12-2022

Evaluating Impacts of Shared E-scooters from the Lens of Sustainable Transportation

Nitesh Shah
University of Tennessee, nshah12@vols.utk.edu

To the Graduate Council:

I am submitting herewith a dissertation written by Nitesh Shah entitled "Evaluating Impacts of Shared E-scooters from the Lens of Sustainable Transportation." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Dr. Chris Cherry, Major Professor

We have read this dissertation and recommend its acceptance:

Dr. Candace Brakewood, Dr. Hamparsum Bozdogan, and Dr. Zhenhong Lin

Accepted for the Council:

Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

Evaluating Impacts of Shared E-scooters from the Lens of Sustainable Transportation

A Dissertation Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Nitesh Raj Shah

December 2022

Dedication

This dissertation work is dedicated to my fiancé, Chantal Davis, who has been my support and encouragement during the challenges of graduate school and life. I am truly thankful to have you in my life.

Acknowledgments

Thank you to the many people who have supported and encouraged me throughout my Ph.D. journey. First of all, I would like to express my deepest appreciation to my supervisor and the chair of my committee, Dr. Chris Cherry. Thank you for constantly motivating and encouraging me to think critically and pursue my interests. I am extremely grateful to my committee members, Dr. Candace Brakewood, Dr. Hamparsum Bozdogan, and Dr. Zhenhong Lin. The competition of my dissertation would not have been possible without your constant support and encouragement.

To my co-authors, Abubakr Ziedan, Wi Yen, Saurav Prajuli, and Sameer Aryal: thank you for your invaluable contributions in my research. To all of my colleagues at the University of Tennessee and the New Urban Mobility Alliance (NUMO) team, hosted by the World Resources Institute (WRI): thank you for many personal, professional, and academic memories that motivated my research and made my graduate school experience enjoyable.

To my partner, Chantal Davis: thank you for being my support system, understanding the stress of being a graduate student, helping me brainstorm ideas, and proofreading my articles. I am fortunate to be able to share every day with you, and I am looking forward to the next adventures of our lives. To my parents, Bharat Lal Shah and Kalpna Shah: Thank you for prioritizing my education above anything else which opened new opportunities for me.

Many thanks to the Oak Ridge National Laboratory (ORNL) and the McClure family for funding and supporting my research. I am also grateful to Nashville Metropolitan Planning Organization (MPO) for providing the shared e-scooter data.

Abstract

As the popularity of shared micromobility is increasing worldwide, city governments are struggling to regulate and manage these innovative travel technologies that have several benefits, including increasing accessibility, reducing emissions, and providing affordable travel options. This dissertation evaluates the impacts of shared micromobility from the perspective of sustainable transportation to provide recommendations to decision-makers, planners, and engineers for improving these emerging travel technologies.

The dissertation focuses on four core aspects of shared micromobility as follows: 1) Safety: I evaluated police crash reports of motor vehicle involving e-scooter and bicycle crashes using the most recent PBCAT crash typology to provide a comprehensive picture of demographics of riders crashing and crash characteristics, as well as mechanism of crash and crash risk, 2) Economics: I estimated the demand elasticity of e-scooters deployed, segmented by weekday type, land use, category of service providers based on fleet size using negative binomial fixed effect regression model and K-means clustering, 3) Expanding micromobility to emerging economies: Using dynamic stated preference pivoting survey and panel data mixed logit model, I assessed the intentions to adopt shared micromobility in mid-sized cities of developing countries, where these innovative technology could be the first wave of decarbonizing transportation sector, and 4) Micromobility data application: I identified five usage-clusters of shared e-scooter trips using combination of Principal Component Analysis (PCA) and K-means clustering to propose a novel framework for using micromobility data to inform data-driven decision on broader policy goals.

Based on the key findings of the research, I provide five recommendations as follows: 1) decision-makers should be proactive in incorporating new travel technologies like shared micromobility, 2) city governments should leverage shared micromobility usage and operation data to empower the decision-making process, 3) each shared micromobility vehicles should be approached uniquely for improving road safety, 4) city governments should consider regulating the number of service providers and their fleet sizes, and 5) decision-makers should prioritize expanding shared micromobility in emerging economies as one of the first efforts to the decarbonizing transportation sector.

Keywords: shared micromobility, sustainable transportation, e-scooters, safety, demand-supply, sustainability, transportation in emerging economies

Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background

Private motor vehicles have become an integral part of peoples' lives during the past century. Construction of the interstates (freeways) supported the boom of private motor vehicles and allowed cities to expand mobility and accessibility to jobs and opportunities (Salingaros, 2006). However, such a sprawl development pattern increased the distance between where people lived and where they worked, consumed services, or went to school (Burchell & Shad, 1998). This, in turn, forced people to drive more and be reliant on private vehicles, which is also referred to as the cycle of automobile dependency (Litman & Laube, 2002; Newman & Kenworthy, 1999). Automobile dependency exacerbates urban transportation problems, such as air pollution, emissions, parking, congestion, social equity, and lack of mobility (Litman & Laube, 2002), contributing to issues like climate change and unsustainable urban development.

Therefore, there is an urgency for a paradigm shift in urban transportation that reduces automobile dependency by providing more sustainable mobility options. Micromobility vehicles, such as bikes, e-scooters, and e-bikes, are one such emerging mobility solution that has maximum travel speeds up to 30 miles per hour, are lightweight (<500 lbs.), and are human- and/or electric-powered (SAE International, 2019). These attributes make micromobility ideal for urban trips less than 5 miles, which account for 60% of all vehicle trips in the United States (NHTS, 2017). The provision to briefly rent these vehicles for a trip is referred to as shared micromobility.

The ridership of shared micromobility has been increasing rapidly in the United States within the past decade, as illustrated in Figure 1. Since 2010, people have completed 342 million shared bike and e-scooter trips, and the total number of yearly trips increased by 424 times in 2019 compared to 2010 (NACTO, 2020). The shared bike and e-scooter trips are 11-12 minutes and 1-1.5 miles on average (NACTO, 2020), which could replace 35% of all personal car or taxi trips under 2 miles (NHTS, 2017).

I focus on shared e-scooters in this dissertation, which is the fastest-growing shared micromobility in the United States. The following subsections provide a background on the increasing popularity of shared e-scooters. The first subsection describes the recent evolution in mobility that enabled the widespread use of micromobility, while the second subsection summarizes the development of shared e-scooters.

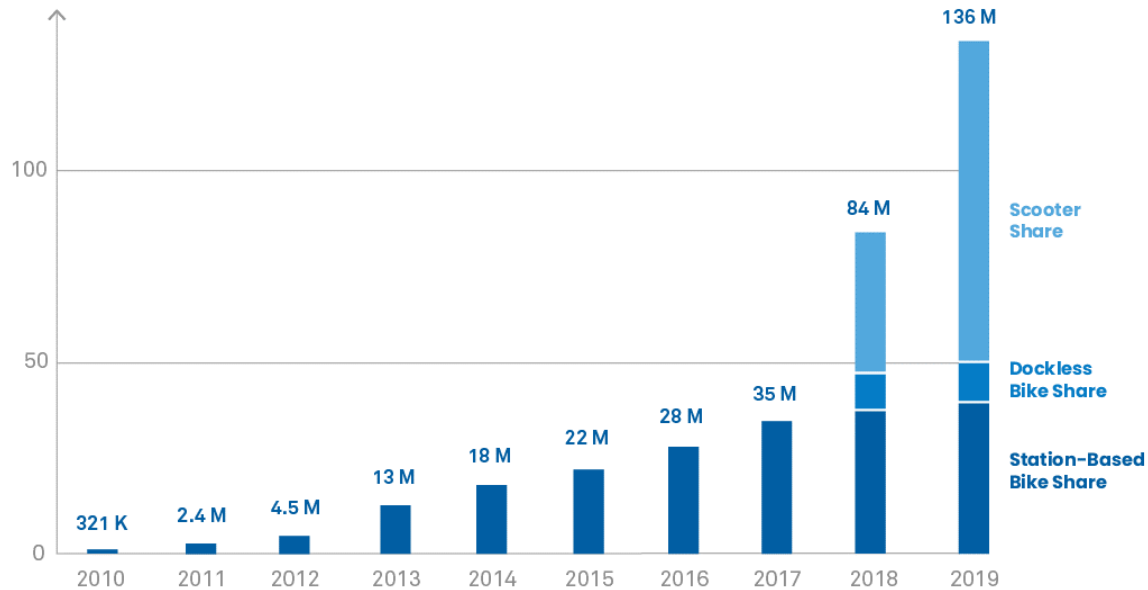


Figure 1 Growth of shared micromobility from 2010-2019 (Source: NACTO (2020)

1.1.1 Evolution in shared micromobility

The first public bike-share system was introduced in 1965 in Amsterdam, Netherlands, and bike-share systems expanded in cities across Europe, North America, Asia, and Australia in the past decades (S. Shaheen, Guzman, & Zhang, 2012). New micromobility modes, including e-scooters and e-bikes, have also emerged recently. Development in travel technology, change in travel behavior, and business model innovations can be considered key drivers to the increased popularity of shared micromobility.

Firstly, travel technology has improved the convenience of using micromobility vehicles and the efficiency of shared micromobility systems through innovations in geo-locating micromobility vehicles, digital payment, and motorization. A user can unlock micromobility vehicles through a Global Positioning System (GPS)-enabled smartphone app or physically locate the vehicles and scan a Quick Response (QR) code to unlock them. The geolocation feature also helps micromobility service providers track, locate, and manage vehicle fleets and improve system operation efficiency (Matute, Cohen-D'Agostino, & Brown, 2020). Digital payment options using smartphone apps, membership cards, and credit/debit cards have improved payment convenience by avoiding cash or coins like early bike-share systems. Partial or full motorization of micromobility vehicles and improvements in battery technology has increased the practical range and convenience of using micromobility vehicles (Cherry & Cervero, 2007). These technologies have supported the rise of shared e-scooter systems.

Secondly, declining preference to own a private car and embracing a shared economy have influenced the change in travel behavior that supports micromobility. Millennials, the largest living generation at present who were born between 1982 and 2000, have a lower rate of driving licensure (Chang, Miranda-Moreno, Clewlow, & Sun, 2019), vehicle ownership (Fry, 2013), and Vehicle Miles Travelled (VMT) (Dutzik, Inglis, & Baxandall, 2014) than previous generations. Millennials tend to make fewer large investments, like houses and cars, or even avoid them entirely (Garikapati, Pendyala, Morris, Mokhtarian, & McDonald, 2016), while embracing a shared or circular economy, where they consume the product rather than acquiring ownership of the product. As a result, the adoption rate of the shared mobility is substantially high (Clewlow, 2019), with the adoption rate of e-scooters being highest among other shared mobility like car-share.

Finally, the business model of shared micromobility has evolved in the past decades, contributing to the realization of innovative concepts like Mobility-as-a-Service (MaaS), where a traveler can access and pay for various transportation services through a single app. While the first bike-share in Amsterdam collapsed due to bicycle theft and vandalism (DeMaio, 2009), the recent generation of micromobility is supported by geolocation features that allow for the monitoring of the location and status of the vehicle fleet. This has enabled the operation of dockless shared micromobility systems, where users can pick up and drop off vehicles anywhere within the designated service area. Furthermore, ride-hailing companies like Uber and Lyft, and automakers like Ford, have invested in the micromobility market to advance the MaaS concept (Bellan, 2021; Lyft, 2021).

1.1.2 A brief overview of shared e-scooters

E-scooters (or electric scooters), as shown in Figure 2, refers to electric motor-powered standing scooter with a top speed of up to 18 mph (SAE International, 2019). These emerging vehicles can either be personally purchased ($200-500 or more) or rented e-scooter vehicles made available by service providers (also referred to as shared e-scooters). To rent an e-scooter, a user can physically find an e-scooter or through a smartphone app, unlock the vehicle for a small fee (usually $1), and pay-per-minute cost (usually $0.15 – 0.35). Most service providers operate dockless fleets, allowing users to end the trip anywhere within the designated service area. Bird was the first service provider to launch dockless shared e-scooters in Santa Monica, USA, in 2017 (Sisson, 2018), while other service providers promptly launched their own operations throughout the country.

Although shared e-scooters are the most recent micromobility vehicles, they already account for two-thirds of the micromobility trips in the United States and are growing the fastest among other micromobility modes. While the total number of shared bikes, e-bikes, and e-scooter trips increased by 60% between 2018-2019, shared e-scooter trips increased by over 100% during the same period (NACTO, 2020). Shared e-scooter systems are also expanding across cities more rapidly than bike-share systems. In 2017, 43 cities had bike-share, and zero cities had shared e-scooters, while in 2021, 51 cities had bike-share, and 92 cities had shared e-scooters (Bureau of Transportation Statistics, 2021).

Figure 2 Shared e-scooter (Credit: Arlington, VA)

Table 1 summarizes the benefits of shared e-scooter systems along with their limitations (Reinhardt & Deakin, 2020). This disruptive technology could provide inexpensive and convenient mobility options for short trips, with broader environmental, safety, and equity benefits. However, these benefits depend on several factors, including the type of modal shift, the level of e-scooter vehicle integration with road infrastructure, and e-scooter fleet distribution and pricing. Nevertheless, shared e-scooters can be considered one of the most promising mobility options in a sustainable urban transportation system.

The response to shared e-scooter systems has been both positive and negative. Supporters of e-scooters claim that they are inexpensive, convenient, and fun travel options, which could also integrate with public transit, to improve mobility, congestion, and emission. On the other hand, expanding shared e-scooters in several cities has also ignited major pushbacks, including tossing e-scooters in the ocean in Los Angeles, CA (Newberry, 2018) and cutting the brake wires in Austin, TX (Streicher, 2019). The mixed response of shared e-scooter systems can be explained in a Gartner Hype Cycle (Fenn & Time, 2007), a graphical illustration of the maturity, adoption, and social application of technology. Kovacevich (2019) developed the hype cycle for shared e-scooters, as presented in Figure 3.

The launch of the shared e-scooters was an innovation trigger, with huge expectations and minimum concerns about its impact. The excitement peaked at an inflated expectation point and started degrading with events like the deaths of a few e-scooter riders or improper sidewalk riding that affected other road users. The general expectations of e-scooter decreased with disappointment up to the trough of disillusionment. In the meantime, city governments started regulating shared e-scooters, and riding behavior are starting to improve, which has gradually increased the expectations. This phase is termed a slope of enlightenment that would eventually level over time, fulfilling the actual promise of shared e-scooter systems.

I believe that shared e-scooter systems are currently on the slope of the enlightenment phase of the Gartner Hype Cycle. City governments are implementing permits and pilot programs to regulate shared e-scooters and targeting to achieve policy goals, such as improving accessibility in low-income areas by ensuring e-scooters are available in such areas. Moreover, there is a need for a systematic understanding of shared e-scooters impacts, including safety, demand, and environment, to integrate them into the current transportation system.

Table 1 Potential benefits and limitations of shared e-scooter systems (Adopted from Reinhardt and Deakin (2020))

Benefit Description	Limitations
Environmental benefits, including greenhouse gas and other pollutants emissions reductions and less noise from automobiles	Depends on mode shift from automobile to e-scooters; Vehicle miles traveled (VMT) reduction also depends on trip lengths
Congestion reduction	Depends on mode shift from automobile to e-scooters, location of use, time and day of use
Better life cycle energy and environmental results than alternatives	Depends on the longevity of e-scooters and scooter components, including batteries; it also depends on the feasibility and cost-effectiveness of vehicle repair, battery replacement, remanufacturing and recycling, waste disposal practices
Affordable compared to other forms of transportation	Unless subsidized, likely to be more costly than walking or biking; may or may not be more affordable than transit, private auto
Can serve mobility-deprived neighborhoods	Depends on how e-scooters are actually deployed and user interest, and comfort with them
Health benefits from using active transportation	May actually reduce activity if e-scooter travel replaces biking, walking; increased potential for user injury; may injure others in collisions or tripping incidents; some benefit for walking to and from pickup/dropoff, but the program is designed to minimize this
Supports high-density development	Depends on how vehicles are deployed

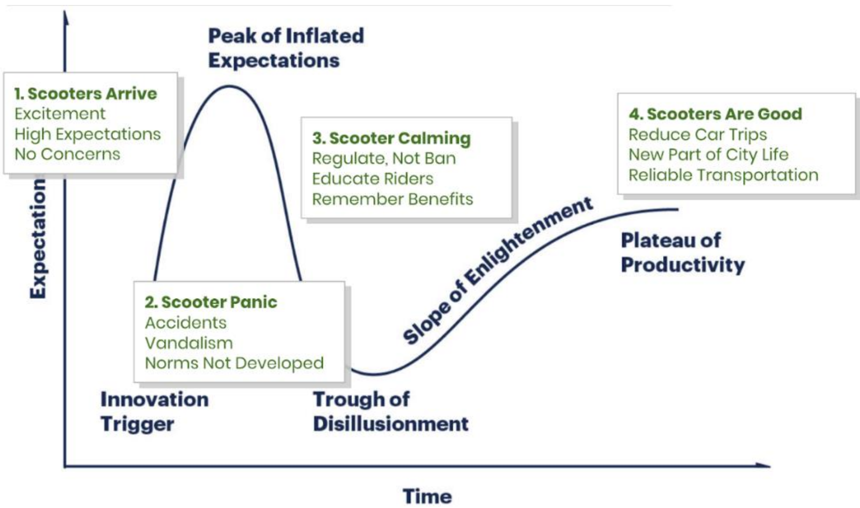


Figure 3 E-scooter hype cycle (Source: Kovacevich (2019))

1.2 Research questions and contributions

In this dissertation, I evaluate the impacts of shared e-scooters systems through the lens of sustainable transportation planning. One of the standard definitions of sustainable transportation is from the Ministry for the Environment, New Zealand, which defines it as “finding ways to move people, goods, and information in ways that reduce [transportation] impact on the environment, economy, and society” (Ministry for the Environment, 2003). These three aspects of sustainable transportation are also known as the triple bottom line. Figure 4 illustrates the balancing of environmental impacts of transportation, economic efficiency of the systems, and societal impacts within the sustainable transportation planning paradigm.

My dissertation focuses on each bottom line of sustainable transportation, as highlighted in blue in Figure 4. The main research questions are as follows:

1.2.1 Scrutinizing e-scooter crash and crash risk (societal bottom line of sustainable transportation)

The increasing ridership of e-scooters ignited a policy debate on where e-scooters should be allowed on the roadways. E-scooter users preferred to ride on the bike lane if available (Portland Bureau of Transportation, 2019). On the other hand, some state legislatures initially banned e-scooter riders from bike lanes, often citing safety issues as e-scooters are motor-powered vehicles (Unagi, 2020). Therefore, I explored an overarching question of whether we should approach e-scooter safety the same as other micromobility modes, like bicycles. Considering only motor vehicle-involved collisions that cause severe injuries and fatality, I evaluated the safety issue through the following three research questions.

Q1: Are crash characteristics and demographics of e-scooter and motor vehicle collisions different than that of bicycle and motor vehicle collisions?

Q2: Is the collision mechanism of e-scooter and motor vehicle collisions (movement and location) different than that of bicycle and motor vehicle collisions?

Q3: Are crashes or crash rates disproportionately higher at night than during the day?

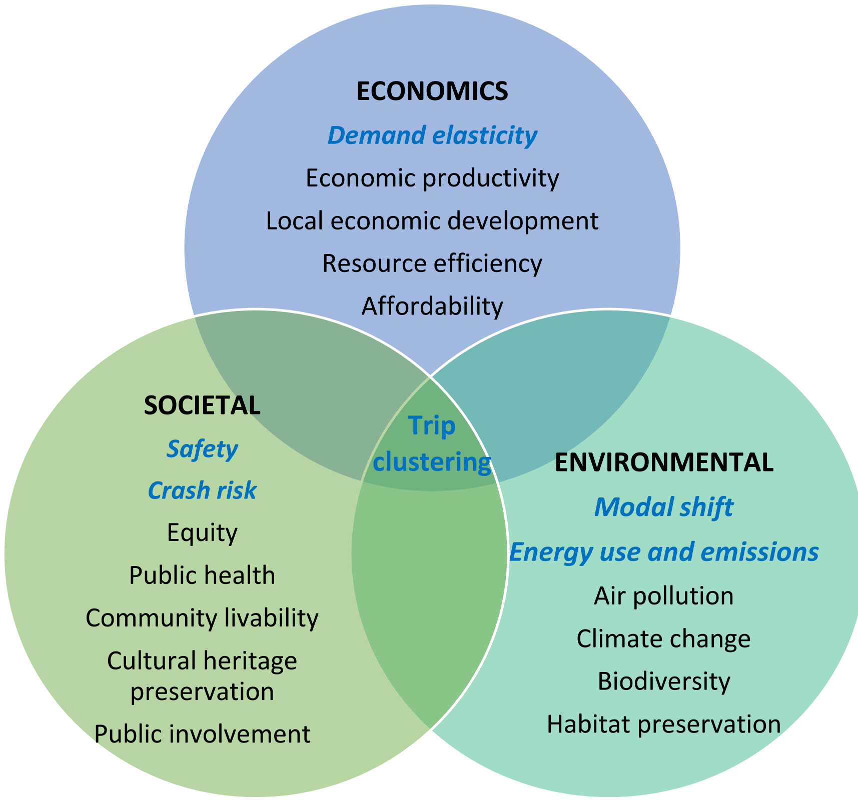


Figure 4 Triple bottom line of sustainable transportation (Adapted from Todd Litman (2006))

Contributions: This study makes three contributions to the transportation literature as follows: 1) based on my knowledge, this study is the first of its kind to provide a comprehensive picture of e-scooter safety based on police crash reports through the understanding of crash characteristics and demographics of riders, 2) I implement the most recent crash typology to compares and contrasts e-scooter and bicycle crash location, and maneuver of e-scooter riders and motorists before the crash, and 3) I evaluate the daytime and nighttime crash risk that could help to improve e-scooter safety. Such information can be insightful for policymakers, transportation planners, and traffic engineers to design and implement the safe system approach to traffic safety.

1.2.2 Demand elasticity of e-scooter vehicles deployed (economics bottom line of sustainable transportation)

During the initial launch of shared e-scooters, service providers often flooded the streets with many vehicles, causing issues like the cluttering of sidewalks. City governments reacted to limit the total number of e-scooters operating within their jurisdiction by regulating the number of services providers and their fleet size, with provisions for adjusting the fleet size of the service providers based on system performance, like the number of trips per e-scooter vehicle per day. However, there is a lack of empirical analysis to evaluate the demand elasticities of e-scooter vehicles, which could be helpful in improving the utilization of e-scooters and the system's overall efficiency. The research questions for this topic are as follows:

Q4: What is the demand elasticity of e-scooters deployed by service providers based on the fleet size, controlling for spatial factors, like built environment and socio-demographics, and temporal factors, such as weather?

