike lanes, adding extra demand load on such infrastructure, which was not designed originally to consider scooters. Infrastructure improvement projects are generally long-term projects that need a large budget and a long time to materialize. However, all of the previous points need further investigation to quantify the actual impacts of replacing active modes and PT with scooters.

When disaggregating the scenarios by population per each of the replaced modes, on average, 19% of the population enhanced their current level of accessibility; this 19%, when filtered by age, physical ability, financial ability, and knowledge to use the service might drop to less than 1% of the overall population showing the small portion of the population that can benefit from the introduction of scooters. Also, we disaggregated the evaluated scenarios by population quarter, and there was no significant difference between the four quarters. There is no doubt that the introduction of scooters would increase accessibility as the number of available modes of transportation will increase; however, scooters and SMS, in general, have structural barriers to using them, such as the need for smartphone and digital banking access, which is not the case of active mobility and PT. In Chicago, the authorities found that around 0.05% of scooter trips were performed by the unbanked population (Abouelela et al., 2023). Also, there was no significant difference in accessibility gains for the different quarters, meaning there are no specific gains for the disadvantaged population. However, there might be an increase in the accessibility gap between the different population groups, giving advantages to those who can afford scooters.

The analysis purposefully ignored structural barriers to using scooters, such as affordability and the ability to use the service, to support our hypothesis that the problem of equitable use is inherited from the urban forms in terms of the building environment. Even if the cost is not the primary barrier to using the service, scooter use is limited in enhancing accessibility under strict conditions. According to Fig. A.3, most enhanced scenarios occurred because a long-duration scooter trip needs to replace a shorter trip done by another mode to enhance the block's current accessibility. The average scooter trip duration is around 15 min, and it costs around 3.5$ compared to the average daily or hourly ticket of a bus trip, which is between $1.5 and $1.75 in Louisville; the comparison of the difference in cost shows the financial burden of scooter costs that might hinder its use in combination with the absence of nearby opportunities; therefore, there should be an effort to promote diversifying and densifying, and designing the urban forms to promote activities within reach to reduce trip length rather than promote longer trips with "new mobility forms" (Cervero and Kockelman, 1997).

Open-source datasets were used to encourage their use for a transparent decision process, especially for transport and city planning policies, which generally have political involvements that the public might need help understanding. We checked the problem of inequitable use of scooters. However, the city has current policies that were issued for the service providers, and the results indicated that the current policies did not allow the service intended equitable use. The policies used in Louisville are similar to most of the programs in the USA; refer to Section 2, showing that there should be a more profound understanding of the city's urban structure before generalizing the operation policies for SMS, specifically scooters. The performed analysis opens the door for investigating the need for SMS before its deployment, and it raises the question of whether extending PT service might be more beneficial for the disadvantaged population groups rather than the new SMS.

5.2. Policy recommendations

Based on the previous discussion, the following recommendations were made for a better implementation of scooter projects based on the analysis and observation from practical experience and literature review. Our policy recommendation for the new service deployment, scooters, should be done collaboratively between the different stakeholders, in this case, users, legislators (city authorities), and providers, with a clearly defined role for each of them. Section 2 shows a gap in the current practices of deploying scooters; projects must start with a mobility need assessment before adopting SMS. A mobility needs assessment study is essential to be performed by the authorities, paying particular attention to the historical discrimination against any of the population groups, if any, and understanding the needs of groups who are most likely to be socially excluded from using the new transport modes and getting their feedback.

After assessing the mobility needs, the authority might opt not to proceed with the project if the proposed service, a scooter in this case, does not fulfill the population's needs. Also, fair use should be the project's focus from the early stage of investigating the need. It should be inspected regularly by the authorities after implementing the project. After getting the feedback and need assessment, the providers should prepare market reach-out plans showing their proposed efforts to target the different population groups and how this would be implemented in line with the equity goals. If the authorities approve or amend these plans, they should be followed up with a pilot project. The pilot project should be monitored closely by the authorities, and providers should provide the needed information transparently to the public for the complete evaluation of the project by the authorities, users, and non-user groups. The feedback should be analyzed, and a public decision should be made based on the consultation between the different stakeholders for continuing the service deployment process or stopping it entirely based on the outcome of the pilot phase. Many decisions should be based on the pilot phase, such as the equitable outcome of the service and not only the equitable reach of the service. Suppose the service is set to be fully deployed. In that case, the authorities must maintain longitudinal follow-up and monitoring procedures dynamically, considering the rapid changes in technology and user preferences. These recommendations are shaping the skeleton of the service deployment process based on centering equity; however, more details and studies are needed to ensure that equity is centered in the design process and that the project should be aligned with the overall sustainability goals.