Q5: What is the land-use specific demand elasticity of e-scooters vehicles deployed by service providers based on the fleet size?

Contributions: This topic of my dissertation makes three contributions as follows: 1) to my knowledge, this is the first study to evaluate the actual demand (e-scooter usage) and supply dimensions (vehicles deployed) of shared e-scooters, 2) I used a year-long geographically disaggregated e-scooter trip summary dataset and location of available e-scooters that updates approximately every five minute to control for unobserved spatial and temporal factors, 3) I estimated the demand elasticity segmented by weekday/weekend, land use types, and shared e-scooter service providers based on their fleet size, which can help city governments identify the appropriate size of shared e-scooter systems operating within their jurisdiction.

1.2.3 Shared micromobility as the first wave of decarbonizing transportation in developing countries (environmental bottom line of sustainable transportation)

Despite the immense benefits of shared micromobility, there are only a limited number of shared micromobility systems in mid-sized cities of developing countries (with more than 500,000 and less than 5 million in population), which makes an overwhelming majority of the world's cities and have the highest population growth rate. Shared micromobility is affordable for users and does not require huge infrastructure investments, making this innovative transportation technology a potential leapfrogging alternative in developing countries. It can serve as a standalone system or complement transit or para-transit systems to improve their service while reducing the need for private motor vehicles. I aim to answer the following research questions in the context of mid-sized cities in developing countries:

Q6: What are the main drivers of adopting shared micromobility modes, and what is the effect of sociodemographic factors?

Q7: Which traditional travel modes would users replace with shared micromobility?

Contributions: This study makes three main contributions as follows: 1) to my knowledge, it is the only large-scale study to evaluate shared micromobility usage focusing on mid-sized cities of developing countries, 2) I deployed a fully online and dynamic stated preference pivoting survey that improves the survey design in real-time by using users' input data to add context in the subsequent questions, and 3) I focused on introducing shared electric-powered or human-powered vehicles, which could contribute to the initial wave of electrification in the transportation sector of emerging economies.

1.2.4 Usage-based clustering of e-scooter trips (intersecting with all three bottom lines of sustainable transportation)

When e-scooters were first launched in the United States, city governments found themselves behind in managing and regulating shared e-scooter operations within their jurisdiction. While many studies have implemented survey design to understand the usage of these emerging vehicles, they have limited data points and does not include information from all e-scooter trips. On the other hand, shared e-scooter systems collect trip data that includes geolocation and timestamp of the trip starting and ending location along with route data. Merging the trip data with contextual data, such as land use, transportation network, and weather, could enhance the understanding of e-scooter usage and help integrate shared e-scooter into the existing transportation systems. The research questions on this topic of the dissertation are as follows:

Q8: What are the distinct e-scooter usage patterns based on temporal and spatial features and weather characteristics?

Q9: How can spatial and temporal visualization improve understanding of e-scooter usage patterns?

Contributions: These research questions make three contributions as follows: 1) Using a high spatiotemporal resolution e-scooter trip data, I propose an unsupervised machine learning technique to identify e-scooter usage patterns that complement existing survey-based studies, 2) the proposed method adds contextual information to the standardized micromobility data, which can be scalable across cities and vehicles, and 3) I applied visualization to illustrate the spatial and temporal patterns of e-scooter usage that provide an understanding of who, where, and why people use shared e-scooters. These findings can inform transportation agencies to make a data-driven decision on such emerging vehicles' safety, sustainability, and mode substitution.

1.2.5 Estimating energy usage and emissions from micromobilty data

Existing studies evaluating the environmental impacts of shared e-scooter systems have made assumptions on the usage phase of the Life Cycle Assessment (LCA) analysis, inducing the lifespan of e-scooter vehicles. Only a few studies have used micromobility data, which includes information like trip distance and battery power level that could better identify the parameters of the usage phase of LCA. Using Big Data that updates the location and status of deployed e-scooters every five seconds, I aim to assess the emissions and energy use of shared e-scooter systems. The two research questions of this objective are as follows:

Q10: What is the operational related emission and energy use of the shared e-scooter system in Nashville, Tennessee, based on the Big Data (micromobility data)?

Q11: Is there a difference between operational and usage emission and energy use between shared e-scooter service providers?

Contributions: This chapter makes the following contributions: 1) to my knowledge, this is the first study to leverage micromobility data to evaluate the energy use and emissions of shared micromobility systems, 2) I implement a probabilistic framework for evaluating energy use and emissions that reflects the actual profile in the real world, 3) the study includes data from three service providers operating in the same city to evaluate differences the energy use and emissions profile.

1.3 Dissertation structure

The remaining dissertation is organized into six chapters as follows:

Chapter 2. Scrutinizing e-scooter crash and crash risk: This chapter compares motor vehicle involving e-scooter and bicycle crashes using standard crash typology as well as general characteristics and demographics of crashes (Nitesh R Shah, Aryal, Wen, & Cherry, 2021). The paper was published in the Journal of Safety Research and presented at the International Cycling Safety Conference in Lund, Sweden, in 2021. The chapter also includes an evaluation of the daytime and nighttime risk of an e-scooter crash (Nitesh R Shah & Cherry, 2022). The paper was published in the Findings Press and presented at the International Cycling Safety Conference in Dresden, Germany, in 2022.

Chapter 3. Demand elasticity of e-scooter vehicle deployment: This chapter evaluates the demand elasticity of e-scooter vehicle deployment segmented by weekday type (weekday vs. weekend), land use types (CBD & commercial, university, park & waterfront, dense residence, and low-density periphery), and category of service providers based on their fleet size (large (>500), medium (500-250), and small (<250)) (Nitesh R Shah, Ziedan, Brakewood, & Cherry, In review). The paper is in review at the Transportation Research Part A: Policy and Practice. This paper was presented at the Transportation Research Board Annual Meeting 2022 in Washington, D.C, and the Tennessee Section Institute of Engineers Summer Meeting 2022 in Gatlinburg, Tennessee. This research paper also received the second position in the Annual Student Paper Competition, Tennessee Section Institute of Transportation Engineers.

Chapter 4. Shared micromobility as the first wave of the decarbonizing transport sector in developing countries: This chapter evaluates the effect of temperature, precipitation, and availability of bike lanes on the propensity to use bikeshare, e-bike share, and e-moped share in Kathmandu, Nepal, as a case study of developing countries (Nitesh R. Shah, Parajuli, & Cherry, In review). The chapter also assesses the model shift from existing modes if these new travel modes are available. The paper is accepted for presentation at the Transportation Research Board Annual Meeting 2023.

Chapter 5. Usage-based clustering of e-scooter trips: This chapter identifies groups of shared e-scooter trips based on the usage using big data and machine learning techniques (Nitesh R Shah, Guo, Lee, & Cherry, In review). It also evaluates the temporal and spatial pattern of these clusters over a year to propose a framework to add contextual information to the micromobility data. The paper was presented at Transportation Research Board 100th Annual Meeting 2021 in Washington, D.C. This research paper also received first place in the 2021 Annual Student Paper Competition, Tennessee Section Institute of Transportation Engineers, and second place in the 2021 Annual Student Paper Competition, Southern District Institute of Transportation Engineers.

Chapter 6. Estimating energy usage and emissions from micromobility data: This chapter identifies the usage and operational phases of shared micromobility systems using high spatial and temporal resolution data to evaluate energy usage and emissions.

Chapter 7. Main findings, recommendations, policy implications, and conclusion: This chapter summarizes the key findings of each chapter and provides recommendations to city governments, transportation practitioners, and researchers, along with its policy implications.

Appendix: This chapter includes a description of the Shared Urban Mobility Device (SUMD) data used in Chapters 2, 3, 5 and 6, maps from Chapter 3, and a survey questionnaire from Chapter 4, and model selection criteria results from Chapter 6.

Chapter 2. Scrutinizing e-scooter crashes and crash risk

This chapter is based on two research papers as follows: 1) published by Nitesh Shah, Sameer Aryal, Yi Wen, and Christopher R Cherry titled "Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology." The paper was published in the Journal of Safety Research and presented at the International Cycling Safety Conference in Lund, Sweden, in 2021. 2) published by Nitesh Shah and Christopher Cherry with the title "The Chance of Getting Struck by a Car on an e-Scooter is Twice as High at Night." The paper was published in the Findings Press and presented at the International Cycling Safety Conference in Dresden, Germany, in 2022.

Abstracts

Paper #1

The market share of e-scooters in the United States has proliferated in cities: 86 million trips were made on shared e-scooters in 2019, a more than 100% increase compared to 2018. However, the interaction of e-scooters with other road users and infrastructure remains uncertain. This study scrutinized 52 e-scooter and 79 bicycle police-reported crashes in Nashville, Tennessee, from April 2018 to April 2020 from the Tennessee Integrated Traffic Analysis Network (TITAN) database. We used descriptive analysis and a recent prototype version of the Pedestrian and Bicycle Crash Analysis Tool (PBCAT) to classify crashes based on the locations of the crashes relative to roadway segments or intersections, as well as the maneuver of the motor vehicle and e-scooter/bicycle relative to the motor vehicle. Two crash typologies can explain the majority of e-scooter crashes, while bicycle crashes are distributed over several crash typologies. Additionally, 1 in 10 e-scooter- and bicycle-motor vehicle crashes leads to the injury or fatality of the e-scooter rider or bicyclist. Furthermore, we noted statistically significant differences in spatial and temporal distribution, demographics, lighting conditions, and crash distance from home for e-scooter and bicycle crashes. The police crash report provides a comprehensive picture of e-scooter safety complementing existing literature. We found that e-scooter crash characteristics do not fully overlap with features of bicycle crashes. A generalized engineering, education, and enforcement treatment to reduce and prevent e-scooter and bicycle crashes, injuries, and fatalities might not result in equal outcomes for each mode. More rigorous enforcement could be implemented to deter e-scooters riders under the age of 18 years and e-scooter safety campaigns could target female riders.

Paper #2

Nighttime crash risk is higher across all modes of transportation. Despite regulatory pressure to intervene in nighttime e-scooter riding, there is limited understanding of the number of crashes and crash rates by daytime and nighttime. Motor vehicle-involved crashes are most dangerous. This study combined 82 police crash reports with data from 3.1 million shared e-scooter trips in Nashville, TN from September 2018 to January 2022 to evaluate the time-of-day and seasonal crash patterns, controlling for exposure. E-scooter crashes, with cars at least, are more likely to occur during the nighttime, as indicated by crash rates estimated from trip count as an exposure variable.

2.1 Introduction

Most of the previous e-scooter safety studies have taken observational, survey-based, epidemiological, and news article mining approaches. However, these data sources and methods do not provide a comprehensive understanding of e-scooter safety and how it relates to other micromobility modes. This study contributes to the literature by applying standardized bicycle crash typology on both e-scooter and bicycle crashes in Nashville, Tennessee. The comparison of crash typology based on location and maneuver, as well as general characteristics and demographics of crashes, can inform targeted educational, design, and enforcement strategies to reduce e-scooter and bicycle crashes.

The remaining chapter is organized as follows. The relevant literature is summarized in the review of the literature section. The methods section describes the data and crash typology framework, with findings in the results section. A discussion of the findings is provided in the discussion section. The conclusion section summarizes the chapter along with limitations and further research.

2.2 Review of literature

This section is organized into three sub-sections. Relevant safety research approaches, including crash typology, is summarized in the first sub-section. The second sub-section provides an overview of prior e-scooter safety studies, while the last sub-section presents the research approach of this research.

2.2.1 Relevant safety research approaches

Macro-level safety analysis evaluates the effect of traffic, roadway, and socio-demographic factors on crashes over a geographical space to provide countermeasures for a long-term perspective (Cai, Lee, Eluru, & Abdel-Aty, 2016). Micro-level crash analysis, on the other hand, can lead to better insights about the cause of the crash (Hertach, Uhr, Niemann, & Cavegn, 2018), and help to identify solutions that can be applied over a short period. Moreover, traffic safety problems can be related to microscopic factors such as a specific design of the road segment or intersection (Huang et al., 2016).

Crash typology analysis is one of the methods for the micro-level analysis of bicycle as well as pedestrian crashes. The National Highway Traffic Safety Administration (NHTSA) classified pedestrian (Snyder & Knoblauch, 1971) and bicycle crashes (Cross & Fisher, 1977), which was later refined for the development of the FHWA Pedestrian and Bicycle Crash Analysis Tool (PBCAT) (Harkey, Tsai, Thomas, & Hunter, 2006). This is the most common crash typology used in practice and contains 56 pedestrian crash types and 79 bicycle crash types based on a combination of the following factors: pedestrian, bicyclist, and motor vehicle direction of travel; traffic control type; location; user behavior; and other circumstances such as school bus-related crashes.

Researchers have also developed other typologies to complement behavior- and circumstance-based PBCAT crash typology. Schneider and Stefanich (2016) developed the Location-Movement Classification Method (LMCM) crash typology that is based on location and movement characteristics of the crash. Other crash types consider the interaction between a bicycle and a motor vehicle (e.g., right hook, head-on, door) (City of Cambridge, 2014; Lusk, Asgarzadeh, & Farvid, 2015), as well as crash characteristics that include the movement patterns of the bicyclist/pedestrian and motor vehicle, roadway attributes, lighting, and weather conditions (Jermakian & Zuby, 2011; MacAlister & Zuby, 2015).

These crash typologies can be used to identify design engineering and enforcement measures as well as educate people to reduce crashes. For example, “Motorists turned left into the path of bicyclist” crash type may be addressed by improving left turn infrastructure and operations, improving intersection lightning, and improving vehicle conspicuity. However, to the authors’ knowledge, the crashes of emerging modes like e-scooters have not been scrutinized using any crash typologies. This research uses the latest prototype version of PBCAT developed by Libby Thomas, Mike Vann, and UNC Highway Safety Research Center (2020) to evaluate the similarities and differences between e-scooter and bicycle crashes.

2.2.2 Prior e-scooter safety research

Unlike motor vehicle as well as bicycle crashes, e-scooter crashes lack national or statewide standardization, which has led researchers to adopt a wide range of data sources to assess e-scooter crashes. Emergency department and trauma center data is the most popular source to evaluate fatalities and the severity of injuries related to e-scooter crashes (Badeau et al., 2019; Beck, Barker, Chan, & Stanbridge, 2019; Sikka, Vila, Stratton, Ghassemi, & Pourmand, 2019; Trivedi et al., 2019). As a part of e-scooter pilot evaluation programs, city transportation agencies have adopted a combination of methods to assess e-scooter safety, which include surveys (Portland Bureau of Transportation, 2019) and hospital records (Austin Public Health, 2019; City of Chicago, 2020).

Several studies have evaluated e-scooter user behavior related to safety that is based on a survey or observation. Curl and Fitt (2019) surveyed 536 Lime e-scooter users in New Zealand and concluded that 90 percent of users used footpaths (sidewalks) to ride e-scooters, and safety was the primary concern among non-users. James, Swiderski, Hicks, Teoman, and Buehler (2019) surveyed 181 e-scooter riders and non-riders in Rosslyn, Virginia, and combined the results with observational parking behavior. The authors found that non-users perceived e-scooters as more dangerous than users perceived them.

Researchers have also used news reports and social media to understand e-scooter crash characteristics and user behavior. Yang et al. (2020) analyzed nationwide news reports to identify 169 e-scooter crashes in the United States between 2017 and 2019 and evaluated general crash characteristics, such as severity, demographics, and locations. Similarly, Allem and Majmundar (2019) evaluated 324 posts from Bird’s official Instagram account and found that many depicted e-scooter users did not use protective gear like helmets.

However, the data sources used in the current e-scooter safety literature are not a comprehensive representation of e-scooter crashes. For example, hospital records are often limited to small sample sizes can be biased towards severe injuries, and lack contextual transportation factors

(Tin, Woodward, & Ameratunga, 2013), while news reports are biased in terms of crash severity, time and place of the crash, as well as the road user type and the victim's personal characteristics (De Ceunynck, De Smedt, Daniels, Wouters, & Baets, 2015). Furthermore, most crashes in those datasets include little information about the motor vehicle, which contributes to 80% of e-scooter rider fatalities (Santacreu, Yannis, de Saint Leon, & CRIST, 2020a). Therefore, there is a need to understand the interaction between e-scooters and motor vehicles and identify the most common crash typologies. To this end, we also hope to understand how e-scooter crashes differ from bicycle crashes to assess if e-scooter-specific safety strategies are warranted.

Furthermore, the existing literature has a limited understanding of time-of-day and seasonal patterns of e-scooter crashes. While many e-scooter safety policies are based on the number of crashes (Austin Public Health, 2019; Santacreu, Yannis, de Saint Leon, & Crist, 2020b), accounting for exposure provides a measure of risk to inform effective safety strategies (Merlin, Guerra, & Dumbaugh, 2020). Nighttime crash risk is generally higher across all modes of transportation and we aim to quantify that relative risk for e-scooter use.

2.2.3 Research objectives

Most fatalities and severe injuries of e-scooter users involve a motor vehicle, while crash typologies focused on the interaction between micromobility and motor vehicles in the literature have only examined bicycle crashes. An evaluation of crash typology considering the location and maneuver of e-scooters and motor vehicles as well as a comparison with other micromobility modes, like bicycles, is lacking in the literature.

E-scooters are smaller than bicycles, which allows them to navigate pedestrian traffic, yet they are also fast enough to travel among cars on the roadway. This flexibility allows e-scooter riders to change when and where they ride, such as switching from riding on a sidewalk to using a traffic lane to avoid groups of pedestrians. Moreover, many policies require scooters ride on the road, but park on the sidewalk in the furniture zone, implicitly endorsing riding between the domains. Such navigation might be unpredictable, thereby increasing the risk of a collision between an e-scooter and a car, resulting in unique crash types. Therefore, the research questions of this study are as follows:

1. Are crash characteristics and demographics of e-scooter and motor vehicle collisions different than that of bicycle and motor vehicle collisions?
2. Is the collision mechanism of e-scooter and motor vehicle collisions (movement and location) different than that of bicycle and motor vehicle collisions?
3. Are crashes or crash rates disproportionately higher at night than during the day?

2.3 Methodology

The research hypothesis was evaluated by analyzing e-scooter and bicycle crash records using descriptive analysis and PBCAT crash typology, as illustrated in Figure 5. The first sub-section describes the police crash reports, while the second sub-section provides an overview of the recent version of the PBCAT crash typology.

2.3.1 Crash Report Data

I accessed all the available e-scooter and bicycle crash reports between April 1, 2018 and April 30, 2020 in Nashville, Tennessee that were reported by the police and documented in Tennessee's Integrated Traffic Analysis Network (TITAN) (Tennessee Highway Safety Office, 2020b). I relied on the tabulated crash data as well as narratives and crash diagrams to code specific information from the crashes. Although the TITAN dataset includes crash records throughout the state, I only analyzed crashes in Nashville, as e-scooter regulations differ between cities, which could influence riding behavior. Nashville additionally has the highest e-scooter deployment and usage amongst Tennessee cities, and crashes were consistently reported by two law enforcement agencies (Nashville Metro Police and Vanderbilt University Police). To legally ride a scooter in Nashville, a person must be 18 years or older, possess a valid driver's license, yield to pedestrians, and follow the rules of the road. A rider must not ride on sidewalks nor drink and ride.

This database includes crashes that involve a motor vehicle on public roadways, parking lots, and private driveways. The crash reports collect information on crash characteristics, general roadway characteristics, details of people and vehicles involved in a crash, as well as a narrative and a crash diagram describing the incident. Some crash reports include photographs. Incidents that do not involve motor vehicles, like e-scooter riders or bicyclists falling off or colliding with

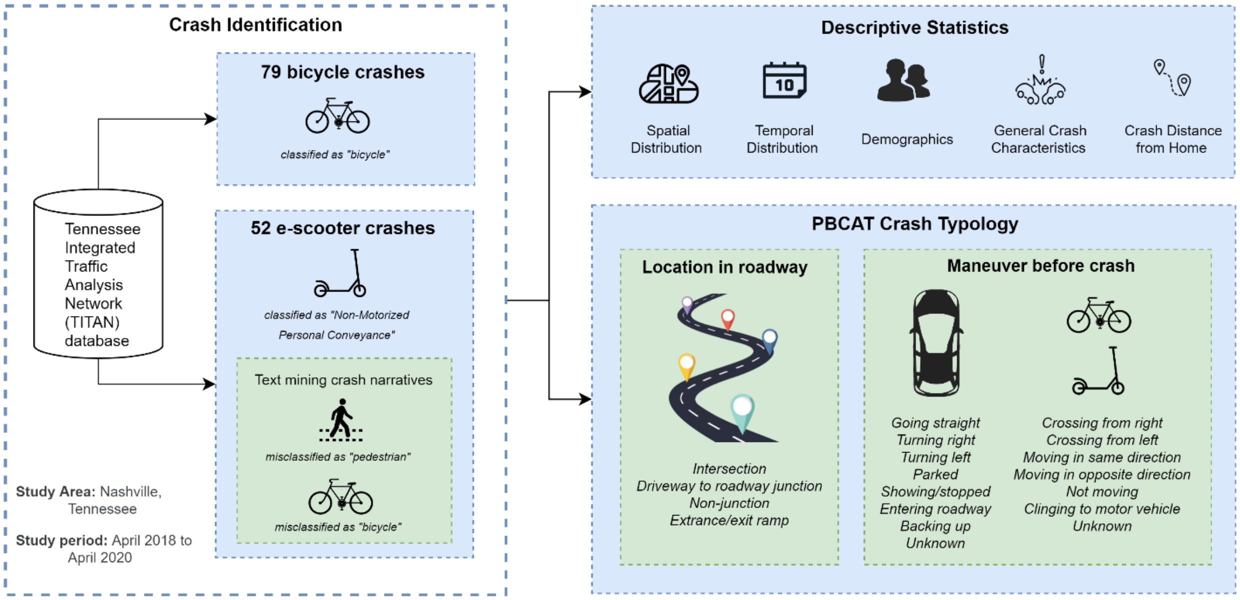


Figure 5 Research design to evaluate e-scooter and bicycle crashes

each other are not included in the TITAN database. This analysis only includes motor vehicle-involved crashes, which tend to be the most severe types of crashes, and evaluation of such incidents is essential in developing countermeasures that reduce bicycle- and e-scooter-motor vehicle crashes.