5.3. Study limitations

This study examined the replacement of scooters in uni–modal trips for other modes uni-modal trips without considering the cases in which scooter is used in multi-modal trips, such as the case of using scooters as a first and last-mile solution, which could be the case in some situations. Furthermore, the analysis exclusively focused on opportunities within the designated scooter service area. Although there might be potential opportunities located outside the operational zones that are closer to the users, we did not include them in our analysis. This omission was due to the spatial limitations imposed by the operation zones, which prohibit scooter usage outside of their boundaries. Consequently, these areas are inaccessible for scooter-based exploration in our study. However, this might have a very low probability due to the spatial structure of the city, where it is bordered by the Ohio River in the north and the west, and urban extension is limited in the east and south of the operation zones. Also, the temporal accessibility to the different services (working hours) was considered fixed, or all the opportunities would be available all the time; moreover, people's ability was considered the same for the whole census block, which is not the case. However, such an aggregated approach is generally accepted in accessibility assessment, and it does not jeopardize the privacy of the subject (Martens, 2016). We also considered that scooters are always available and uniformly distributed in all the study areas, which might not be the case, but generally, scooter distribution data is not publicly available. Our conclusion validates our hypothesis that the problem is not mainly related to scooters but rather the built environment. Also, the accessibility measure, the cumulative number of opportunities, is simple. It is clear that there are other more sophisticated methods to measure accessibility; however, there is no best way to do so, and our goal here was to have an indicator for the possible level of participation, noting that the relationship between accessibility and activity participation is not always clearly defined, as the high level of activity participation might still take place under low levels of accessibility (Martens, 2016, Chapter 8). Also, other more advanced and complex measures of accessibility, such as time-geography-based measures, need more individual-level information, which might not be publicly available, and they might jeopardize the subject privacy (Ilägcrstrand, 1970).

6. Conclusion

The proposed methodology and the subsequent analysis focused on the chances of equitable accessibility of all members of the society to the different activities, which are more likely to be missed in transport planning processes (Meyer and Miller, 1984; Martens, 2016). The analysis was based on the enhancement of accessibility level, which is the core of transport planning; however, we did not find any significant gains that might lead to sustainable results, but scooters needed to replace sustainable modes to have a positive impact on accessibility, and definitely, such behavior is not expected reduce CO_2 emissions, especially for the disadvantaged population groups. Even so, scooter introduction might lead to a lower life quality for disadvantaged groups; however, more investigation for the impacts of trip replacement on emission, safety, and health is required. We attribute the no-gains of scooter accessibility to the urban forms, represented by the less diverse land uses in poor areas and the limited opportunities. We are not opposing the deployment of the scooters in this research, but we are highlighting the need to consider their direct and indirect impacts before the deployment process. Also, other modes could be of better use and impact, such as the case in Washington, D.C., where Su et al. (2022) found that bikesharing promotes more equitable use than scooters. Our analysis highlights that groups historically have faced a lack of access to opportunities that should be prioritized while planning and introducing new services, as such historical challenges might still be evident to date.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Additional analysis

See Tables A.1–A.4 and Figs. A.1–A.3.

Table A.1
Disadvantage variables summary.

Variable	Low income	Zero car	Non-White	Unemployed
Mean	38.7%	16.8%	38.2%	7.7%
Std.Dev	22.2%	17.1%	34.6%	9.2%
Min	0.0%	0.0%	0.0%	0.0%
Q1	19.8%	2.6%	6.8%	1.4%
Median	36.8%	11.4%	27.0%	4.4%
Q3	55.4%	27.4%	70.9%	11.4%
Max	97.0%	91.3%	100.0%	59.1%
Variable	Low-education	Low housing	45 and older	PT to Work
Mean	59.8%	10.9%	41.5%	6.0%
Std.Dev	24.9%	19.5%	14.0%	9.5%
Min	0.0%	0.0%	0.0%	0.0%
Q1	37.9%	0.0%	32.3%	0.0%
Median	64.0%	0.4%	41.2%	1.9%
Q3	80.9%	12.4%	50.2%	8.2%
Max	100.0%	91.4%	100.0%	77.6%

All variables are calculated as a Pct. (%) of population of each census block.