I identified 33 unique e-scooter crashes in the TITAN database under the *Non-Motorized Personal Conveyance* category. E-scooter crashes were relatively consistently coded under this category several months after the launch of shared e-scooters in Nashville. In the early months of the launch, e-scooter crashes were reported as either bicycle or pedestrian crash types. Therefore, I used a text mining approach to identify these misclassified e-scooter crash reports by examining nine keywords (including company names) that may indicate an e-scooter involvement. The non-case sensitive search keywords are *scooter*, *sumd*, *bird*, *lime*, *lyft*, *spin*, *jump*, *gotcha*, and *bolt*. I used the *pdfminer* library in Python to read the narratives from the PDF format crash reports, which identified nine e-scooter crashes in the bicycle crash records and ten in the pedestrian crash records. With that, I identified a total of 52 unique e-scooter crashes in Nashville during this period.

While the e-scooter crashes were mostly located in the downtown area of Nashville (Figure 1 (b)), the TITAN database also contains bicycle crashes in the suburban areas. However, the road infrastructure and bicycle riding behavior are likely different in the suburban area than the city center, which may not be comparable to e-scooter crashes. Therefore, I identified bicycle crashes in the urban area by visualizing the crash locations in ArcGIS, and selected bicycle crashes within 1 mile of the nearest e-scooter crash. I extracted 79 bicycle crashes for the analysis.

I consolidated a few variables that would allow a better comparison of the results. The redefined injury levels fall into three values: fatal, injury, and minor or no injury. *Incapacitating* and *Suspected serious injury* were classified as *Injury*, while *No injury*, *Non-incapacitating evident*, *Possible injury*, *Suspected minor injury*, and *Unknown* were classified as *Minor or no injury*. I also combined the *clear* and *cloudy* value of the weather condition field. Also, I extracted the home zip codes of the motorists as well as the bicyclists and e-scooter riders to calculate the distance of the crash location to their home to understand if they were Nashville residents or visitors.

2.3.2 Crash Typology

The Pedestrian and Bicycle Crash Analysis Tool (PBCAT) crash typology framework is undergoing significant redevelopment in Summer 2020 (Libby Thomas et al., 2020). This analysis relies on version 3.0 of the framework that is expected for public release in Fall 2020. The PBCAT framework allows for consistent crash typology assignment and aims to understand factors that contribute to Vulnerable Road User (VRU) crashes. The framework classifies crashes based on the location of a crash (e.g., intersection) and the type of maneuver by the road users (e.g., left turn). Though relying on the most up-to-date version of the PBCAT framework, I also recorded other variables to compare e-scooter and bicycle crashes. The framework uses a series of codes that enable comparison between modes (Table 2). For example, the crash type "S-CR" means that motor vehicle is going straight, while the vulnerable road user is crossing from the right of the motorist.

2.3.3 Statistical Test

The relatively small sample size of observed motor vehicle-involved e-scooter and bicycle crash records restricted the crash comparison to univariate statistical analysis. Most variables, such as gender, weather condition, and PBCAT typology, are categorical variables. I also converted continuous variables, like age and crash distance from home, into bins to further examine the distribution. I used Fisher's Exact test of independence, which is more accurate than the chi-square test for small samples, to evaluate if the distribution of the e-scooter crash depends on the distribution of bicycle crashes. I also used a t-test for continuous variables to evaluate the difference in means for e-scooter and bicycle crashes.

2.3.4 Crash exposure analysis

Building upon the crash database described earlier, I extracted identify 82 motor vehicle-involved e-scooter crashes from September 2018 to January 2022. I acquired the Shared Urban Mobility Device (SUMD) dataset for e-scooter exposure for September 2018 to February 2020 from the City of Nashville through a data request. Through a similar request, Populus Technologies, Inc, which currently curates e-scooter data for the City of Nashville, provided trip data through January 2022. I extracted dawn and dusk time for each day to identify the

Table 2 PBCAT crash typology

VRU Maneuver / Motorist Maneuver	CR: Crossing from motorist's right	CL: Crossing from motorist's left	PS: Moving in same basic direction as the motorist	PO: Moving in opposite direction as the motorist	ND: Not moving or unknown direction	OV: Pushing, on, or clinging to a motor vehicle	UO: Unknown/ Other circumstances
S: Going straight	S-CR	S-CL	S-PS	S-PO	S-ND	S-OV	S-UO
R: Turning right (or preparing to turn right)	R-CR	R-CL	R-PS	R-PO	R-ND	R-OV	R-UO
L: Turning left (or preparing to turn left) or making a U-turn	L-CR	L-CL	L-PS	L-PO	L-ND	L-OV	L-UO
P: Parked (not in transport)	P-CR	P-CL	P-PS	P-PO	--	P-OV	P-UO
D: Slowing or stopped in traffic (in transport)	D-CR	D-CL	D-PS	D-PO	D-ND	D-OV	D-UO
E: Entering roadway or traffic lane	E-CR	E-CL	E-PS	E-PO	E-ND	E-OV	E-UO
B: Backing up	B-CR	B-CL	B-PS	B-PO	B-ND	B-OV	B-UO
O: Other/Unknown	O-C	O-C	O-P	O-P	O-ND	O-OV	O-UO

proportion of trips completed and crashes occurring during daytime and nighttime hours (Kennedy, 2020).

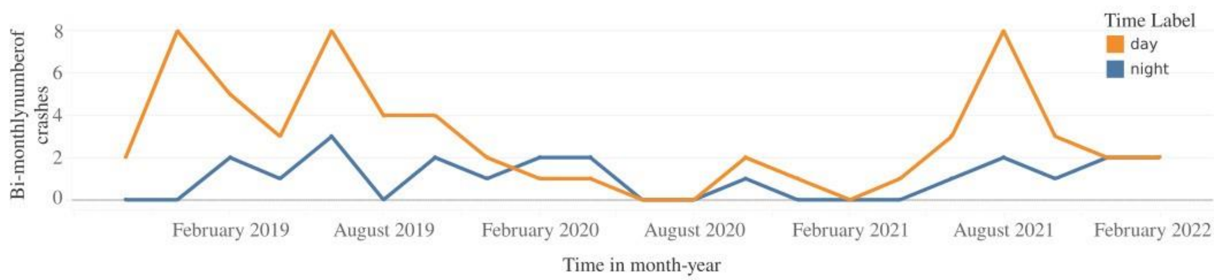
I received hourly aggregated data from Populus with basic data cleaning (a total of 1,758,327 trips from March 2020 to January 2022). I cleaned the SUMD trip dataset from September 2018 to February 2020 following similar criteria as Populus (i.e., duplicates, trips with two or fewer GPS coordinates or more than five thousand GPS coordinates, and trips greater than seven hours). I also removed trips less than 200 feet, leaving 3,162,728 trip records throughout the study period for the analysis.

Figure 6 summarizes the bi-monthly number of crashes, number of e-scooter trips, and the number of crashes per e-scooter trip (crash rate) segmented by day and night throughout the study period. We used the bi-monthly level of aggregation because some months did not have any daytime or nighttime e-scooter crashes. The number of daytime crashes was generally higher than the number of nighttime crashes, as illustrated in Figure 6 (a). The number of daytime trips was also higher than the number of nighttime trips, as illustrated in Figure 6 (b). However, nighttime crash rates were generally higher than daytime crash rates, as indicated in Figure 6 (c).

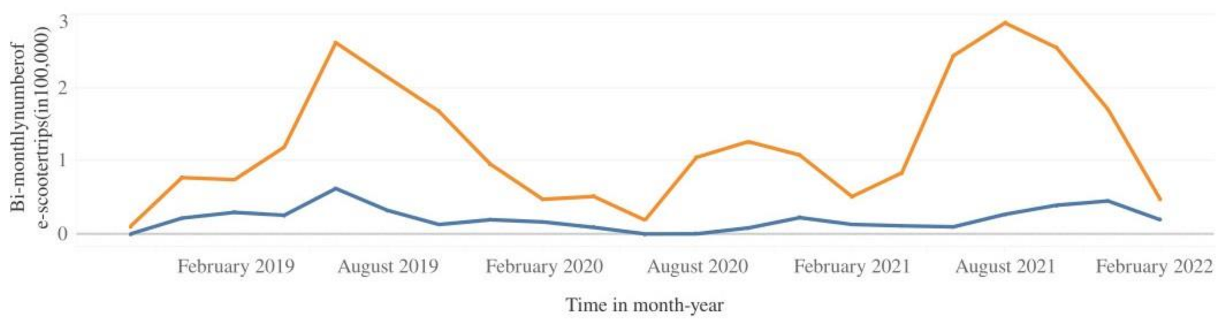
I used negative binomial regression in Stata to evaluate the statistical difference in the daytime and nighttime crash rates, with the number of trips as the exposure variable. The dependent variable is the number of bi-monthly crashes, and the independent variable is a dummy variable indicating nighttime crashes. I removed the data for peak COVID-19 months between March 2020 to May 2020, as there was low vehicular traffic. I also added a dummy variable for crashes observed between March 2020 to December 2020 as a control for COVID-19 since travel behavior was dramatically disrupted then. I also used dummy variables for bi-monthly observations to control for seasonal variation in e-scooter usage.

2.4 Results

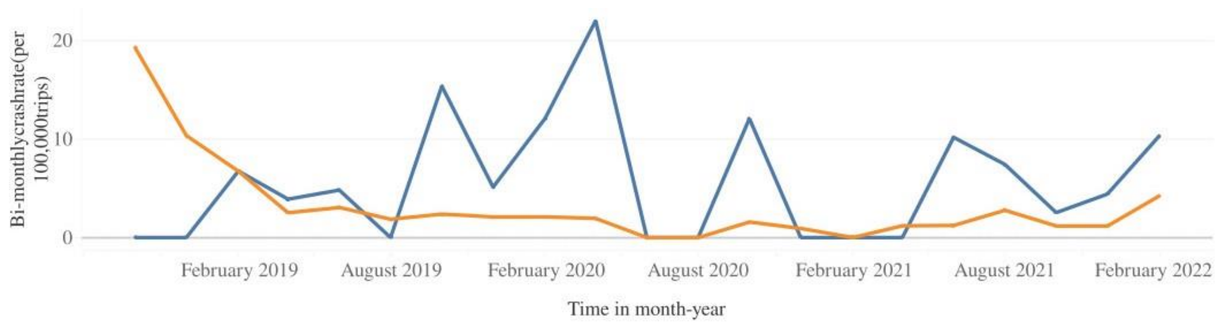
This section summarizes the key findings from the study, which are organized into two sub-section. The descriptive analysis of the crashes is presented in the first sub-section, followed by the crash typology in the next sub-section.



(a)



(b)



(c)

Figure 6 Bi-monthly number of e-scooter crashes, trips, and crash rates segmented by day and night

a) number of crashes, b) number of trips, c) crash rates

2.4.1 Descriptive Analysis of Crashes

I evaluated the differences in the characteristics of e-scooter and bicycle crashes that are not inherently included in the PBCAT crash typology. This sub-section summarizes the descriptive analysis of such characteristics.

2.4.1.1 Temporal and Spatial Distribution

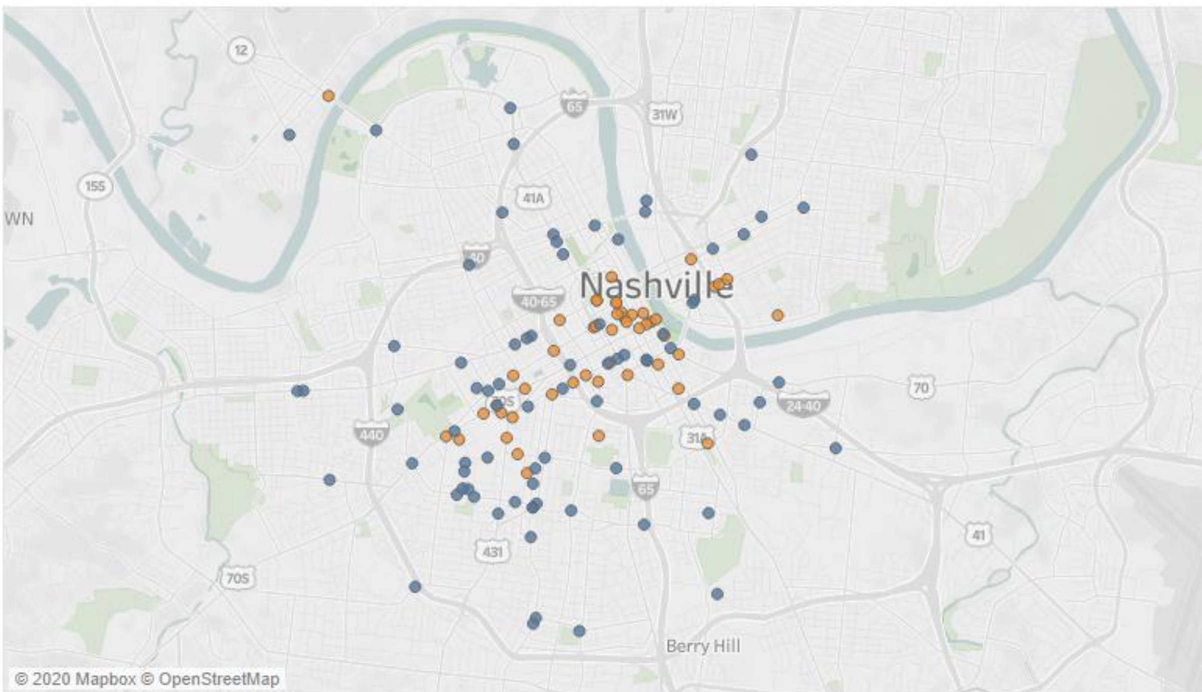
Figure 7 (a) presents the monthly crashes of bicycles and e-scooters (represented as a percentage of total crashes of each mode) from April 2018 to April 2020, whereas the locations of crashes for both modes are plotted in Figure 7 (b). The first e-scooter crash was reported in May 2018, while the first peak of e-scooter crashes was observed in October 2018, and the crash rate peaked in May 2019. The peak of bicycle crashes during the study period was observed in August 2018 with smaller subsequent peaks. The number of crashes for both modes increased during the summer of 2019. Figure 7 (b) illustrates that the e-scooter crashes were mostly concentrated in the city center of Nashville, whereas the bicycle crashes were more spatially dispersed.

2.4.1.2 Crash Characteristics and Demographics

Figure 8 shows the general characteristics and demographics of the bicyclists and e-scooter riders involved in crashes. The weather and light conditions of crashes of both modes are illustrated in Figure 8 (a) and Figure 8 (b), respectively. E-scooter and bicycle crashes have similar weather conditions (Fisher's Exact test p-value=0.779) and lighting conditions (Fisher's Exact test p-value=0.134). Most of the e-scooter and bicycle crashes occur in clear or cloudy weather conditions and daylight. Although not statistically significant, it is worth noting that e-scooter crashes occurred more frequently in dark and lighted conditions than bicycles (26% vs. 17%) and less frequently in no light condition (4% vs. 12%). It is likely that Downtown Nashville, where most of the e-scooter crashes occurred, is better lit during the nighttime than bicycle crash locations, mostly outside the city center on potentially unlit roads.

Figure 8 (c) and (d) reflect the intoxication level of the bicycle/e-scooter riders and the motorists, respectively. There is no significant difference in the intoxication level (about 20%) among e-scooter riders and bicyclists involved in the crash (Fisher's Exact test p-value = 1.000) and motorists colliding with e-scooter or bicycle (Fisher's Exact test p-value = 0.827). I found only

(a)



(b)

Figure 7. Temporal and spatial distribution of bicycle and e-scooter crashes
(a) Temporal distribution, (b) spatial distribution

two motor vehicle-involved e-scooter crashes (4% of e-scooter-related crash in the study) involved intoxicated e-scooter riders, including one fatal crash. On the other hand, most bicyclists, e-scooter riders, and motor vehicle drivers were not reported to be intoxicated during other crashes. This contrasts findings that many injured scooter riders are intoxicated (Kobayashi et al., 2019). It is worth mentioning that most of the intoxication tests are based on observation of the police officer at a crash location, and they are not reliable unless the breath test is administered for both motor vehicle driver and bicycle/e-scooter rider. However, 1 in 5 bicycle-motor vehicle and e-scooter-motor vehicle crashes involved a hit and run, where motor vehicle drivers most often fled the crash scene. I found a few instances of bicyclists and e-scooter riders leaving the scene before police arrived for minor crashes. Thus, a significant number of motor driver intoxication data is not available, as the drivers fled in a hit-and-run event.

The age distribution of bicyclists and e-scooter riders recorded in police crash reports are plotted in Figure 8 (e). E-scooter riders crashing with motor vehicles tend to be younger in age than bicyclists colliding with a motor vehicle (t-test p-value = 0.010 and Fisher's Exact test p-value = 0.021 for age group). Although the legal age to ride e-scooters in Nashville is 18 years, 13% of e-scooter riders crashing with motor vehicles were below 18 years old. 65% of e-scooter riders were below 30 years compared to only 47% of bicyclists in the same age group. Similarly, Figure 8 (f) indicates the gender distribution of bicyclists/e-scooter riders involved in a crash, which is statistically different (Fisher's Exact test p=0.015). Males riding bicycles or e-scooters were more represented in crashes with a motor vehicle. Amongst crashes involving female riders, the proportion of e-scooter crashes is higher: 31% of e-scooter riders were females, while only 13% of bicyclists were females. This potentially reflects the higher proportion of women using scooters (Sanders, Branion-Calles, & Nelson, 2020).

2.4.1.3 Crash distance from home

Figure 9 summarizes the crash distance from home observed in the police crash report, estimated as the straight line distance of the centroid of the zip code of the driver or rider to the coordinates of the crash location. Figure 9 (a) shows a histogram of crash distance away from home for bicyclist/e-scooter riders. E-scooter riders are farther from home than bicyclists (Fisher's Exact Test p=0.000). More than 70% of the bicyclists lived within 3 miles of the crash location, while only 7% lived more than 50 miles away. On the other hand, only 40% of the e-scooter riders lived within 3 miles of the crash location, while approximately 38% of e-scooter riders lived more than 50 miles away. Though a substantial portion of e-scooter riders in the crash records appear to be visitors (e.g., tourists) in Nashville, a majority of scooter crash victims are local riders. In contrast, almost all bicyclists crashed within bicycling range of home.

Similarly, Figure 9 (b) shows the histogram of crash site distance from home for the motorists involved in a crash with bicycles and e-scooters. This is important because drivers from suburban and rural areas outside the city might not be experienced driving around bicycle and scooter riders. I did not find a statistical difference in motorist's crash distance crashing with an e-scooter or bicycle (Fisher's Exact test p-value = 0.747). However, most vehicle drivers involved in crashes live outside the core area of Nashville compared to e-scooter and bicycle riders who tend to be more local.

2.4.2 PBCAT Crash Typology

I used the PBCAT tool to identify the locations and maneuver of bicycles and e-scooter crashes reported in Nashville. The general location of e-scooter and bicycle crashes (road type such as intersection and driveway) is similar (Fisher's Exact test p-value = 0.644). Figure 10 summarizes the PBCAT typology on location factors. The vertical axis is a general crash location on vertical axes, and the horizontal axis is the bicycle or e-scooter rider's location during the crash.

As depicted in the diagram, most e-scooter and bicycle crashes occurred at an intersection (65% of e-scooter and 67% of bicycle crashes). Driveway-to-roadway junctions accounted for the second-largest number of crashes (17% of both e-scooter and bicycle crashes). Non-junctions along the roadway ranked third in the proportion of crash locations (13% of e-scooter and 14% of bicycle crashes). The distribution of bicycle crash locations is consistent with the national average (National Transportation Safety Board, 2019), and the locations of e-scooter crashes are similar to bicycle crash locations.