Table A.2
Trip characteristics summary.

Variable	Mean ± Std.Dev	Min	Q1	Median	Q3	Max
Distance (km)	2.06 ± 2.25	0.1	0.64	1.27	2.6	32.19
Duration (min)	15.6 ± 17.2	1.0	5.0	9.0	19.0	120.0
Speed (km\h)	9.1 ± 4.5	0.1	5.8	8.6	12.0	25.0

Table A.3
Summary for 34 studies investigating modes replaced by scooter.
Source: Data retrieved from Dibaj et al. (2021).

Mode	Avg	Min	Max
Micromobility	12%	4%	59%
Driving alone	16%	3%	46%
PT	16%	1%	59%
Taxi or TNC	24%	5%	51%
Walk	46%	5%	80%

Table A.4
Summary statistics of the percentage of the population gaining enhancement in accessibility.

Mode	Mean	SD	Minimum	Median	Maximum
Walk	22.0%	14.3%	0.1%	21.0%	59.6%
Bike	11.5%	13.4%	0.1%	5.5%	58.2%
PT	16.8%	14.1%	0.1%	13.4%	59.0%
TNC	2.2%	2.1%	0.3%	1.2%	11.4%
Car	8.0%	8.4%	0.3%	4.8%	36.4%

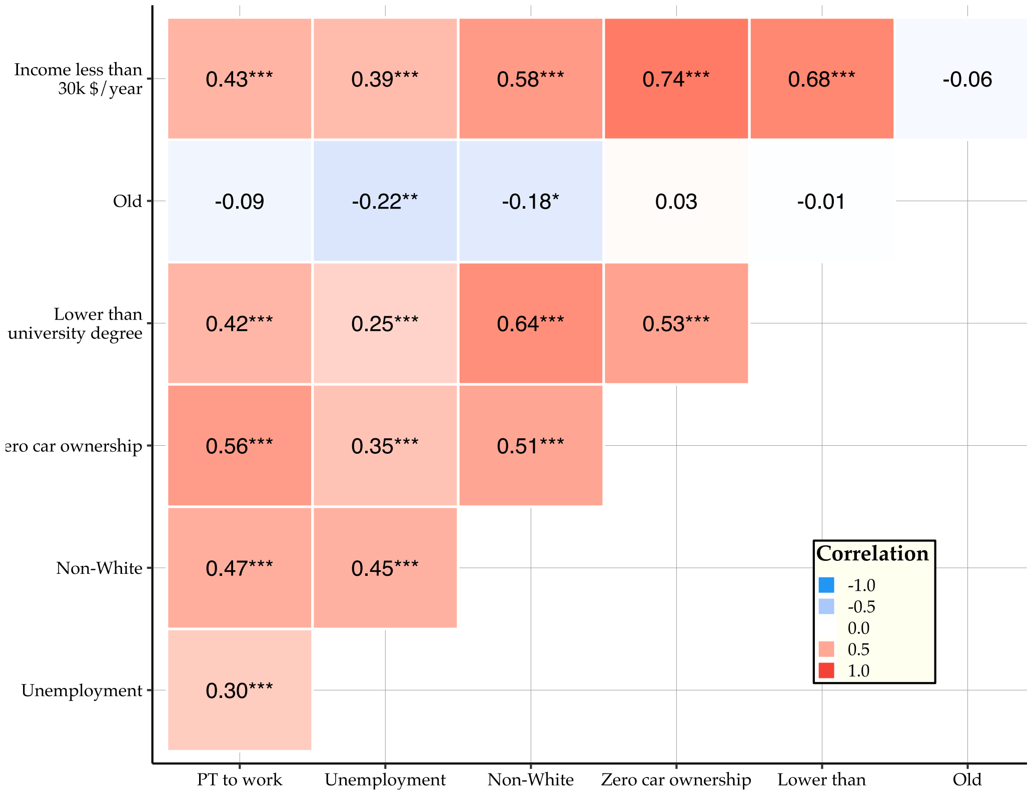
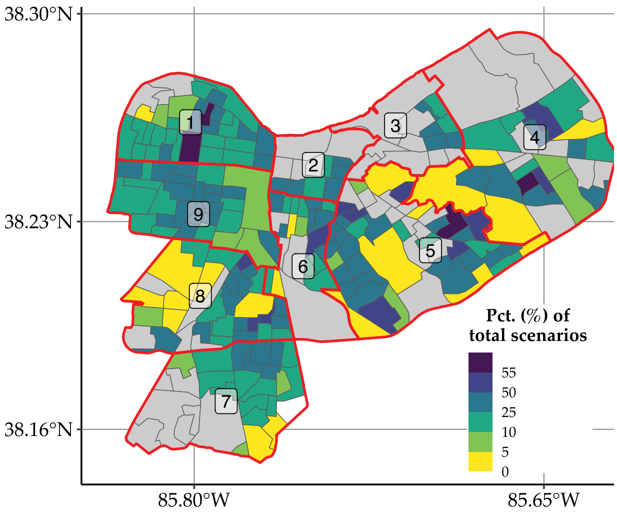
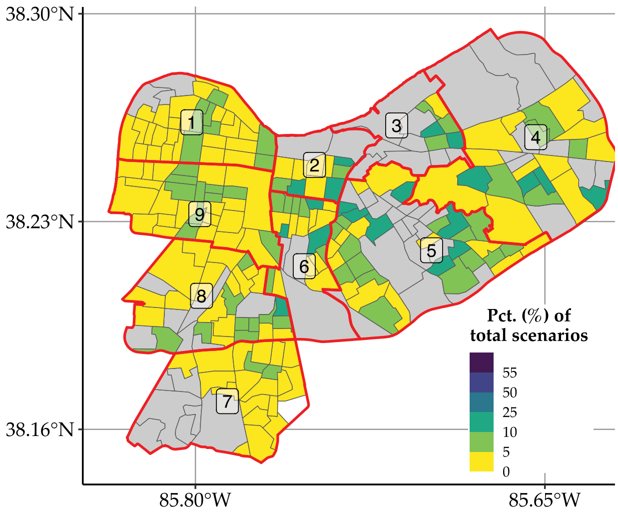


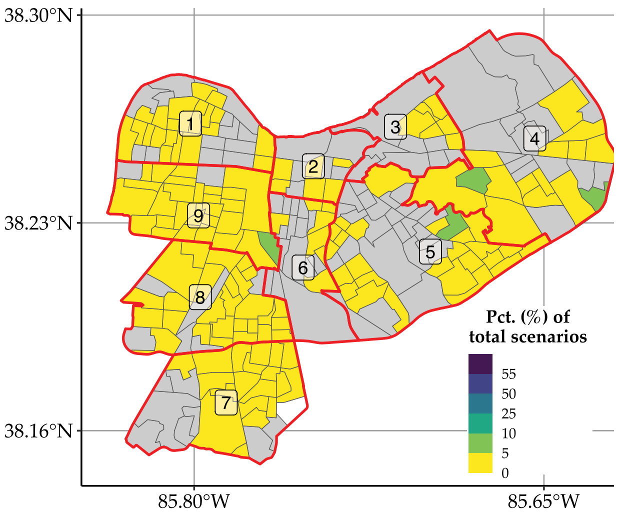
Fig. A.1. Pearson correlation matrix for disadvantaged population characteristics.



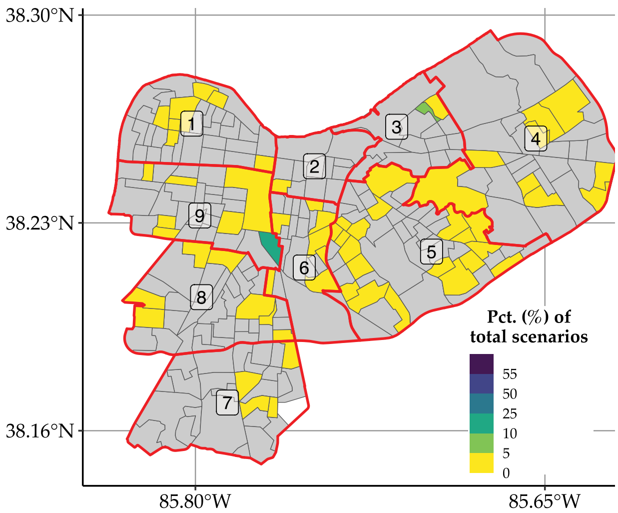
(a) Walking scenarios



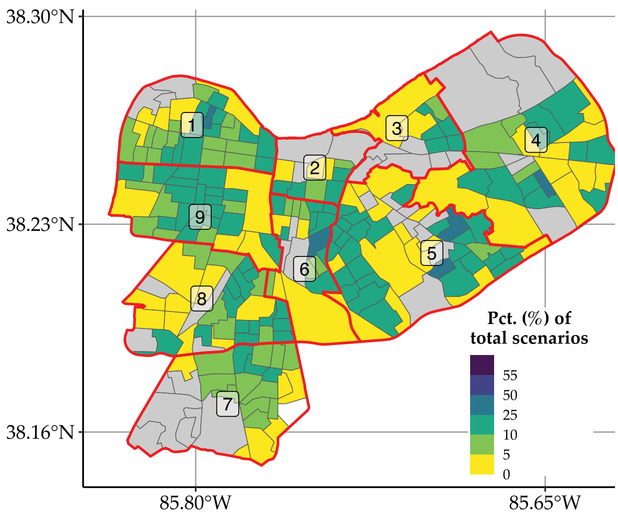
(b) Bike scenarios



(c) Car scenarios



(d) TNC scenarios



(e) PT scenarios