In contrast, the motor vehicle maneuvers during a crash with an e-scooter are different than colliding with a bicycle (Fisher's Exact test p-value 0.087), as illustrated in Figure 11. A motor vehicle turning left (L) contributed to 23% of e-scooter crashes and 9% of bicycle crashes, while the straight maneuver of the motor vehicle (S) accounted for 44% of e-scooter crashes and 31% of bicycle crashes. 33% of e-scooter and bicycle crashes occurred during the right maneuver of

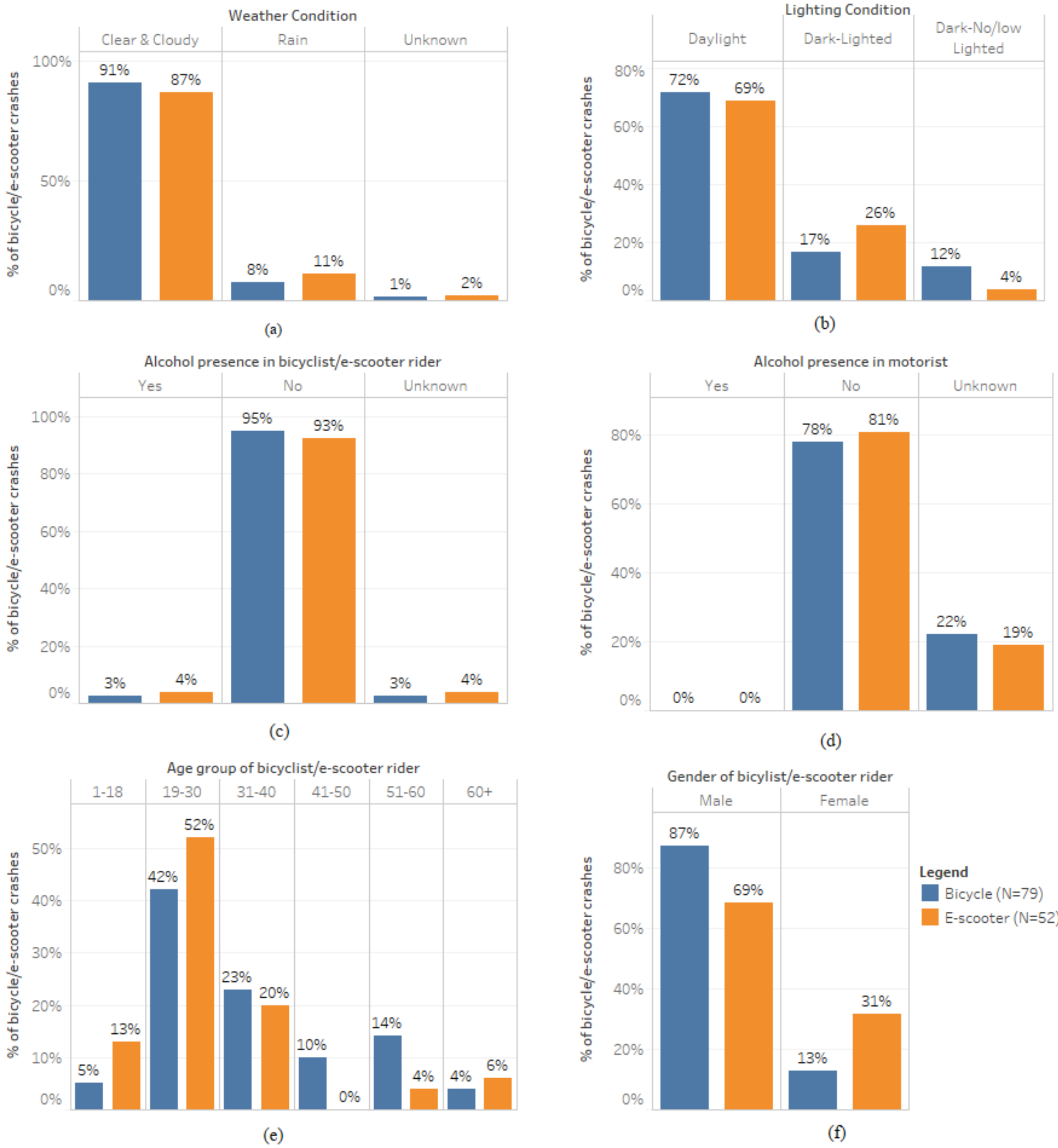
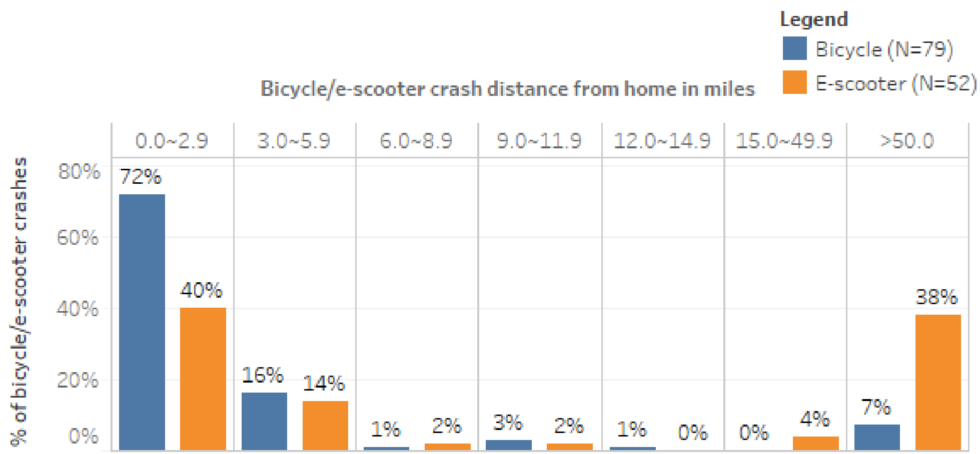
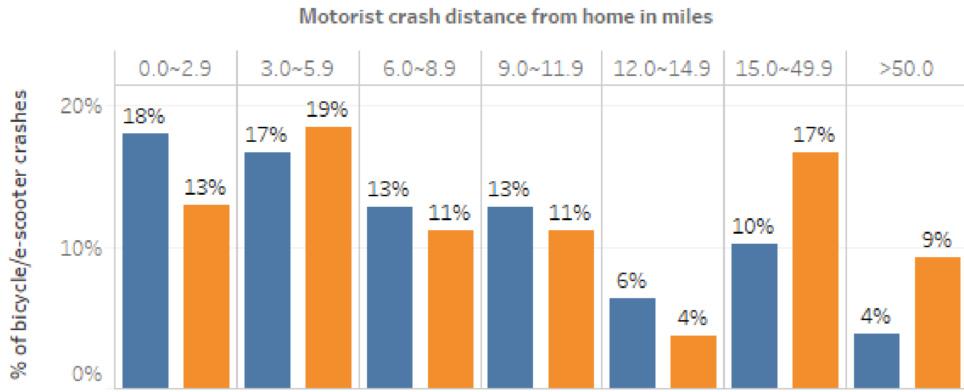


Figure 8. General characteristics of bicycle and e-scooter crashes

(a) weather condition, (b) light condition, (c) bicycle/e-scooter rider intoxication, (d) motorist intoxication, (e) age distribution of bicyclist and e-scooter riders, (f) gender distribution of bicyclist/e-scooter rider



(a)



(b)

Figure 9. Crash distance from home

(a) bicyclist/e-scooter riders; (b) motorists

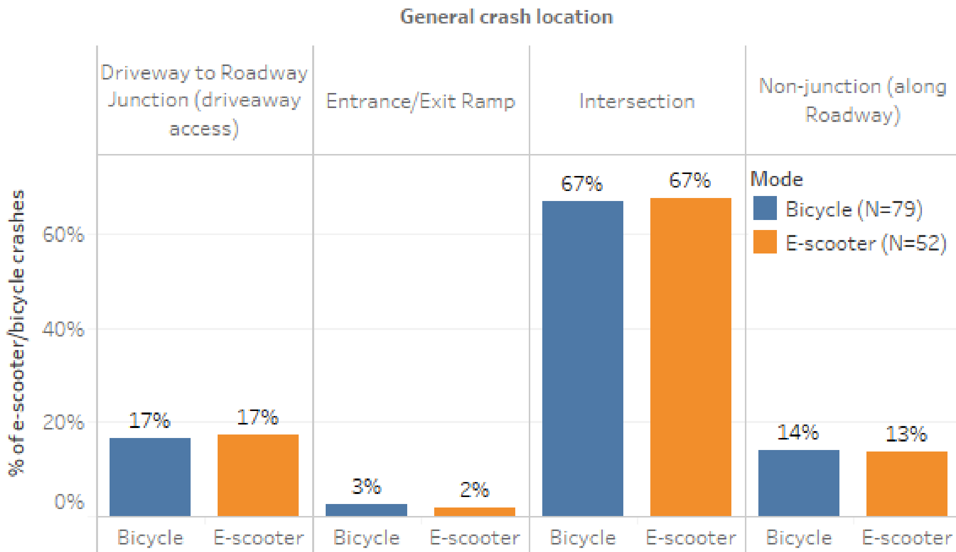


Figure 10. PBCAT typology – location

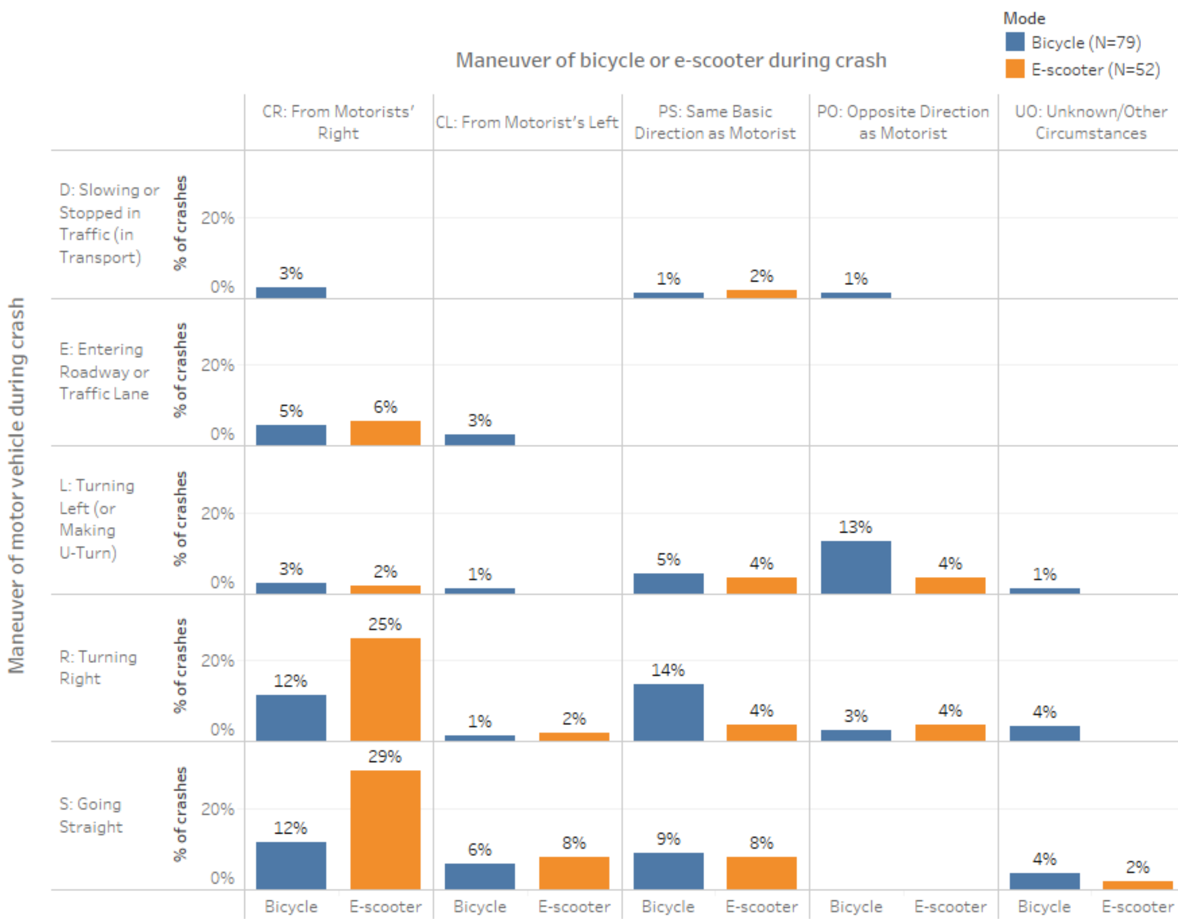


Figure 11. PBCAT typology - maneuver

the motor vehicle (R). Other maneuvers of motor vehicles contributed to a fraction of crashes for both modes.

Maneuvers of e-scooter riders before a crash is also different than bicyclists (Fisher's Exact test p-value = 0.055), as illustrated in Figure 11. The maneuver of e-scooter riders or bicyclists from the right side of the motor vehicle (CR) contributed to the most frequent crashes; however, the proportion is much higher for e-scooter crashes (59% of e-scooter crashes as compared to 33% of bicycle crashes). These were often e-scooters or bicyclists riding on sidewalks, approaching intersections from the driver's right side (opposite to drivers' expectations). E-scooters moving in the same direction as a motor vehicle (PS) accounted for 20% of e-scooter crashes, whereas 29% of bicycle crashes occurred for the same direction of maneuver. While other maneuver directions of e-scooters during crashes were not recorded in a substantial number, the maneuver of bicyclists from the opposite direction of the motor vehicle (PO) contributed to 17% of bicycle crashes, and maneuver from the left of a motor vehicle (CL) accounted for 12% of bicycle crashes. In summary, only two maneuvers (CR and PS) accounted for 80% of e-scooter crashes, whereas bicycle crashes were distributed among several maneuvers.

2.4.2.1 Intersection Crashes

Since more than 60% of the bicycle and e-scooter crashes occurred at an intersection, I further scrutinized these crashes. There is a strong difference in the distributions of e-scooter and bicycle crashes among the PBCAT crash typology (Fisher's Exact test p-value = 0.033). Table 3 summarizes the maneuvers of the motorists, bicyclists, and e-scooter riders at different locations of an intersection. The motor vehicle approaching the leg of an intersection is labeled as *Entering*, leaving the intersection as *Exiting*, and located in other areas of the intersection as *Middle/other areas*.

As shown in the Table 3, only a few PBCAT crash types contain the majority of e-scooter crashes. The most common types of e-scooter crashes at an intersection were S-CR and R-CR, which accounted for 31% and 29% of all e-scooter intersection crashes, respectively. As depicted in Figure 12 (a), the S-CR crash type indicates a motor vehicle moving straight with an e-scooter arriving from the right of the motor vehicle, while the R-CR type indicates a motor vehicle turning right with an e-scooter arriving from the right. 12% of e-scooter crashes at intersections

Table 3 PBCAT crash typology at intersections

Motorist maneuver	Location at intersection	CL: From the Motorist's Left		CR: From the Motorists' Right		PO: Opposite Direction as the Motorist		PS: Same Basic Direction as the Motorist		UO: Unknown/ Other Circumstances		Grand Total of motorist maneuver	
		B	**S**	**B**	**S**	**B**	**S**	**B**	**S**	**B**	**S**	**B**	**S**
D: Slowing or Stopped	Entering			2%					3%			**2%**	**3%**
	Middle / Other area			2%								**2%**	**0%**
E: Entering Roadway	Entering			2%								**2%**	**0%**
L: Turning Left	Entering				3%							**0%**	**3%**
	Exiting	2%		2%		12%	3%	6%	3%	2%		**23%**	**6%**
	Middle / Other area			2%		6%		2%				**10%**	**0%**
O: Other/ Unknown											3%	**0%**	**3%**
R: Turning Right	Entering		3%	10%	23%			8%	3%	4%		**21%**	**29%**
	Exiting			2%	6%	2%	6%	8%				**12%**	**12%**
	Middle / Other area	2%		2%								**4%**	**0%**
S: Going Straight	Entering	2%	3%	2%	11%			2%			3%	**6%**	**17%**
	Exiting	2%			11%					4%		**6%**	**11%**
	Middle / Other area	6%	9%	8%	9%							**13%**	**18%**
Grand total of either bicycle or e-scooter crashes		**13%**	**15%**	**33%**	**63%**	**19%**	**9%**	**25%**	**9%**	**10%**	**6%**		

Note: *the percentage indicated in the table is the percentage of either bicycle or e-scooter crashes*
Legend: *B = Bicycle and S = E-scooter*

were S-CL, where a motor vehicle was moving straight and an e-scooter collided from the left of the motor vehicle.

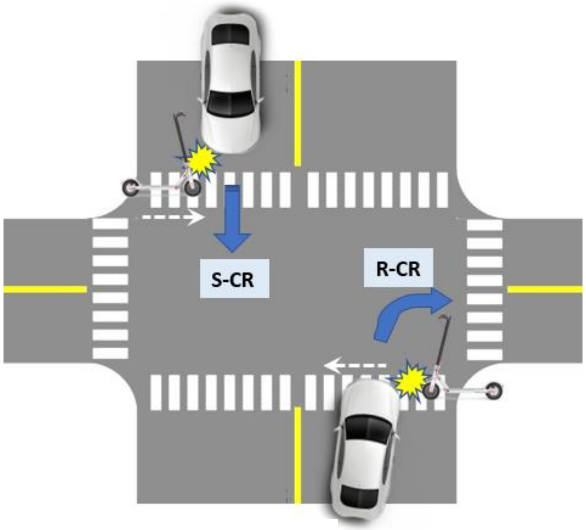
In contrast to the e-scooter crashes, the bicycle crashes are somewhat evenly distributed among the PBCAT crash typology. L-PO is the most common type with 17% of bicycle crashes at intersections. As depicted in Figure 12 (b), the L-PO crash type indicates a motor vehicle and bicycle traveling in opposite directions, and a collision occurs while the motor vehicle is turning left. The R-PS type accounts for 15% of bicycle crashes at intersections, where both the motor vehicle and bicycle are traveling in the same direction, and the motor vehicle turns right. Other bicycle crash typologies are R-CR, S-CR, and S-CL, each containing about 10% of bicycle crashes at the intersection.

2.4.2.2 Severity Levels of Crash Typology

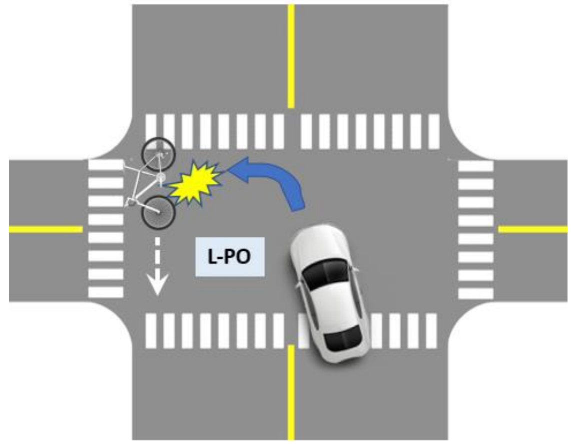
Approximately 1 in 10 e-scooter- and bicycle-motor vehicle crashes led to an injury. The distribution of severity by location is similar for both bicycle and e-scooter crashes; most crashes with injury and minor/no or unknown severity occur at the intersection, followed by driveway access and non-junction. The only fatal e-scooter crash reported in Nashville during the study period occurred at an intersection when the motor vehicle was traveling straight, and the e-scooter crossed from the right of the motor vehicle (S-CR).

Four e-scooter riders were injured among the 52 e-scooter crashes, with none of the motorists being injured. The predominant crash types for these e-scooter crashes are (1) the motor vehicle entering roadway with the e-scooter rider crossing from the right (E-CR) in a driveway, (2) the motor vehicle moving straight with the e-scooter crossing from the right (S-CR) at an intersection, (3) the motor vehicle turning right with the e-scooter crossing from the left (R-CL) at an intersection, and (4) the motor vehicle moving straight with e-scooter also moving in the same direction (S-PS) along a non-junction roadway.

Six out of 79 bicyclists were injured in bicycle-motor vehicle crashes, while none of the motorists were injured. Two such crashes occurred at intersections while the motor vehicle was moving straight and the bicyclist was crossing from the right side of the motor vehicle (S-CR). Two other crashes occurred while the motor vehicle was turning left with the bicyclist traveling in the same direction in the exiting leg of the intersection (L-PS). I reviewed one bicycle crash



(a)



(b)

Figure 12 Most common PBCAT crash typology at intersection
(a) e-scooter, and (b) bicycle

each for motor vehicles turning right with a bicyclist moving in the same direction (R-PS) at the intersection (a typical "right hook" crash) and a motor vehicle moving straight with unknown maneuver for the bicyclist (S-UO) at a non-junction roadway.

2.4.3 Crash exposure

Figure 13 summarizes the total number of e-scooter crashes and bi-monthly crash rates by daytime and nighttime. Out of 82 motor vehicle-involved crashes, 60 (73% of all crashes) occurred during the daytime, while 22 (27% of all crashes) occurred during the nighttime. On average, we observed 2.6 crashes per 100,000 trips. When segmented by daytime and nighttime, the crash rate during the night was higher than during the daytime (4.8 vs. 2.2 crashes per 100,000 trips).

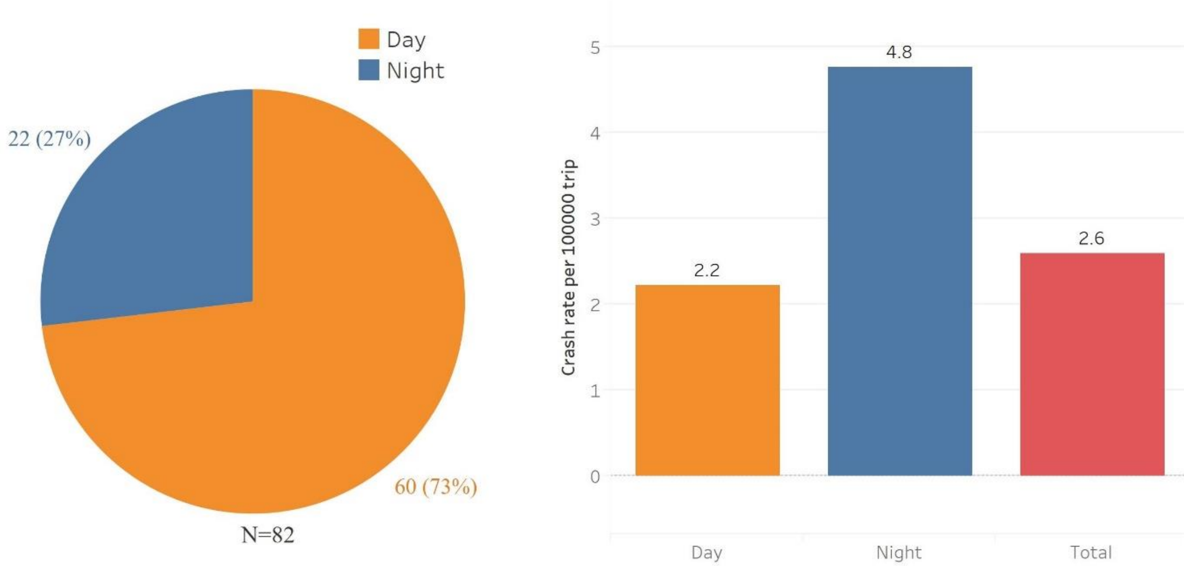
Table 4 includes the negative binomial regression model results of bi-monthly daytime and nighttime e-scooter crash rates. The model is statistically significant (probability of LR test statistics is 0.027). The dummy variable for nighttime crashes is significant, indicating that the likelihood of nighttime crashes is 1.81 times greater than daytime crashes. The COVID-19 control is also significant, suggesting that the number of crashes decreased by a factor of 0.28 during the peak pandemic era, when accounting for exposure.

2.5 Implications

Based on the findings of bicycle- and e-scooter-motor vehicle crashes in Nashville, the following four subsections provide a discussion on the general crash characteristics of bicycles or e-scooters colliding with a motor vehicle. The next two subsections emphasize the location and maneuver of bicyclists/e-scooter riders and motorists before the crash.

2.5.1 Temporal and spatial distribution of crash

I observed higher crash rates during the summer. A higher number of bicycle and e-scooter trips could contribute to an increase in exposure, as e-scooter ridership is predominantly high during weekends and summer months (N. R. Shah, 2020) and bicycle volumes are also higher in summer (Miranda-Moreno, Nosal, Schneider, & Proulx, 2013). Additional hours of daylight during the summer could also contribute to increased exposure. Therefore, educational campaigns on bicycle and e-scooter safety could be most effective during weekends and summer



(a) (b)

Figure 13 Total number of e-scooter crashes and crash rates per 100,000 trips aggregated bi-monthly

a) Distribution of daytime and nighttime crashes, b) Crash rates based on the number of trips

Table 4 Results of the negative binomial regression of e-scooter crash rates aggregated bi-monthly

Dependent variable: number of crashes	**Incidence Rate Ratio (IRR)**	**Standard Error**	**p-value**
Nighttime crashes (dummy variable)	2.81	0.50	0.034
COVID-19 control (dummy variable)	0.28	0.15	0.018
Constant	4.51	1.39	0.000
Alpha	0.05	0.11	
Model statistics			
Time control	Bi-monthly		
Number of observations	38		
Log-likelihood	-59.31		
Probability of LR test	0.027		

months, as ridership and crash rates are highest during these times. Furthermore, COVID-19 may have affected the crash rates at the end of the study period by contributing to lower motor vehicle traffic, a change in e-scooter/bicycle ridership, or a combination of both.

The compact spatial distribution of e-scooter crashes around downtown Nashville and Vanderbilt University is consistent with the general e-scooter usage locations revealed by other studies (Bai & Jiao, 2020; N. R. Shah, 2020). E-scooters have high levels of exposure in this area, which is influenced by device availability, as most e-scooters are distributed in densely built environments. On the other hand, bicycle crash locations were also spread outside the core part of the city. E-scooter safety measures should be prioritized in downtown and university areas, while bicycle safety measures should also target areas further away from downtown areas.

2.5.2 Crash characteristics

Most of the e-scooter- and bicycle-motor vehicle crashes occur during daylight. However, the second-highest proportion of e-scooter crashes occurred during nighttime in lit conditions, whereas bicycle crashes occurred more frequently during nighttime in no-light conditions. E-scooters are mainly used in the densely built environments of downtown Nashville and Vanderbilt University (N. R. Shah, 2020), which are usually well-lit, while bicycle crash locations, which are usually away from the core area of the city, might not have adequate lighting. Therefore, additional confounding factors other than lighting could contribute to e-scooter crashes at night, whereas improving lighting at nighttime bicycle crash hotspots could reduce bicycle crash rates.

Other crash characteristics can reveal safety implications to reduce e-scooter and bicycle-related crashes and injuries. Despite common perceptions, only a few e-scooter or bicycle riders were reported as intoxicated at the time of the crash, even in nighttime entertainment districts. But 1 out of 5 crashes involved a hit-and-run, with most hit-and-run cases including motorists and a few cases of the bicyclist or e-scooter riders leaving the crash scene before the arrival of police. The reduction of such hit-and-run might require stronger education and enforcement, such as a surveillance camera at crash hotspots. Of those involved in crashes with motor vehicles, 1 in 10 bicycle/e-scooter riders were injured while none of the motorists were injured. This disproportionate injury rate reinforces that bicyclist and e-scooters riders are vulnerable road user group who requires additional safety measures compared motor vehicles.

2.5.3 Demographics of crash victims

Bicyclist and e-scooter riders who collided with a motor vehicle in Nashville were predominantly male. Amongst the crashes involving female riders, the proportion e-scooter crashes are higher than bicycle crashes (29% vs. 13%) in our police-reported data. Pilot evaluations of shared e-scooter programs also reported that approximately one-third of e-scooter riders are females (City of Chicago, 2020; Portland Bureau of Transportation, 2018). Women are generally more represented as e-scooter riders than as bicyclists. Therefore, the e-scooter safety campaign should also be geared toward female riders.

The e-scooter riders crashing with a motor vehicle are younger than bicyclists involved in crashes. This does not necessarily prove that younger age groups have risky riding behavior, as younger demographics have higher ridership and crash exposure on e-scooters (Bai & Jiao, 2020; Caspi, Smart, & Noland, 2020; City of Chicago, 2020). The survey result of e-scooter pilot programs also found that these emerging modes are popular among the age group of 18 to 40 years (Austin Public Health, 2019; City of Chicago, 2020). Adapting safety campaigns to the ridership age group could increase their effectiveness, such as e-scooter campaigns targeted towards younger adults and bicycle campaigns geared towards older age groups.

I found that 13% of all e-scooter riders were below the age of 18 in our police crash report, despite the legal age of 18 to ride an e-scooter in Nashville. Although the crash report does not necessarily represent the actual ridership for this age group, a significant number of minors could be riding e-scooters. Organizations such as the American Academy of Pediatrics (AAP) do not recommend children below the age of 16 to operate e-scooters (Morgan, 2019). More vigilant enforcement, as well as educational strategies, by law enforcement agencies and advocacy groups could help discourage the use of e-scooters amongst this vulnerable age group. As e-scooter service operators require users to upload a valid driver's license before the first trip (Fawcett, Barboza, Gasvoda, & Bernier, 2018), the e-scooter service operators could also take proactive steps to ensure that their active users are above the legal age to operate e-scooters.

2.5.4 Crash distance from home

The home location of e-scooter riders, bicyclists, and motorists can influence riding or driving behavior and road safety approaches. Over 70% of bicyclists lived within three miles of the crash location. Additionally, 38% of e-scooter crashes occurred more than 50 miles from home, compared to 7% for bicyclists. In the absence of extensively available bikeshare options, it is possible that a majority of bicyclists in Nashville own their bikes, and the limitation in the geographical coverage of bicycling could therefore explain the number of bicycle crashes near home. In contrast, shared e-scooters are more visible and accessible to visitors in Nashville, which could explain that a high number of e-scooters rider crashed more than 50 miles from home. Visitors using e-scooters might not be familiar with roadway and traffic conditions of Nashville, which could have led to crashes. Still, even in a tourist-oriented city, more than half of the crash-involved scooter riders are local to Nashville.

Similarly, motorists involved in crash live further from home than e-scooter or bicycle riders. As e-scooters are popular in dense urban areas, motor vehicle drivers living in suburban or rural areas could be unfamiliar with the interaction of e-scooters, leading to crashes. Other studies have also found the crash distance from home as a significant predictor of mode of travel (Haas et al., 2015; Steinbach, Edwards, & Grundy, 2013).

A combination of educational, wayfinding, and infrastructure improvements could reduce e-scooter- and bicycle-motor vehicle crashes that involve visitors to metro areas. Educational efforts could focus on educating drivers to expect e-scooters and bicyclists when entering the downtown area, while visitors could be cautioned about the specific risk of riding e-scooters in the city. Multimodal street design that accommodates e-scooters in combination with well-visible signs and markings could also guide e-scooter users to avoid crash risks and dangerous infrastructure.

2.5.5 Crash locations

I did not find any difference in the distribution of e-scooter- and bicycle-motor vehicle crash locations by road type in the police crash report database of Nashville, Tennessee. Both bicycle and e-scooter crashes followed the national average distribution of bicycle crashes by location (NHTSA, 2008). Traffic designs, enforcement, and education for bicycle and e-scooter safety should prioritize intersections, as more than 60% of e-scooter- and bicycle-motor vehicle collisions occur at these locations. Protected intersection designs that slow down vehicles and emphasize vulnerable road users, such as raised pavements, can reduce conflicts among road users.

Safety measures to increase visibility of e-scooters and bicyclists can also reduce intersection crashes. I recommend intersection design to increase the conspicuity of e-scooters and bicyclists, and at night, combined with improved head and taillights and retro-reflectivity on bicycles and e-scooters may help overcome this visibility challenge. The infrastructure design should be complemented with enforcement strategies and educational campaigns that deter traffic rule violations and risky behaviors. For example, the combination of corridor improvement approach and speed camera enforcement reduced the likelihood of incapacitating or fatal injury by 39% in Virginia (Hu & McCartt, 2016).

2.5.6 Maneuvers before the crash

Only a few PBCAT crash typologies could explain most e-scooter-motor vehicle crashes in Nashville, Tennessee. Of all e-scooter crashes, 54% occurred at an intersection with a motor vehicle traveling straight or turning right and an e-scooter rider entering the crosswalk from the right. Intersection safety designs, like curb extensions and raised pavement, can force drivers to reduce speed and check their far-side view for vulnerable road users. Removing right-turn-on-red allowance could reduce conflicts by allowing drivers to focus on traffic from all directions. Educating both motor drivers and e-scooter users on these common crash mechanisms could improve risk awareness and reduce such crashes.

In contrast, bicycle-motor vehicle crashes were distributed among several PBCAT crash typologies. I found significant bicycle-related crashes in some maneuvers, such as a motor vehicle turning left while a bicycle was traveling in the opposite direction of the motor vehicle, but there were few such e-scooter crashes. We cannot reasonably speculate why those crash mechanisms differ. Nevertheless, the difference in crash typology distribution points to different collision mechanisms between e-scooter- and bicycle-motor vehicle crashes. Therefore, safety measures targeted towards bicycles, for example, might not reduce e-scooter crashes.

2.5.7 Crash exposure

Possible reasons that e-scooter rides are riskier at night compared to daytime could be a) low conspicuity as e-scooters are small and are not equipped with powerful lights, b) low visibility due to poor lighting of streets that makes it difficult for motor vehicle drivers and e-scooter riders to be aware of their environment. I did not see strong evidence of alcohol impairment in the police crash reports from drivers or e-scooter riders for the same crash dataset. The policy implication of the nighttime crash rate being higher than daytime could justify policy or technology interventions to improve the safety of e-scooter riders at night. Like other Vulnerable Road Users (VRU) (Ferenchak & Abadi, 2021), e-scooter riders are more vulnerable to crashes at night. Future research can perform exposure analysis on the network to identify riskier infrastructure and evaluate exposure with rider demographics (gender and age group) and riders' experience (first time vs. regular riders).

2.5.8 Limitations and future research

This study has several limitations. First, the relatively small sample size of the e-scooter and bicycle crashes did not allow rigorous multivariate statistical analysis. A breakdown of variables increases the degree of freedom to reduce the power of statistical analysis and mask any significant relationship. This limitation did not allow us to scrutinize the crash typology and injury severities further. Second, the results should not be generalized for every cities as this study is based on evaluation e-scooter and bicycle crashes with motor vehicle in Nashville, Tennessee and crashes tend to show spatial heterogeneity. Third, I only evaluated motor vehicle collisions, whereas bicycle and e-scooter crashes can also occur due to additional causes, such as falling and colliding with stationary objects.

Furthermore, crashes are generally underreported as some of the non-injury and small property damage incidents are not reported to the police. Severity of crashes is reported by police and emergency department data is known to provide better diagnostic performance. Future work linking emergency department and crash data would illuminate this area. Finally, the crash database lacks exposure information, total ridership, that would allow for the evaluation of scalable risks relative to the number of road users and the use of infrastructure.

Future research can combine methods and multiple data sources to provide better nuances of e-scooter safety. For example, naturalistic data collection methods, like video cameras and sensors, can evaluate near-miss crashes involving e-scooters. The comparison of multiple crash databases, such as police crash reports and hospital data, can help to derive correction factors for estimating accurate crash statistics. Furthermore, a comparison of e-scooter safety among different cities could provide insights on the geographical heterogeneity of e-scooter crashes, as well as the impacts of certain safety-related policies, such as no riding on the sidewalk. It is possible that tourists, students, or first-time riders are more prone to crashes with cars. Researchers can also explore crash severity and types of infrastructure used during the day or night as well as compare the crash rates over time.

2.6 Conclusion

I evaluated two years of bicycle and e-scooter crashes in the urban part of Nashville, Tennessee, using the police crash report maintained by the Tennessee Department of Transportation. I noted differences in e-scooter- and bicycle-motor vehicle crashes in temporal and spatial distributions, crash characteristics, crash distance from home, and maneuver of motorists and bicyclists or e-scooter riders before the crash. However, I did not find an apparent difference concerning the locations by road type of the crashes. I also found that nighttime e-scooter riding is twice as risky as daytime. Additionally, I made design, enforcement, and education recommendations to prevent and reduce those crashes in the future. Moreover, this study reinforces the importance of standardization of crash records that would better enable the data-driven evaluation of emerging transportation modes like e-scooters.

Chapter 3. Demand elasticity of e-scooter vehicle deployment

This chapter is based on a research paper by Nitesh R Shah, Abubakr Ziedan, Candace Brakewood, and Christopher Cherry titled "Shared E-Scooter Service Providers with Large Fleet Size Have a Competitive Advantage: Findings from E-Scooter Demand and Supply Analysis of Nashville, Tennessee." The paper is in review at the Transportation Research Part A: Policy and Practice. This paper was presented at the Transportation Research Board Annual Meeting 2022 in Washington, D.C, and the Tennessee Section Institute of Engineers Summer Meeting 2022 in Gatlinburg, Tennessee. This research paper also received the second position in the Annual Student Paper Competition, Tennessee Section Institute of Transportation Engineers (TSITE).

Abstract

Shared e-scooter systems are one of the fastest-growing micromobility modes in the United States. In response to service providers' rapid deployment of e-scooter vehicles, several city governments have regulated shared e-scooters through permits and pilot programs, including the number of service providers, their fleet size, and provisions for expanding/downsizing the fleet size. However, the literature lacks an empirical analysis of the demand elasticity of shared e-scooters. We used a negative binomial fixed effect regression to evaluate the demand elasticity of e-scooter vehicle deployment using the Shared Urban Mobility Device (SUMD) dataset from Nashville, Tennessee, between April 2019 and February 2020. This dataset included disaggregated e-scooter trip summary data and vehicle location data that updates approximately every five minutes. We also estimated land-use specific demand elasticity of e-scooter vehicle deployment by clustering Traffic Analysis Zones (TAZs) using the K-means algorithm. We found that the average daily demand elasticity of e-scooter vehicle deployment is inelastic (0.55). Service providers with large fleet sizes (>500) have a demand elasticity of e-scooter deployment that is 2.5 times higher than that of medium fleet-sized service providers (250-500). We also found a significant difference in demand elasticity of e-scooter deployment for land use types, with university and park & waterfront land uses having the highest elasticity values. These findings could be helpful for city governments to identify the optimal number of service providers and fleet sizes to permit so that demand is fulfilled without an oversupply of e-scooter vehicles in public spaces.

3.1 Introduction

Soon after the first launch of e-scooters in the United States (Santa Monica in 2017), e-scooter service providers rapidly expanded in other cities (Reinhardt & Deakin, 2020). Some city governments quickly moved to regulate scooter operators and introduced permits and pilot programs to control negative impacts, test the viability of e-scooters, and evaluate policies to manage public spaces. These permits and pilot programs have a wide range of dimensions to regulate the demand and supply of shared e-scooters, including the number of service providers allowed to provide service, each operator's fleet size and limits, geographic bounds, and the potential for expansion and downsizing of operations (Janssen et al., 2020; NACTO, 2019). The fleet size influences the availability of e-scooters, with a required minimum number of e-scooter vehicles ensuring robust availability while a maximum cap limits oversupply. Several cities also have provisions for increasing or decreasing the total number of e-scooter vehicles deployed based on performance metrics (like riders per vehicle per day) or compliance with permits (such as the specific proportion of trips serving targeted service areas) (NACTO, 2019).

These policy dimensions vary across cities without a common consensus on best practices (Ma et al., 2021). Most guidelines recommend that the city government determine the number of service providers and fleet size based on policy goals and metrics (like population size and density) and lessons learned from comparable cities (NACTO, 2019; Remix, 2018). Janssen et al. (2020) found that the number of service providers, their fleet size, and cities' expansion/downsizing plans varied among ten cities comparable in population size and density, government structure, and level of bicycling infrastructure. They found that many cities changed and adapted these policies over time, either based on their own experience or learning from other cities. Moreover, the literature lacks an empirical analysis of the effect of the number of service providers and their fleet sizes on the volume of e-scooter trips.

This chapter estimates the demand elasticity of deployed e-scooter vehicles by comparing actual demand (e-scooter usage) with supply dimensions (vehicles deployed). I use a nearly year-long geographically disaggregated e-scooter trip summary dataset and location of available e-scooters that updates approximately every five minutes for our analysis. The elasticity values segmented by weekday/weekend, land use types, and shared e-scooter service providers based on their fleet size can help city governments identify the appropriate size of shared e-scooter systems operating within their jurisdiction.

3.2 Review of literature

Several studies have investigated temporal and spatial characteristics influencing the demand of e-scooters, while few studies have considered the supply aspect of shared e-scooters. This section summarizes the existing studies in three subsections. Section 3.1.1 provides an overview of temporal factors (e.g., trip starting time and weather) influencing e-scooter trips, followed by spatial factors (e.g., land use and transportation infrastructure) in section 3.1.2. Section 3.1.3 summarizes relevant studies that include the availability of e-scooter vehicles (supply side).

3.2.1 Temporal factors influencing e-scooter trips

E-scooter usage has a strong correlation with time (time-of-the-day, day-of-the-week, and month-of-the-year). McKenzie (2019) compared the e-scooter trip start times with bikeshare in Washington, DC to find that e-scooter use closely resembled casual bikeshare trips, with one daily peak in the evening and higher weekend peaks compared to other days of the week. Comparing e-scooter usage between Austin, Texas, and Minneapolis, Minnesota, Bai and Jiao (2020) found that the peak usage time of e-scooter varied between these two cities; Austin showed peak hour use in the afternoon and weekends, while the Minneapolis peak hour was in the evening. Previous shared e-scooter studies in Nashville found that the usage peaks in the evening and on weekends (N. Shah, 2020; Nitesh R Shah, Jing Guo, et al., In review).

A few studies have found that weather and major events in the city affect e-scooter trip volume. Younes, Zou, Wu, and Baiocchi (2020) found that special events like the Cherry Blossom Festival and high gas prices significantly increased e-scooter usage in Washington, DC. The authors also found a negative influence of precipitation, humidity, and wind speed on hourly e-scooter trip volume, but days with warmer temperatures had higher trip volume. Similarly, Mathew, Liu, and Bullock (2019) found that the number of trips dropped significantly for days with a mean temperature below freezing in the City of Indianapolis, Indiana.

3.2.2 Spatial factors influencing e-scooter trips

Studies have found a significant relationship between the built environment and e-scooter usage. Bai and Jiao (2020) found that e-scooter trips predominantly occur in downtown and university areas in Austin, Texas, which corroborates the finding that most e-scooter crashes were observed in downtown and Vanderbilt University in Nashville, Tennessee (Nitesh R Shah et al., 2021). Several studies have found that land use density (e.g., commercial, public, and industrial) and diversity influence e-scooter usage (Bai & Jiao, 2020; Caspi et al., 2020; Hosseinzadeh, Algomaiah, Kluger, & Li, 2021a). Similarly, urbanism scores (e.g., walk, bike, and transit scores) and infrastructure-related variables, including transportation-related variables (e.g. proximity to transit stops), also impact the number of e-scooter trips (Bai & Jiao, 2020; Hosseinzadeh, Algomaiah, et al., 2021a).

Studies exploring factors of e-scooter usage have found a correlation between socio-demographic variables, like gender and age, and e-scooter trip demand using data aggregated at the Census Block Group (CBG) or Traffic Analysis Zone (TAZ) level. Caspi et al. (2020) found that low-income CBGs with student populations had higher e-scooter trips than low-income CBGs without a student population. Similarly, Hosseinzadeh, Algomaiah, Kluger, and Li (2021b) found a strong and positive correlation between e-scooter usage and TAZs with a higher percentage of 18-29 year-old male residential population. Survey-based studies have also found that e-scooters are popular among certain socio-demographic groups, mainly white younger populations in Santa Monica and San Francisco, California (City of Santa Monica, 2019; San Francisco Municipal Transportation Agency, 2019).

3.2.3 E-scooter vehicle distribution and pricing among service providers

Shared e-scooter usage is also influenced by the availability of e-scooter vehicles, which depends upon many factors, such as fleet deployment strategies and competition among multiple service providers. E-scooters have a relatively low unit cost, with the convenience of redistributing the fleet to maximize the profit for services providers (Button, Frye, & Reaves, 2020). Moran, Laa, and Emberger (2020) compared the geofences (service areas) of six e-scooter service providers over three months in Vienna, Austria. They found that e-scooter deployment was influenced by high/low usage location, hotspots of e-scooter vandalism and damage, and the convenience of e-scooter collection for charging and rebalancing.

The presence of an e-scooter nearby strongly influences the user's decision to make an e-scooter trip. Reck, Haitao, Guidon, and Axhausen (2021) evaluated the choice of using dockless e-scooters (among two service providers), dockless e-bikes, and docked bikes considering vehicle density within a 2-minute walking distance at the trip origin, battery charge level, and price of the trip in Zurich, Switzerland. They found that higher vehicle density corresponded to higher use of e-scooters. On the other hand, the probability of e-scooter use was lower for battery power levels of less than 50%, with significant variation among the two service providers. This study did not evaluate the elasticity of e-scooter vehicles at a city level.

3.2.4 Research objectives

Existing studies have evaluated the temporal and spatial factors influencing the demand for e-scooters, mostly without considering the effect of e-scooter availability and the presence of multiple service providers. However, there is evidence of e-scooter vehicle density affecting trip volume (Reck et al., 2021). Several recent studies have identified estimating the demand elasticities of e-scooter deployment at a city level as a key research gap (Button et al., 2020; Lo, Mintrom, Robinson, & Thomas, 2020). This study combines both demand and supply aspects of shared e-scooters with the following research objectives:

1. Estimate the demand elasticity of e-scooters deployed (measured as e-scooter hours deployed) of service providers based on the fleet size, controlling for spatial factors, like built environment and socio-demographics, and temporal factors, such as weather
2. Estimate the land-use specific demand elasticity of e-scooters vehicles deployed by service providers based on the fleet size

The remainder of the chapter is organized into the following sections. Section two provides a brief description of the study design in the methodology section. Section three summarizes the model results, while section four highlights the study's key findings. Finally, section five summarizes the study.

3.3 Methodology

This section provides an overview of methods implemented to estimate the demand elasticities of shared e-scooters. Section 2.1 describes the study area and study duration, while section 2.2

explains data sources and processing. Section 2.3 includes the details of the model used in the study.

3.3.1 Study area

Nashville is the largest metropolitan area and the state capital of Tennessee, with a population of 2 million in 2021 (U.S. Census Bureau, 2021). Mainly renowned for being the center of country music, Nashville is one of the region's largest tourist destinations – 16.1 million people visited Nashville in FY 2019-20 (Music City, 2021). Downtown Nashville has diverse attractions, including entertainment, dining, cultural, and high-rise office buildings. It has seen a large growth in urban housing development in recent years. In terms of travel mode split, driving alone is the predominant mode for commuting in Nashville (80.8% of the working residents), followed by 9.4% carpool, 1% public transit, and 1.3% walking, according to the 2019 American Community Survey 5-Year Estimates (American Community Survey, 2019).