Fig. A.2. Disaggregated enhanced scenarios per mode and census block, the percentage is calculated as a percentage of the overall number of scenarios per block.

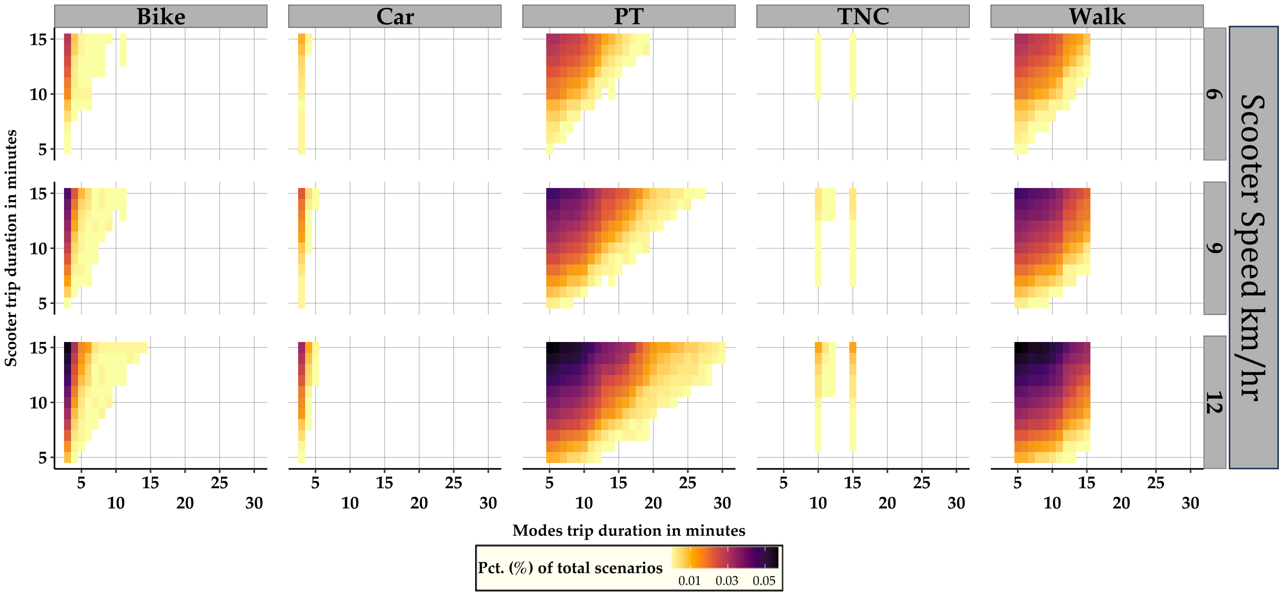


Fig. A.3. Disaggregated enhanced scenarios per mode and travel duration.

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