INRIX ranked Nashville third among the cities of the United States for the potential success of micromobility considering the topography, climate, and proportion of trips with a short distance – 51% of trips in Nashville are less than 3 miles (Reed, 2019). Shared e-scooters were first launched in Nashville in May, 2018, and the City of Nashville started a pilot program in August, 2018 (Tamburin, 2019). Seven e-scooter services providers (Bird, Jump, Bolt, Gotcha, Lime, Lyft, and Spin) were operating in the city during our study period of April 1, 2019, and February 29, 2020. The study period was limited by the availability of a complete shared e-scooter dataset prior to April 1, 2019, as well as the beginning of the COVID-19 pandemic after February 29, 2020.

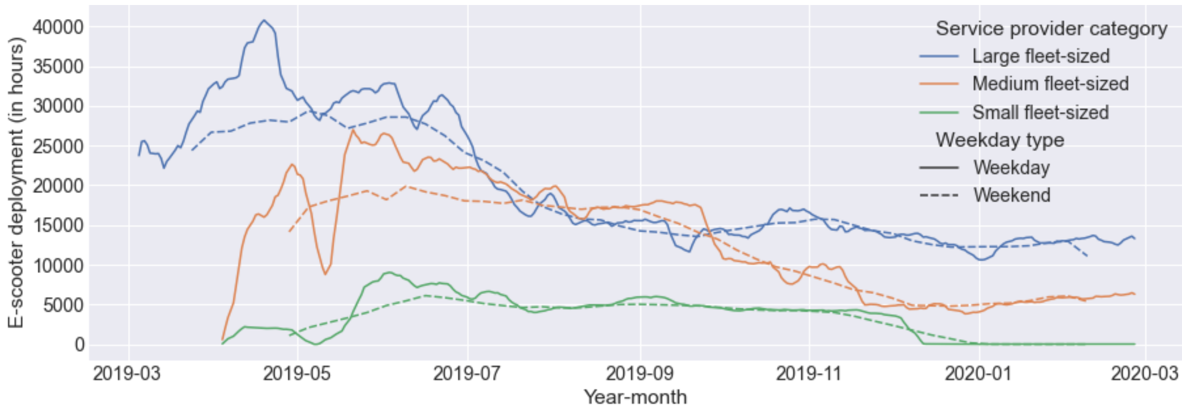
3.3.2 Data sources and processing

I acquired the e-scooter trip summary and device availability dataset of Shared Urban Mobility Device (SUMD) data through a data request made to the City of Nashville. The e-scooter trip summary dataset includes the timestamped geolocation of trip origin and destination and basic trip information, such as trip distance and trip duration. After dropping duplicate records, there were 1,495,253 trips for all seven service providers during the study period. The SUMD trip summary dataset includes raw data, which could be recorded during the rebalancing of e-scooters and users unlocking e-scooters but not starting the trip. I removed 27% of the trips that were unlikely e-scooter trips based on the following criteria: 1) trips distance less than 200 feet (22% of records), 2) trip distance more than 5 miles (5% of records), 3) trip duration less than 1 minute (less than 1% of records), and 4) trip duration more than 2 hours (4% of records). Some of the trip records were flagged under multiple abovementioned criteria. I retained 1,086,528 trips after the trip data cleaning process.

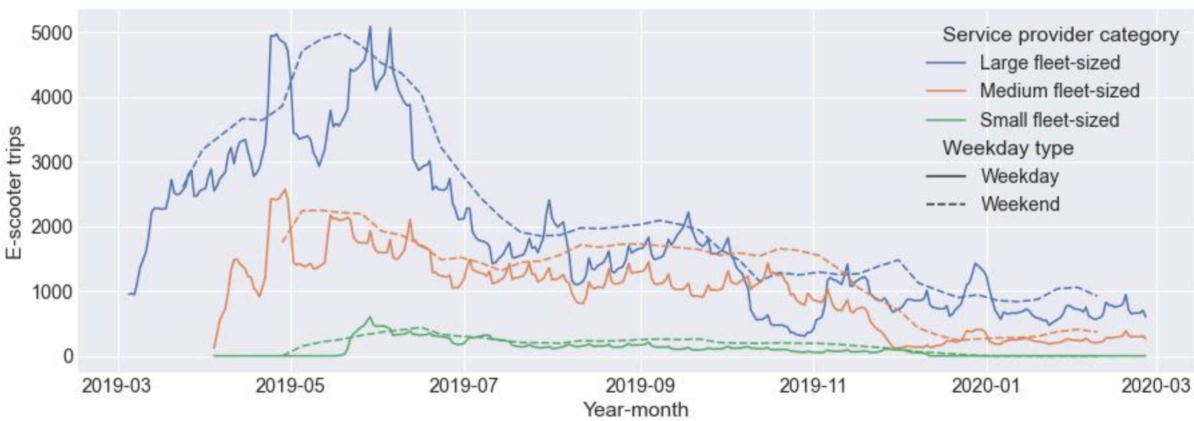
The device availability dataset is the second SUMD dataset, which contains the geolocation of parked e-scooter vehicles with status information, updating approximately every five minutes. This dataset contains information on the supply of shared e-scooters, which is measured as e-scooter-hours. Based on the average fleet size per day (or e-scooter-hours), I grouped seven shared e-scooter service providers into three categories as follows: large (>500 scooters or >12,000 e-scooter-hours), medium (250-500 scooters or 6,000-12,000 e-scooter hours), and small (<250 scooters or <6000 e-scooter hours). This grouping was to explore demand elasticity for the different service providers based on their fleet size and to remove the brand name of service providers to protect potentially sensitive market information.

Figure 14 illustrates seven days' rolling average of e-scooter vehicles deployed (measured in e-scooter hours) and the number of daily trips, segmented by day of the week (broken down into weekdays (Monday to Friday) and weekends (Saturday and Sunday)) and the fleet size of service providers. Figure 14 **(**a) illustrates the daily average number of e-scooter vehicles deployed over time, indicating a strong pattern among the large, medium, and small fleet-sized service providers. Figure 14 **(**b) shows that the e-scooter trip volume is much higher during the warmer months (April-July). I observed higher usage of e-scooter on weekend days than on weekdays, similar to findings of other studies (Bai & Jiao, 2020; McKenzie, 2019; N. Shah, 2020; Nitesh R Shah, Jing Guo, et al., In review). I also observed higher e-scooter vehicles deployed and a higher number of e-scooter trips during the summer.

I aggregated datasets by Traffic Analysis Zone (TAZ) to control for factors that vary over space, such as built environment and socio-demographics. I obtained the TAZ boundary from the travel demand model of Nashville (Greater Nashville Regional Council (GNRC), 2021) and only retained 244 TAZs for the analysis. The inclusion criteria for the TAZs were to have an e-scooter deployment of more than 500 e-scooter-hours, which is equivalent to one e-scooter being deployed for a total of about 20 days throughout one year of the study period.



(a)



(b)

Figure 14 Seven days rolling average of e-scooters supply and demand aggregated daily by shared e-scooter service providers' category and weekday type

a) E-scooters deployed (in e-scooter hours) b) E-scooter trips

Figure 15 illustrates the map of total e-scooter trips and vehicles deployed throughout the study period aggregated at the TAZ level. The pink hue (vertical color gradient in the map) represents the total number of scooter trips starting at each TAZs, while the blue hue (horizontal color gradient in the map) indicates the total e-scooter vehicle deployment per square mile by all service providers throughout the study period. Most e-scooter trips and vehicle deployments were in downtown Nashville, Vanderbilt University, and commercial areas in the periphery of downtown Nashville. When plotting the map by service provider groups (attached in the Appendix A2), I also observed a difference in e-scooter trips and deployment among these segments, suggesting that service providers' service areas differ based on their fleet size.

Based on the observation of Figure 14**,** Figure 15**,** and findings from the existing studies summarized in the background section, I aggregated both the e-scooter trip summary and device availability dataset in the following manner. The temporal unit of analysis is daily trips, and I also segmented data into weekdays (Monday to Friday) vs. weekend days (Saturday and Sunday) to control for temporal factors and capture the different demands by day of the week. The spatial unit of the analysis is TAZ to control for the built environment and socio-demographic factors. I also segmented e-scooter deployment by large, medium, and small fleet-sized shared e-scooter service providers. Table 5 summarizes the model variables, stacked by daily, weekday, and weekend.

3.3.3 Modeling Framework

This section provides an overview of the modeling framework in two subsections. The first subsection describes the model to estimate demand elasticities of shared e-scooter deployed, followed by methods for clustering TAZs to estimate heterogeneous elasticity estimates based on land use.

3.3.3.1 Demand elasticities of all shared e-scooter deployed

I applied fixed-effects regression techniques to estimate the elasticity of the shared e-scooters deployed. This approach allows us to explore the change in the number of shared e-scooters trips made as a function of the change in the number of vehicles deployed (Berrebi & Watkins, 2020; Watkins et al., 2021; Ziedan, Darling, Brakewood, Erhardt, & Watkins, 2021). Since the number of shared e-scooter trips is a non-negative integer, I used count models for this analysis.

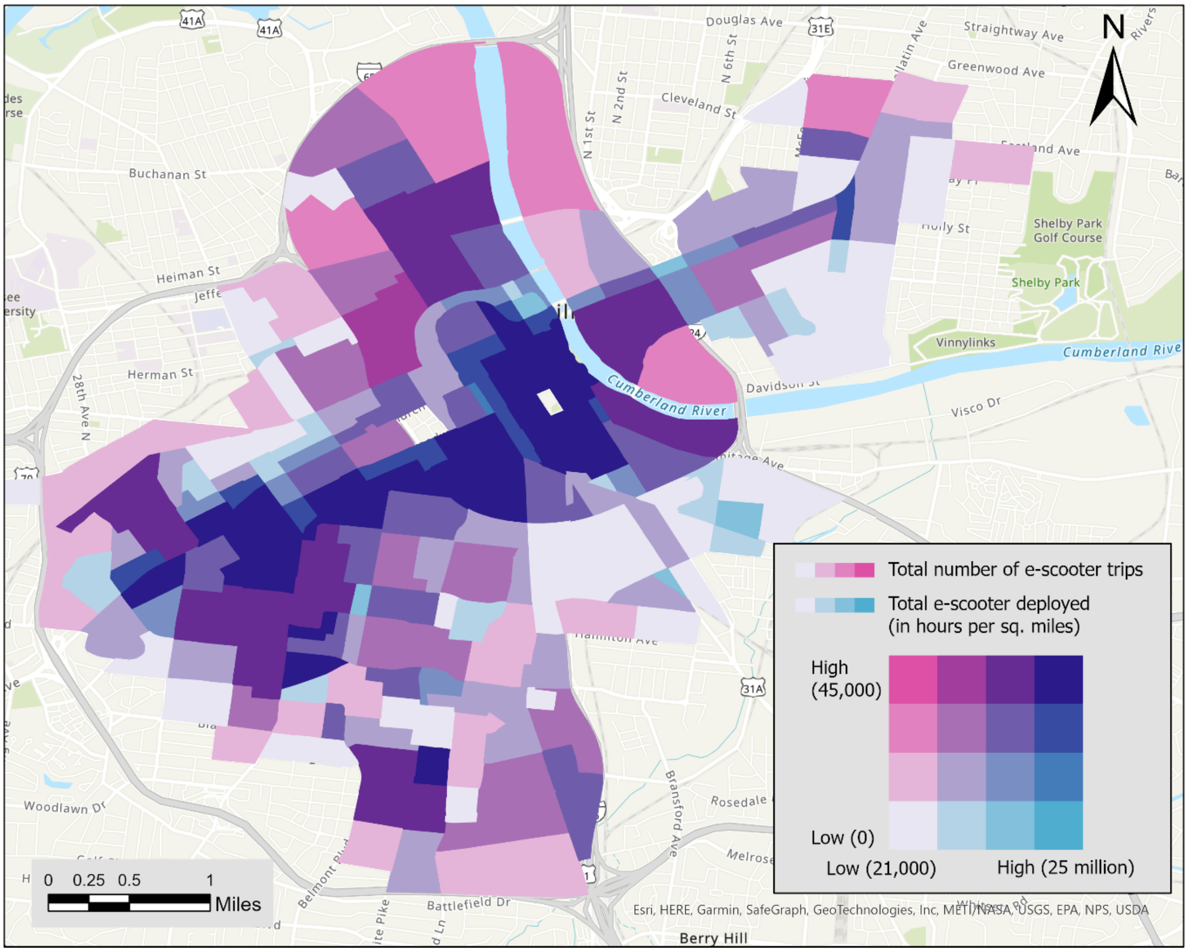


Figure 15 Bivariate map of the total e-scooter trips and vehicles deployed at each TAZ throughout the study period

Table 5 Descriptive statistics of key variables used in the analysis

Variables	Mean	Standard deviation	Minimum	Maximum
Daily (N=88,572)				
Total number of trips starting in TAZ	11.8	28.1	0.0	974.0
Total e-scooter deployed in TAZ (in e-scooter-hours)	139.5	212.1	0.0	3113.5
E-scooter deployed among large fleet-sized service providers in TAZ (in e-scooter-hours)	79.5	119.1	0.0	2112.5
E-scooter deployed among medium fleet-sized service providers in TAZ (in e-scooter-hours)	47.5	94.0	0.0	2320.4
E-scooter deployed among small fleet-sized service providers in TAZ (in e-scooter-hours)	12.5	46.5	0.0	1053.7
Weekday (75,884)				
Total number of trips starting in TAZ	11.3	27.2	0.0	974.0
Total e-scooter deployed in TAZ (in e-scooter-hours)	141.1	215.9	0.0	3113.5
E-scooter deployed among large fleet-sized service providers in TAZ (in e-scooter-hours)	80.3	120.9	0.0	2112.5
E-scooter deployed among medium fleet-sized service providers in TAZ (in e-scooter-hours)	48.1	96.0	0.0	2320.4
E-scooter deployed among small fleet-sized service providers in TAZ (in e-scooter-hours)	12.7	47.8	0.0	1053.7
Weekend (N=12,688)				
Total number of trips starting in TAZ	14.3	33.0	0.0	695.0
Total e-scooter deployed in TAZ (in e-scooter-hours)	130.1	187.7	0.0	2398.8
E-scooter deployed among large fleet-sized service providers in TAZ (in e-scooter-hours)	74.8	107.6	0.0	1738.8
E-scooter deployed among medium fleet-sized service providers in TAZ (in e-scooter-hours)	43.9	81.6	0.0	1519.9
E-scooter deployed among small fleet-sized service providers in TAZ (in e-scooter-hours)	11.3	37.9	0.0	893.1

Although Poisson regression is typically used for count data, I used negative binomial models as the shared e-scooters trip data are overdispersed (i.e., the variance is larger than the mean) (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020). The probability equation for the fixed effect negative binomial model is as follows (Hausman, Hall, & Griliches, 1984; StataCorp, 2021):

$$\Pr(Y_{i1} = y_{i1}, \ldots, y_{i1} = y_{in_i} \mid X_i, \textstyle\sum_{i=1}^{n_i} Y_{it} = \sum_{i=1}^{n_i} y_{it})$$

$$= \frac{\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it}\right) \Gamma\left(\sum_{i=1}^{n_i} y_{it}+1\right)}{\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it}+\left(\sum_{i=1}^{n_i} y_{it}\right)\right)} \prod_{t=1}^{n_i} \frac{\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it}+y_{it}\right)}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}$$

The likelihood equation of the fixed effect negative binomial model is as follows:

$$\ln L = \sum_{i=1}^{n} w_i \Big[ln\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it}\right) + ln\Gamma\left(\sum_{i=1}^{n_i} y_{it} + 1\right) - ln\,\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it} + \left(\sum_{i=1}^{n_i} y_{it}\right)\right) + \sum_{t=1}^{n_i}\Big\{\Gamma\left(\sum_{i=1}^{n_i} \lambda_{it} + y_{it}\right) - ln\Gamma(\lambda_{it} + y_{it}) - ln\Gamma(y_{it}) - ln\Gamma(y_{it}+1)\Big\}\Big]$$

where:

$\lambda_{it} = \exp(\mathbf{x}_{it}\boldsymbol{\beta} + \text{offset}_{it})$ and

w_i is the weight for the ith group

y_{it}: dependent variable for group i during time t

x_{it}: explanatory variables for group i during time t

I should note that I used the log scale of the variables so that the estimated coefficients could be interpreted as elasticities (Berrebi, Joshi, & Watkins, 2021). The entity fixed effect controls for any time-invariant unobserved variables for a TAZ that could affect e-scooter demand. The time fixed effect captures unobserved variables that happened during a specific week, for example, the NFL Draft weekend that had extreme increases in ridership.

The equation of the model is as follows:

$$E(y_{it}|x_{it}) = EXP(\beta * x_{it} + \alpha_i EF_i + \rho_t TF_t + \varepsilon_{it})$$

Where:

y_{it}: shared e-scooter trips for TAZ i during time t (day)

x_{it}: explanatory variables for TAZ i during time t (e.g., e-scooter counts for operators with different fleet sizes)

EF_i: Entity fixed effect dummy, equal 1 for TAZ i and 0 otherwise

TF_t: Time fixed effect dummy, equal 1 for the t^{th} period and 0 otherwise

ε_{it}: dispersion parameter

I estimated bootstrap standard error to control for possible heteroscedasticity and serial autocorrelation (Gonçalves, 2011).

3.3.3.2 Clustering Traffic Analysis Zones (TAZs)

Previous studies have found a strong spatial relationship between e-scooter usage and land use, where high e-scooter trips were observed in specific built environments such as downtown areas and university areas. In order to identify heterogeneous characteristics of TAZs that influence e-scooter usage, I adopted a similar approach to Guzman, Beltran, Bonilla, and Cardona (2021), where authors used the clustering technique to identify Bus Rapid Transit (BRT) stations based on their spatial, temporal, and socio-demographic characteristics. This research uses a K-means clustering technique to categorize land use based on key built environment variables influencing e-scooter usage, as summarized in the background section. The TAZ clustering does not include dependent and explanatory variables of the negative binomial model described above.

The K-means clustering method is one of the most common methods in data mining, which groups similar observations by separating each group as much as possible (MacQueen, 1967). The K-means algorithm uses squared Euclidean distance to measure the dissimilarity between observations as follows:

$$d_{ij}^2 = \sum_{v=1}^{p} \left(x_{iv} - x_{jv}\right)^2 = \left\|x_i - x_j\right\|^2$$

Where, d is Euclidean distance, x is the observation, i and j are observations, and p is the number of variables. The algorithm minimizes the objective function of the squared difference between observation values in each cluster, and the corresponding cluster means as follows:

$$\min(W) = min \sum_{h=1}^{k} n_h \sum_{i \in h} (x_i - \bar{x}_h)^2$$

Where W is within-cluster similarity and k is the total number of clusters.

I used six variables for clustering TAZs: population density (in square miles), university housing density (in square miles), employment density (in square miles), intersection density (in square miles), the proportion of park area at each TAZ, and entropy, which is a measure of land use diversity in a TAZ. I obtained population density and university housing density data from the 2020 Census at the census tract level (U.S. Census Bureau, 2021), with a higher spatial resolution than TAZ but overlapping boundaries. Therefore, I spatially joined the census tract with the TAZ boundary and aggregated these variables at the TAZ level. I acquired the employment density from the travel demand model of Nashville (Greater Nashville Regional Council (GNRC), 2021).

I obtained intersection density from Open Street Map using the OSMnx library in Python (Boeing, 2017) and counted the number of intersections within each TAZs. I downloaded the park area boundary from the City of Nashville data portal (Metropolitan Government of Nashville and Davidson County, 2021). I spatially joined park data to estimating the proportion of park area of each TAZs. To estimate entropy, I manually scraped Google Map's Point of Interest data for the City of Nashville and categorized land use into eight groups: basic amenities, entertainment, government institutions and organizations, hotels, restaurants, bars, retail and services, and transportation. Then, I used Shannon entropy to estimate the land use diversity using the following equation:

$$H = -\sum_{i=1}^{n} (p_i) * \log_n(p_i)$$

Where, $H$is Shannon entropy, p_i is the percentage of POIs in i^{th} category, and n is the total number of categories

I performed a standardized transformation of variables (mean of the transformed variable being 0 and the standard deviation being 1), so that the values of each variable have a similar effect on the objective function and algorithm controls for outlier values. I used default opinions of the K-

Means algorithm in Geoda open-source software, such as the K-means++ initialization method, 150 initialization re-runs, and 1000 maximum iterations. To find the optimum number of clusters, I used a combination of Elbow Method plots and interpretation of clusters (Anselin, Syabri, & Kho, 2010).

3.4 Results

This section summarizes the results of the analysis of elasticity of the e-scooter deployed, followed by the clustering of TAZs, and the results of land use specific elasticity of e-scooters deployed.

3.4.1 Demand elasticities of all shared e-scooter deployed

Table 6 summarizes the elasticity of deployed e-scooters on trip volume estimated by daily, weekday (Monday to Friday), and weekend (Saturday and Sunday) days. The top part of the table includes elasticity estimates of the total e-scooter deployment, while the bottom part summarizes the elasticity estimates of e-scooter deployment by service providers segmented based on their fleet size. The p-value of the Likelihood Ratio (LR) test is less than 0.025, representing a good fit for the models. All the estimates are statistically significant (p-value <0.01) and can be interpreted as demand elasticities.

The demand elasticity of the total e-scooters deployed is 0.55, which suggests that a 1% increase in e-scooter deployment (measured in e-scooter-hours) would result in a 0.55% increase in e-scooter trips on average in a TAZ. This estimated elasticity suggests that shared e-scooter demand is inelastic, similar to other transportation modes. When segmenting by the size of the service providers, larger fleet-sized services providers have a higher demand elasticity of e-scooter vehicles deployed. Based on the weekly model, a 1% increase in the e-scooter deployment would result in a 0.36% increase in trip volume for larger fleet size service providers compared to 0.14% for medium fleet size. The e-scooter vehicle elasticity is 0.01% for small-sized service providers. The elasticity estimate of the total e-scooter deployed is the sum of the elasticity estimates of service providers segmented by their fleet size. The total demand is a function of total e-scooter deployment in the first model, whereas the total demand is the function of e-scooter deployment of each service provider segmented by fleet size in the second

Table 6 Demand elasticity of e-scooter vehicles, segmented by service providers' fleet size

Estimated elasticity **(Dependent variable: the daily number of e- trips)**	**Average daily model**	**Average weekday model (Monday to Friday)**	**Average weekend day model (Saturday and Sunday)**
Log of all e-scooter vehicles deployed (per square miles)	0.55*** (0.02)	0.55*** (0.02)	0.59*** (0.02)
Constant	-3.15*** (0.16)	-3.08*** (0.16)	-4.75*** (0.16)
TAZ fixed effect	Yes	Yes	Yes
Time fixed effect	Day	Day	Day
Likelihood of model	-191284	-161962	-27702
P-value for Likelihood Ratio (LR) test	0.000	0.000	0.000
Number of observations	88,572	75,884	12,688
Service providers segmented by fleet size			
Log of e-scooter vehicles deployed (per square miles) of large fleet-sized service providers'	0.36*** (0.01)	0.36*** (0.01)	0.38*** (0.02)
Log of e-scooter vehicles deployed (per square miles) of medium fleet-sized service providers'	0.14*** (0.00)	0.14*** (0.00)	0.14*** (0.00)
Log of e-scooter vehicles deployed (per square miles) of small sized service providers'	0.01*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Constant	-1.655*** (0.13)	-1.584*** (0.13)	-3.110*** (0.13)
TAZ fixed effect	Yes	Yes	Yes
Time fixed effect	Day	Day	Day
Likelihood of model	-191131	-161935	-27643
P-value for Likelihood Ratio (LR) test	0.000	0.000	0.000
Number of observations	88,572	75,884	12,688
*Note: *** P < 0.01, ** P<0.05, * P<0.1, and standard errors in parenthesis*			

model. The sum of e-scooter deployment of three segmented service providers is the total e-scooter deployment.

The average demand elasticity estimate of e-scooter vehicles deployed on the weekend is slightly higher than on weekdays (0.59 vs. 0.55). However, the weekdays and weekend demand elasticity of e-scooter vehicles deployed is not much different compared to service providers' size. The weekend elasticity is 0.02 percentage points higher than the weekday estimate for large service providers and 0.01 percentage points higher for small-sized service providers but no different for mid-sized service providers.

3.4.2 TAZ clustering

I evaluated 11 K-means models, whose number of clusters ranged from 2 to 12 with an increment of one. Figure 16 illustrates the Elbow Plot of the Within Sum of Squares (WSS) for an incremental number of clusters, where there is a discontinuity around five clusters, and WSS does not drop substantially further. At least one cluster starting at six clusters had only one TAZ indicating a misbalance in the distribution of TAZs among the clusters. Interpreting five clusters, I obtained an additional cluster with a distinct residential land use attribute as compared to four clusters (please refer to the next paragraph for more details). Therefore, I concluded that five clusters were the optimum model based on the Elbow Plot and interpretation of clusters.

Table 7 presents the summary of the optimum cluster model, including the average of six clustering variables, the number of TAZs in each cluster, and the ratio of population and employment densities for interpretation. Figure 17 illustrates the optimum clusters in a map of Nashville. Based on Table 7 and Figure 17, a brief description of each cluster is as follows:

- **Central Business District (CBD) & Commercial:** This group has the highest average employment density and entropy among all clusters, indicating diversity in land use. On the other hand, the population and employment densities ratio is the least, suggesting a built environment predominantly for employment. When plotting the cluster map, the TAZs are in the CBD and commercial area of Nashville.
- **University**: This cluster has the highest average university housing density, and the TAZs are located around Vanderbilt University. As suggested by the population and

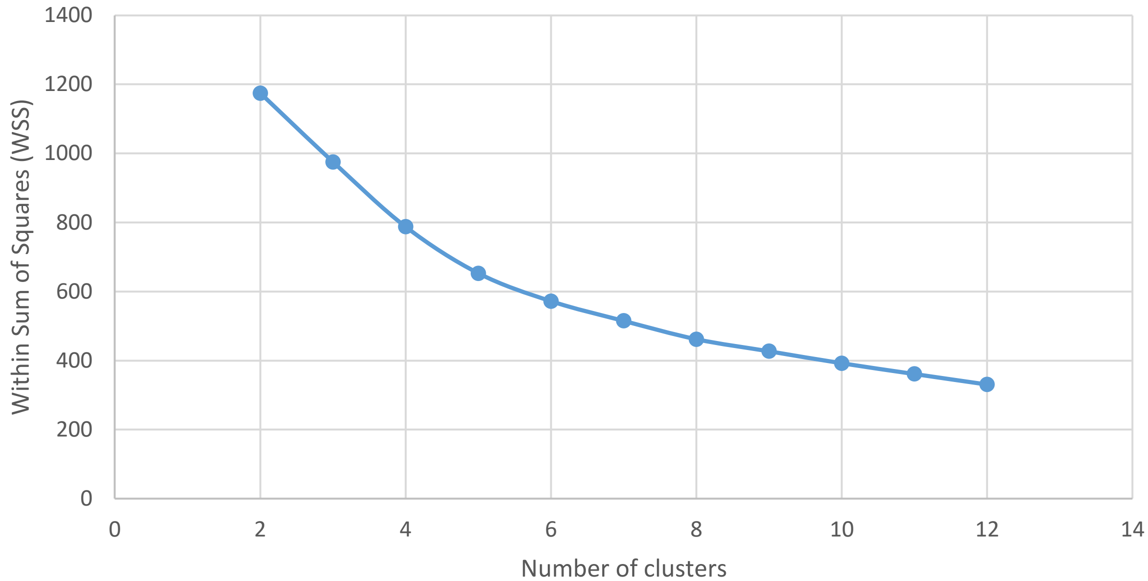


Figure 16 Elbow plot indicating Within Cluster Squared Sum (WCSS) of clusters ranging from 2 to 12

employment densities ratio, these TAZs have a higher residential population than employment.

- **Park & waterfront**: This group has the highest average proportion of park area and has the lowest land-use diversity, indicated by the entropy, among all clusters. As suggested by the population and employment densities ratio, the TAZs had more employment than the residential population.
- **Dense residence**: The built environment of this cluster is mainly for population compared to employment, as indicated by the ratio of population and employment densities and the least average entropy compared to other clusters.
- **Low density periphery**: This cluster includes TAZs with the least population and employment densities among other clusters. The map of these TAZs indicates that these are somewhat on the periphery of downtown Nashville, Vanderbilt University, and Centennial Park.

3.4.3 Land use specific elasticities

Similar to the general elasticities, Table 8 summarizes daily, weekday (Monday to Friday), and weekend (Saturday and Sunday) models for five TAZ clusters: CBD & commercial, university, park & waterfront, dense residence, and low-density periphery. The p-value of the Likelihood Ratio (LR) test is less than 0.025, representing a good fit for the models. All the estimates were statistically significant (almost all the coefficients had p-values < 0.01, and some had p-values < 0.1). The top part of each table includes the demand elasticities of the total e-scooters deployed, whereas the bottom part contains the demand elasticities of e-scooters deployed by service providers segmented based on their fleet size.

Figure 18 complements Table 6 and Table 8 by visually summarizing heterogeneous weekday and weekend demand elasticities and comparing them with the general daily elasticity. The demand elasticities are grouped into two levels; the first grouping is the land use clusters, with the labels on the top of the figure and separated by vertical lines. The second grouping is the weekday type, which is nested within each land use cluster and labeled at the bottom of the figure. The solid lines represent the heterogeneous demand elasticity of e-scooter vehicles, while the dotted lines indicate the general daily elasticity.

Table 7 Summary of optimum clusters

Cluster labels/ variables	Average populatio n density (sq miles)	Average university housing density (sq miles)	Average employmen t density (sq miles)	Averag e entropy	Average proportio n of park area	Average intersectio n density (sq miles)	Numbe r of TAZs	Ratio of population and employmen t densities
CBD & Commercial	28555.2	7.4	137315.0	0.8	0.0	558.7	24	0.2
University	70307.2	2080.2	32082.5	0.6	0.0	289.3	18	2.2
Park & waterfront	8398.6	0.3	27328.2	0.5	0.4	228.5	15	0.3
Dense residence	28015.2	18.3	13819.7	0.2	0.0	385.0	48	2.0
Low density periphery	11608.3	26.1	12738.7	0.7	0.0	267.9	139	0.9

Note: Red color indicates lower values while blue color indicates higher values among clusters

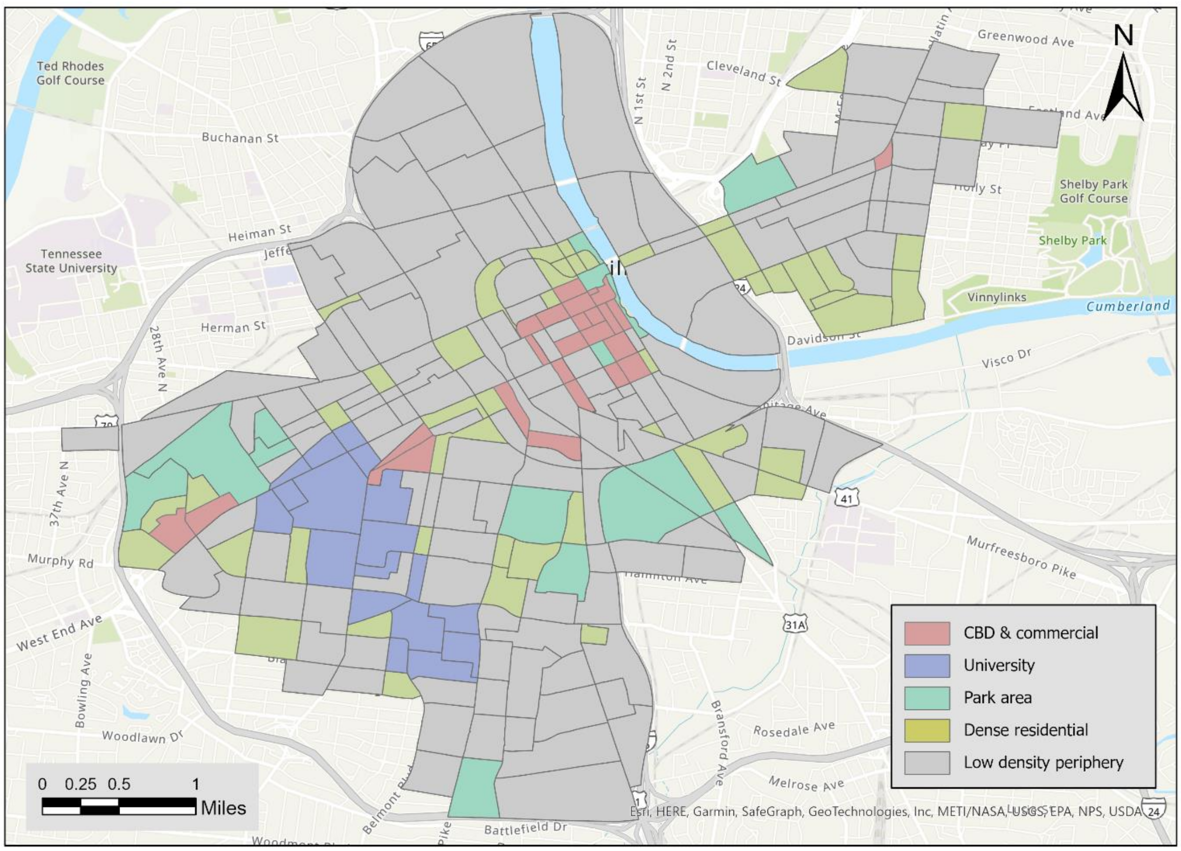
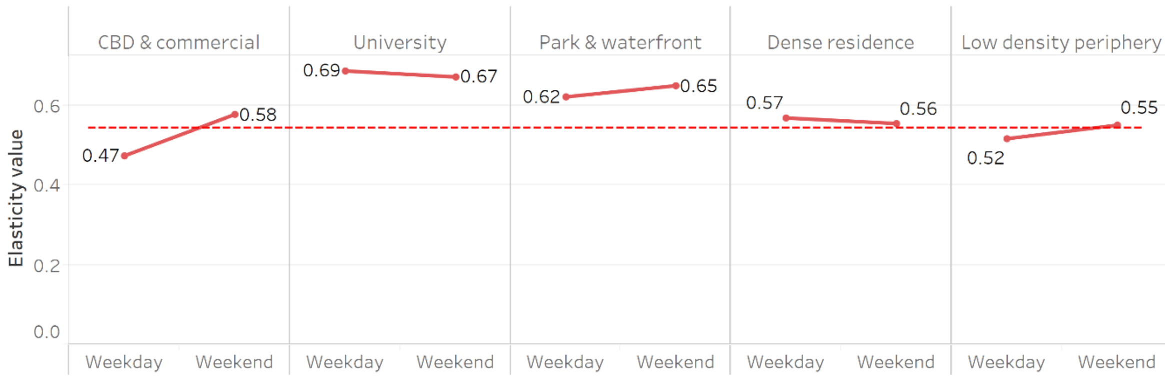


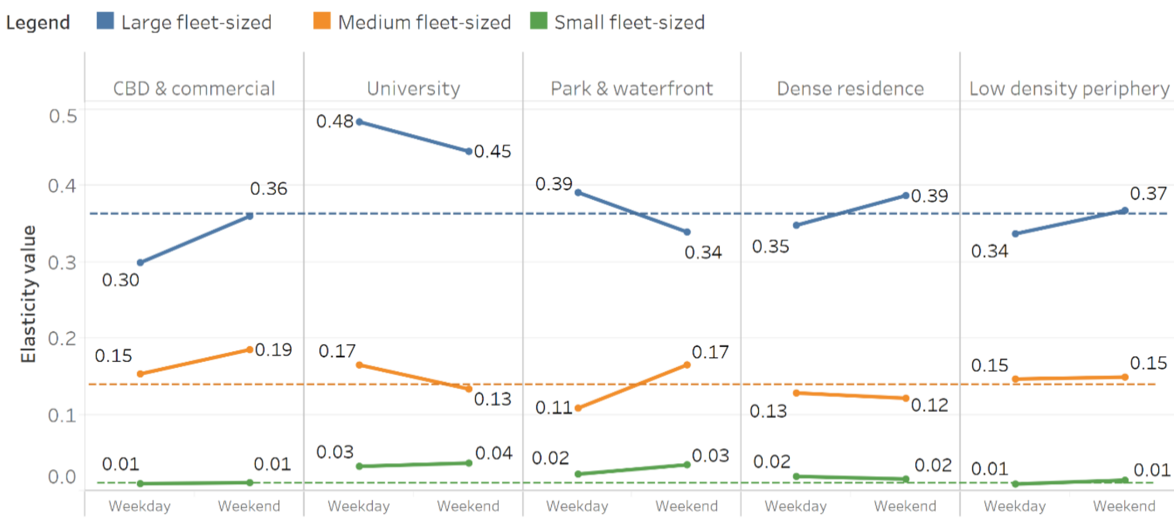
Figure 17 Mapping of TAZs of the optimum clustering model

Table 8 Heterogeneous demand elasticity of e-scooter vehicles, segmented by land use and service providers' based on fleet size

TAZ cluster	**CBD & Commercial**			**University**			**Park & waterfront**			**Dense residence**			**Low density periphery**		
Day-of-the-week	**Daily**	**Weekday**	**Weekend**	**Daily**	**Weekday**	**Weekend**	**Daily**	**Weekday**	**Weekend**	**Daily**	**Weekday**	**Weekend**	**Daily**	**Weekday**	**Weekend**
Log of all e-scooter vehicles deployed	0.496*** (0.04)	0.474*** (0.01)	0.578*** (0.02)	0.689*** (0.07)	0.687*** (0.12)	0.672*** (0.04)	0.626*** (0.07)	0.622*** (0.02)	0.65*** (0.04)	0.567*** (0.03)	0.569*** (0.01)	0.555*** (0.03)	0.522*** (0.02)	0.517*** (0.00)	0.551*** (0.01)
Constant	-1.94*** (0.44)	-1.7*** (0.12)	-4.3*** (0.28)	-4.65*** (0.61)	-4.63*** (0.20)	-5.44*** (0.40)	-3.47*** (0.92)	-3.36*** (0.20)	-5.39*** (0.46)	-3.52*** (0.38)	-3.55*** (0.19)	-4.24*** (0.34)	-2.8*** (0.18)	-2.72*** (0.08)	-4.42*** (0.15)
TAZ fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day
Likelihood of model	-28071.8	-2.4e+04	-4.1e+03	-18283.2	-1.6e+04	-2.5e+03	-10679.7	-9.0e+03	-1.6e+03	-23953.1	-2.0e+04	-3.3e+03	-107168	-9.0e+04	-1.6e+04
Likelihood Ratio (LR) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	8712	7464	1248	6534	5598	936	5082	4354	728	16698	14306	2392	50457	43229	7228
Service providers segmented by fleet size															
Log of e-scooter vehicles deployed of large fleet-sized service providers'	0.32*** (0.03)	0.30*** (0.03)	0.36*** (0.03)	0.49*** (0.06)	0.48*** (0.07)	0.45*** (0.06)	0.37*** (0.06)	0.39*** (0.06)	0.34*** (0.07)	0.35*** (0.03)	0.35*** (0.03)	0.39*** (0.03)	0.34*** (0.02)	0.34*** (0.02)	0.37*** (0.02)
Log of e-scooter vehicles deployed of medium fleet-sized service providers'	0.16*** (0.02)	0.15*** (0.02)	0.19*** (0.03)	0.16*** (0.03)	0.17*** (0.03)	0.13*** (0.04)	0.12*** (0.03)	0.11*** (0.03)	0.17*** (0.04)	0.13*** (0.01)	0.13*** (0.01)	0.12*** (0.02)	0.15***' (0.00)	0.15*** (0.00)	0.15*** (0.00)
Log of e-scooter vehicles deployed of small sized service providers'	0.01** (0.00)	0.01** (0.00)	0.01* (0.00)	0.03*** (0.00)	0.03*** (0.00)	0.04*** (0.01)	0.02* (0.01)	0.02* (0.01)	0.03** (0.01)	0.02** (0.00)	0.02** (0.00)	0.02* (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Constant	-0.30 (0.29)	-0.10 (0.35)	-2.28*** (0.33)	-2.94*** (0.58)	-2.90*** (0.62)	-3.52*** (0.54)	-1.70* (0.94)	-1.70*** (0.48)	-3.01*** (0.54)	-1.92*** (0.32)	-1.90*** (0.35)	-2.92*** (0.39)	-1.49*** (0.15)	-1.41*** (0.14)	-3.02*** (0.18)
TAZ fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day	Day
Likelihood of model	-28107	-23816	-4098	-18218	-15576	-2485	-10748	-9066	-1587	-24020	-20497	-3291	-106887	-90294.1	-15792.1
Likelihood Ratio (LR) test p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	8712	7464	1248	6534	5598	936	5082	4354	728	16698	14306	2392	50457	43229	7228
Number of TAZs	24	24	24	18	18	18	14	14	14	46	46	46	139	139	139
*Note: *** P < 0.01, ** P<0.05, * P<0.1, and standard errors in parenthesis*															



(a)



(b)

Figure 18 Elasticity estimates of the number of vehicles deployed for land use segmentation
a) Total e-scooters deployed b) E-scooter deployed by service providers segmented based on fleet-size

The heterogeneous demand elasticity of the total e-scooter vehicles deployed based on land use is different from the general daily elasticity of the total e-scooter vehicles deployed, indicated by the solid and dotted red lines in Figure 18 (a). The maximum difference in heterogeneous demand elasticity of e-scooter vehicles is for university land use, with more than 0.1 percentage point greater value than the general daily elasticity, followed by park & waterfront land use. Increasing e-scooter vehicle deployment would increase trips at a higher rate than other built environments. Furthermore, large fleet-sized service providers likely influence the overall difference in heterogeneous demand elasticity of e-scooter vehicles compared to medium and small fleet-sized service providers, as indicated by the solid blue, orange, and green lines in Figure 18 (b). The demand elasticity values of vehicles deployed by medium and small fleet-sized service providers for all land use types are distributed around daily general elasticity estimates of the corresponding group of service providers.

Unlike general elasticity estimates of e-scooter vehicles deployed, there is a difference in weekends and weekdays estimates for each land use segment, as indicated by the segmented solid red lines in Figure 18 (a). The demand elasticity of e-scooters deployed by all service providers is higher on weekends compared to weekdays for CBD & commercial, park & waterfront land use, and low density periphery land uses. In contrast, university and dense residence land-use types have the reverse pattern of higher weekday estimates than weekends. The difference in weekdays vs. weekends elasticity estimates is highest for CBD & commercial land use, with 0.11 percentage points. Increasing the supply of e-scooters at specific land use on certain weekdays can capture more e-scooter trip demand.

Most of the day-of-the-week differences in demand elasticity of e-scooter vehicles deployed follow a similar pattern for all land-use groups with few exceptions, comparing the demand elasticity of all e-scooters deployed (Figure 18 (a)) with service providers' segmentation (Figure 18 (b)). For example, the demand elasticity of e-scooter vehicles of mid-sized service providers at parks & waterfront is higher on weekends than in other service provider groups, which influences the pattern of demand elasticity estimates of all e-scooter vehicle deployment. Such pattern difference could indicate that some service providers' groups drive the e-scooter market at certain land use and weekday types.

3.5 Discussion

3.5.1 Demand elasticity of e-scooter vehicles deployed

The demand elasticity of e-scooter vehicles deployed is positive and inelastic. The average demand elasticity of e-scooter vehicles is 0.55, with the elasticity value slightly greater on weekends compared to weekdays. Some land uses, such as university and park & waterfront areas, have much higher demand elasticity than the average estimates of the city. Previous studies also found a high volume of e-scooter trips around the university and downtown (Caspi et al., 2020; Hosseinzadeh, Algomaiah, et al., 2021a; Tuli, Mitra, & Crews, 2021). I also found a significant difference in demand elasticity of e-scooter vehicles deployed among land-use groups and weekday types (weekdays vs. weekends). Existing studies have also found higher demand for shared e-scooters during weekends (Bai & Jiao, 2020; McKenzie, 2019).

This finding can be helpful for city governments to manage public spaces by allocating sufficient e-scooter parking during the weekends while using the space for other purposes on weekdays. Similarly, e-scooter service providers can mobilize their resources to deploy more e-scooters to meet the higher demand in particular land use areas and weekday types while redistributing the e-scooter vehicles to other areas at other times. E-scooter trip volume can be increased by deploying more e-scooters in CBD, commercial areas, parks, and waterfronts on weekends, while reallocating those e-scooter vehicles in university and dense residence areas on weekdays. However, increasing supply might not increase utilization rates for e-scooter operators, as the demand elasticity of e-scooter vehicles deployed is still inelastic. An extension of this work could be evaluating the utilization rates of e-scooter vehicles to assess the factors influencing the trip turnover of a vehicle.

3.5.2 Number of shared e-scooter providers and their fleet size

The demand elasticity of e-scooter vehicles deployed for a large service provider (fleet size more than 500) is 2.5 times more than mid-sized service providers (fleet size between 250 to 500) and 36 times more than small service providers (fleet size below 250). Those service providers who started operating first and with a larger fleet could have a competitive advantage over others. First-time e-scooter users need to download an app on their phone, create a profile, and setup a digital payment method. Therefore, they are more likely to keep using the same service provider if they consistently find e-scooters nearby when needed (Aman, Smith-Colin, & Zhang, 2021). Other factors, such as brand loyalty, marketing, and vehicle redistribution strategies, could also contribute to higher vehicle elasticity for service providers with larger fleet sizes.

The lower vehicle elasticity of mid- and small-fleet-sized shared e-scooter providers indicates that shared e-scooters systems still have barriers to market entry for new service providers. Incumbent service providers with larger fleet sizes can dominate the market share and somewhat dictate the price, potentially reducing consumer benefits. On the other hand, a few shared e-scooter service providers with larger fleet sizes are better at capturing the trip demand from the perspective of city governments in terms of shared e-scooter system efficiency. Small fleet-sized service providers would need to deploy more vehicles to capture the same demand, leading to issues like cluttering of sidewalks. A low trip turnover rate of e-scooter vehicles would also contribute to higher operational emissions related to collecting e-scooters for charging, distribution, and rebalancing the fleets (Hollingsworth, Copeland, & Johnson, 2019; Moreau et al., 2020). Spin, a nationwide shared e-scooter service provider, recently decided to stop operating in the cities without any regulations or limits on fleet size and the number of service providers (Herbert, 2020). The CEO of Spin explained that "[they were not] able to offer a reliable and high-quality service."

3.5.3 Limitations of the study and future research areas

This study has several limitations. First, endogeneity could be present in the panel data model due to simultaneity between dependent and independent variables. Service providers might be changing their distribution strategy based on the observed demand, so the demand for e-scooter could also drive e-scooter deployment. Future studies might consider using other methods like instrumental variables or Dynamic Panel data regression. Second, I did not consider the spatial correlation between e-scooter usage and vehicle deployment. A few studies have found that spatial models better explain e-scooter demand compared to non-spatial models (Caspi et al., 2020; Hosseinzadeh, Algomaiah, et al., 2021b). Finally, I used one week (including weekdays and weekends) as the temporal unit of our analysis and TAZs as the spatial unit, which does not capture time-of-the-day dynamics at higher spatial resolution. Future studies can further improve the temporal and spatial resolution of the analysis. An extension of this study could be to explore the cross elasticity of e-scooter deployed among service providers segmented on fleet size. Last, this study relies on data that was collected in Nashville when there were many (seven) operators. Most cities (including Nashville) have since reduced the number of operators. Understanding the competitive landscape related to the number of operators is still an understudied area.

3.6 Conclusion

With the increasing popularity of shared e-scooters, city governments are regulating the supply of shared e-scooters using permits and pilot programs. I estimated the demand elasticity of e-scooter vehicle deployment, segmented by land use and weekday type (weekdays vs. weekends). I also estimated the demand elasticity of e-scooter vehicles deployed by grouping shared e-scooter service providers based on their average daily fleet size. I found that the demand elasticity of e-scooter vehicles deployed varies by land use and week day type, and that service providers with larger fleet sizes (>500) could capture trip demand at a higher rate than service providers with medium fleet sizes (250-500) and small fleet sizes (<250).

These findings can help city governments identify the appropriate number of shared e-scooter service providers and their fleet size to meet user demand without oversaturating streets and sidewalks with e-scooters. The higher demand elasticity of e-scooter vehicles for service providers with larger fleet sizes indicates that city governments should consider permitting fewer service providers with larger vehicle fleet sizes. Higher demand elasticity during the weekend for certain land use types suggests that city governments can also consider permitting dynamic e-scooter fleet sizes that are higher during weekends while using the space for other purposes on weekdays.

Chapter 4. Shared micromobility as the first wave of decarbonizing transport sector in developing countries

This chapter is based on a research paper by Nitesh R Shah, Saurav Parajuli, and Christopher Cherry titled "Ride-hailing users are likely early adopters of shared micromobility in mid-sized cities of developing countries: A case study of Kathmandu, Nepal." The paper is accepted for presentation at the 2023 Transportation Research Board Annual Meeting.

Abstract

While shared micromobility has been gaining popularity in developed countries, these innovative technologies have yet to penetrate the market of mid-sized cities in developing countries, which make up the overwhelmingly majority of cities in the world. Shared micromobility includes inexpensive systems that could drive the first wave of electrification in the transportation sector in these regions. We designed and implemented a dynamic stated preference pivoting survey and used a panel data mixed logit model to assess the effect of temperature, precipitation, and availability of bike lanes on the propensity to use bikeshare, e-bike share, and e-moped share, controlling for sociodemographic factors. Using Kathmandu, Nepal, as a case study, where shared micromobility does not currently exist, we also assessed modal shift from the existing travel modes. We found heavy rain negatively impacts users' preference for shared micromobility, while users preferred e-moped share during cold temperatures. The effect of bike lane availability was positive but weak on bikeshare and e-bike share. Gender also had an effect on the choice of shared micromobility vehicles – females preferred e-mopeds over other vehicles. Ride-hailing users had a high preference for e-moped share, while introducing bikeshare and e-bike share caused a uniform modal shift among existing travel modes. We recommend that transportation agencies begin micromobility pilot programs by combining this study's findings with best practices of existing micromobility programs. We also suggest collecting usage and operations data to empower data-driven decision-making.

4.1 Introduction

The advent of smartphone apps and internet payment features has enabled the innovation of transportation technologies and the shared economy model, giving rise to shared micromobility modes, such as bikes, e-bikes, and e-scooters (Abduljabbar, Liyanage, & Dia, 2021). The micromobility sharing systems have soared in North America, Europe, and East Asia in past decades (National Association of City Transportation Officials, 2020; Wortmann, Syré, Grahle,

& Göhlich, 2021; Zhao et al., 2022), with the market predicted to be worth $500 billion by 2030 (Figueroa). The rising popularity of shared micromobility can be attributed to convenience in short-distance travel and accessibility (Fishman & Allan, 2019; National Association of City Transportation Officials, 2020). A modal shift toward shared micromobility can offset private motorized vehicle trips to reduce overall emissions (Abduljabbar et al., 2021; Cazzola & Crist, 2020) that frees up valuable space in urban areas, improving congestion and traffic safety issues. Shared micromobility can also integrate with other sustainable urban transportation systems, such as Transit-Oriented Development (TOD) and Mobility-as-a-System (MaaS) (Ziedan, Shah, et al., 2021), and can increase access to jobs and other destinations.

Despite the immense benefits, there are only a limited number of shared micromobility systems in mid-sized cities of developing countries. According to the United Nations, mid-sized cities (with more than 500,000 and less than 5 million in population) make up an "overwhelming majority" of the world's cities and have the highest population growth rate (DESA, 2011). Although a number of mass transit options exists, widespread use is limited by a number of factors, such as comfort, safety, reliability, and ease of access (Vergel-Tovar & Rodriguez, 2018). The need for travel with speed and comfort in these urban areas has caused a proliferation of private vehicles, including cars and two-wheelers, at the expense of increased traffic fatalities, more congestion, poorer air quality, and higher emissions. Shared micromobility is an affordable option for users and does not require huge infrastructure investments, making this innovative transportation technology a potential leapfrogging alternative in developing countries. It can serve as a standalone system or complement transit or para-transit systems to improve their service while reducing the need for private motor vehicles.

While most relevant studies on shared micromobility are based on large cities in affluent countries (Elmashhara, Silva, Sá, Carvalho, & Rezazadeh, 2022), this research focuses on mid-sized cities of developing countries planning for shared micromobility systems. The information on users' inclination to adopt and use these innovative technologies can help set goals, allocate budgets, and plan for infrastructure. I designed a stated preference survey and used a panel data mixed logit model to evaluate the factors influencing the choice of shared micromobility as well as assess the modal shift from existing travel modes. As a case study in Kathmandu, Nepal, I implemented the methods to assess the choice of bikeshare, e-bike share, and e-moped share options if they were to be introduced. Although the policy and planning implications are based on the context of Kathmandu, the results and lessons can be cautiously generalizable in other cities of similar population sizes with diverse travel options.

This study makes three main contributions to the literature on transportation as follows: 1) to my knowledge, it is the only large-scale study to evaluate shared micromobility usage focusing on mid-sized cities of developing countries, 2) I deployed a fully online and dynamic stated preference pivoting survey that improves the survey design in real-time by using users' input data to add context in the subsequent questions, and 3) I focused on introducing shared electric-powered or human-powered vehicles, which could contribute to the initial wave of electrification in the transportation sector of emerging economies.

The remaining chapter is organized as follows: The first subsection synthesizes shared micromobility research in developing countries, while the second subsection summarizes factors influencing the use of shared micromobility. The last subsection includes the research objectives of the study.

4.2 Review of literature

4.2.1 Shared micromobility in developing countries

The overall travel behavior in cities of developing countries is different from developed countries, mainly due to transportation infrastructure influenced by factors like standards of living, cultural norms, and demographics. Motorized two-wheelers are the predominant private transportation mode in most South Asian and Southeast Asian cities (Elmashhara et al., 2022). Despite hopes that bikeshare or other shared micromobility could transform urban mobility in developing cities, barriers such as insufficient infrastructure, such as bikes deployed, lighting, and bike lanes, has been a primary deterrent for bikeshare (Sharmeen, Ghosh, & Mateo-Babiano, 2021; Sombatphanit, Panyasakulchai, Chenyawanich, Adunyarittigun, & Chuenmanuse, 2020). A study in Penang, Malaysia, highlights the importance of outreach strategy, payment methods, and safety concerns pertaining to the addition of new bikeshare program in the city (Kadir, Ghee-Thean, & Law, 2019). In India, Kathait and Agarwal (2021) found that most cities lack long-term planning for these systems, leading to a lower investment return for shared micromobility companies.

The literature provides various tools for measuring the acceptability and perception of emerging travel modes, such as technology adoption models, perception analysis, and preference surveys. Öztaş Karlı, Karlı, and Çelikyay (2022) implemented an extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model for assessing the acceptance of shared e-scooters in Turkey. The study found a positive association between the propensity to adopt new modes and the users' familiarity with similar travel modes, performance potential, convenience, social influence, and price. Other studies have adopted factor analysis and structural equation modeling to assess adoption intentions of shared e-scooters (Eccarius & Lu, 2020b) and intentions to continue using bikeshare (Y. Liu, Huang, Wang, & Wang, 2020). Patel and Patel (2020) used the analytical hierarchy process (AHP) to assess barriers to bikeshare adoption from the stakeholders' perspective.

Several studies have adopted stated preference surveys to evaluate factors influencing emerging travel modes. Campbell, Cherry, Ryerson, and Yang (2016) implemented a stated preference pivoting method to determine factors that affect the modal shift choice from existing transportation modes to bikeshare and e-bike share in Beijing. The pivoting method allows for the designing of stated preference choice scenarios based on real previous choices made by survey participants that provide a reference point and familiar context to make a hypothetical decision. Most stated preference studies implement fractional factorial design to develop efficient stated preference surveys by reducing the number of choice sets while evaluating the effect of multiple factors, such as weather, vehicle characteristics, transportation infrastructures, and trip attributes (Abouelela, Al Haddad, & Antoniou, 2021; Farahmand, Gkiotsalitis, & Geurs, 2021).

4.2.2 Factors influencing shared micromobility

Weather is one of the most prominent factors affecting shared micromobility trips. Shared micromobility ridership is negatively affected during extreme temperatures (Kim, 2018) and adverse weather conditions such as wind and rainfall (Campbell et al., 2016; Hosseinzadeh, Karimpour, & Kluger, 2021). Users prefer warm temperatures, with the highest demand for bikeshare at temperatures of 20–30 °C (Eren & Uz, 2020). Shared micromobility ridership is higher during the summer and spring and lowest during the winter, mainly due to weather factors (Elmashhara et al., 2022; Nitesh R Shah, Jing Guo, et al., In review). Rain not only reduces the number of trips but also the length and duration of the trips (Lin, Weng, Liang, Alivanistos, & Ma, 2020; Robert B. Noland, 2021). However, research shows that, compared to human-powered vehicles, demand for electrified modes such as shared e-scooter and shared e-bikes are less affected by adverse weather and environmental conditions (Campbell et al., 2016; Hosseinzadeh, Karimpour, et al., 2021).

The built environment and topographic features influence the ridership and preference for shared micromobility modes. Bikeshare riders favor routes with protected bike lanes (Sun, Mobasheri, Hu, & Wang, 2017) and traffic signals dedicated to bicycles, while e-scooter users also prefer similar road characteristics (W. Zhang, Buehler, Broaddus, & Sweeney, 2021). Economic hubs with higher population and employment density also have a high demand for shared micromobility trips (Elmashhara et al., 2022), and studies have found high ridership at locations with more docking stations and vehicle density (Nitesh R Shah, Abubakr Ziedan, et al., In review). Although steeper terrain is a deterrent for bikeshare users, e-bike share and e-scooter share riders do not avoid steep slopes as these motorized vehicles do not require extensive physical effort (Langford, Cherry, Yoon, Worley, & Smith, 2013; W. Zhang et al., 2021). However, users prefer bikeshare and e-bike share over e-scooter share on bumpy surfaces as e-scooters have a smaller tire size and require an upright steering angle, making the vehicle less stable (W. Zhang et al., 2021).

Shared micromobility is popular among certain demographics, with variation amongst specific modes. The majority of bikeshare, e-bikeshare, and e-moped share users are young, affluent males with a college degree (Aguilera-García, Gomez, & Sobrino, 2020; Kaviti, Venigalla, & Lucas, 2019; Maas, Attard, & Caruana, 2020; Reck & Axhausen, 2021). A few studies have found that e-scooter share has more female ridership than other micromobility modes (Reck & Axhausen, 2021; Nitesh R Shah et al., 2021). Some shared micromobility modes like e-scooters are also associated with social and recreational purposes in addition to commuting (Raptopoulou, Basbas, Stamatiadis, & Nikiforiadis, 2020). Other factors that affect the demand for shared micromobility are the availability of nearby public transportation facilities, access to bicycling infrastructure, attitudes and values towards new travel modes, and road safety factors (Eren & Uz, 2020; Ziedan, Shah, et al., 2021).

4.2.3 Research objectives

With the focus on mid-sized cities of developing countries, this research implements a stated preference survey to assess users' intentions to adopt shared micromobility systems that are new to the study area. This study evaluates three electric or human-powered micromobility vehicles: bikeshare, e-bike share, and e-moped share. I adopt the micromobility terminology proposed by the International Transport Forum (ITF) (Santacreu et al., 2020b). Bikes are two-wheelers propelled by the muscular energy of the rider, while e-bikes are pedal-assisted bicycles supported by an electric power unit that cuts off when a vehicle reaches approximately 25 km/h. E-mopeds are electric motor-powered vehicles with design speeds of 25-45 km/h operating only on the road lane. The suffix "share" indicates that users can rent a vehicle based on per-unit time or distance usage. These three vehicles encompass a wide range of features and are also similar to existing travel modes in the study area.

The study also focuses on temperature, precipitation, availability of bike lanes, and key sociodemographic factors influencing the choice of shared micromobility systems. This study aims to answer the following research questions in the context of mid-sized cities in developing countries:

1. What are the main drivers of adopting shared micromobility modes and what is the effect of sociodemographic factors?
2. Which traditional travel modes would users replace with shared micromobility?

4.3 Methodology

4.3.1 Study area

Kathmandu is the capital of Nepal and among the world's most densely populated and compact cities, with a population exceeding 2.5 million and an annual growth rate of four percent (World Bank, 2013). Motorized two-wheelers have emerged as the primary form of transportation during the last decade. In 2012, gasoline-powered two-wheelers made up 26 percent of trips in Kathmandu, a three-fold increase from 1991 (Japan International Cooperation Agency (JICA), 2018). There was a staggering 65 percent increase in vehicle registration between 2012 and 2017, with two-wheelers contributing 78 percent of the total registered vehicle fleet in 2017

(Department of Transport Management, 2017). Existing public transportation his hindered by lack of capacity, security, and reliability to serve rising travel demand (Gautam, Sapakota, Shrestha, & Regmi, 2019), further driving the rate of private motorization.

Although widespread use of smartphones with internet access and online payment existed in Kathmandu, the COVID-19 pandemic further acted as a catalyst for the shift toward digitizing commodities (Didier, Feyen, Montanes, & Alper, 2021). The popularity of ride-sharing services, such as Tootle and Pathao, skyrocketed in Kathmandu during the pandemic (Hamal & Huijsmans, 2022). However, shared micromobility is yet to penetrate the market. The majority of all trips in Kathmandu (~70%) have short distances (average trips being 5 km) (Japan International Cooperation Agency (JICA), 2018), which is within the practical range of micromobility vehicles. These combined factors — the availability of background data related to transportation, residents' familiarity with emerging technology components, and the majority of trips being within the practical range of micromobility — make this city an ideal location for the case study.

4.3.2 Data collection and cleaning

This research builds upon the experimental design framework of Campbell et al. (2016) by designing and implementing a fully online and dynamic stated preference pivoting survey and conducting several choice experiments from each survey participant. I included four attributes in our experimental design: temperature, precipitation, bike lane availability, and sensitivity level for travel cost and travel time, with three levels each. The levels of temperature are cold (<10 °C), normal (10-25 °C), and hot (>25 °C), while the levels of precipitation are heavy rain, light rain, and sunny. I used three levels of attribute for bike lane availability: no bike lane, unprotected bike lane, and protected bike lane. I used sensitivities of -0.2, 0.0, and 0.2 to add variation in travel cost and travel time for the three modes. I estimated the base travel cost as a sum of the fixed cost and marginal cost per trip distance (in km). The fixed cost for bikeshare, e-bike share, and e-moped share was assigned a value of Nepalese Rupees (NRs) 5, 7, and 10, respectively, while the marginal cost per km was assumed to be NRs 2, 5, and 20, respectively. The base travel time for bikeshare, e-bikeshare, and e-moped share was estimated using assumed travel speeds of 9.1 km/h, 12.1 km/h, and 20 km/h, respectively. I used the fractional factorial design with blocking technique in the statistical software JMP to generate a six scenario sets of six scenarios each (a total of 36 scenarios), ensuring all attribute levels described above appeared at the same frequency in order to maximize the statistical power of the experiment (Rose & Bliemer, 2009). Each respondent randomly received six scenario question sets in the survey.

I designed the survey in Qualtrics, which started with a short introduction explaining the purpose of the survey and a prompt for consent. I screened participants based on two criteria: 1) the participant's age should be at least 18 years, and 2) the participant should have completed at least one trip between 0.5 km to 10 km within the past week. The first part of the survey prompted respondents to recall the most recent trip within the past week, recording trip distance, origin, and destination to create a familiar context for subsequent questions. The choice experiment was pivoted from this trip. In the second part, respondents were presented with a scenario of weather conditions and bike lane availability for the same trip and were asked to select their preferred traditional travel mode alongside entering the travel time and cost information for the selected mode (illustrated in Figure 19 (a)). For the same scenario, respondents were then asked to choose between bikeshare, shared e-bike, shared e-moped, and the chosen travel mode from the earlier question, which acted as a reference point (illustrated in Figure 19 (b)). In order to make an informed decision, travel time and cost along with road rules for travel modes, such as driving license requirements, pictorial illustration of bike lane type, and permission to ride in the bike lane, were summarized in a table. The last part of the survey contained questions about the sociodemographic information of the respondents, such as gender, level of education, and household income. Upon completing the survey, respondents received a NRs 50 (equivalent to USD 0.40) gift card of their choice.

The online survey was designed in both Nepali and English so that the study could also include non-English speaking residents. The Nepali language is the most common language used in Kathmandu, and the English language is widely used for educational and business purposes. A participant could start the survey in either of the languages following one of two URLs or QR (quick response) codes and could toggle between English and Nepali at any point during the survey. I deployed the online survey in Kathmandu between May 2, 2022, and July 12, 2022, using the following mediums to recruit participants:

- Distributing flyers in ten busy locations of Kathmandu, such as bus stops, intersections, and park areas.

Suppose it is ***normal temperature (10-25 °C), raining lightly, and the route has unprotected bicycle lane*** (illustrated in the picture below). You have to complete the trip you mentioned in the previous section (4 km trip from Home to Work).

In this scenario, which travel mode would you prefer?

- Bus/micro/tempo
- Motorbike/scooter
- Car
- Two-wheeler Pathao/Tootle
- Four-wheeler Pathao/Tootle
- Taxi
- Walking
- Bicycling
- Others

What would the approximate travel time be (in minutes)?

15

What would the approximate trip cost be in Rupee? (including fare, parking, and approximate fuel)

35

(a)

Now suppose you had an opportunity to use a bicycle share, shared pedelec e-bicycle, or shared electric scooters (illustrated in the table below with a description of key features and picture). **Similar to Pathao and Tootle, you do not need to own the vehicle**. You would need to pay for using the service and would need to drive it yourself. Also suppose it is ***normal temperature (10-25 °C), raining lightly, and the route has unprotected bicycle lane*** (illustrated in the picture below) throughout the 4 km trip from Home to Work.

The travel time and cost for the trip above are as follows:

Mode	**Motorbike/scooter**	**Bicycle share**	**Shared pedelec e-bicycle**	**Shared electric scooter**
Picture	-			
Required physical effort	-	Entirely	Some, assisted by motor	None
License required?	-	No	No	Yes
Allowed in bicycle lane?	-	Yes	Yes	No
Travel time (in minutes)	15	25▲	20▲	10▼
Cost (in Rupees)	35	10▼	25▼	75▲

In this scenario, which travel mode would you choose for the trip?

- Motorbike/scooter
- Bicycle share
- Shared pedelec e-bicycle
- Shared electric scooter

(b)

Figure 19 Example of scenario question viewed by participants' in Qualtrics

a) First part of the scenario question, b) Second part of the scenario question

- Sharing the survey details on social media through Facebook groups and public pages, as well as through direct messages, including Facebook instant messages and emails.

By the end of the study period, 1,241 participants started the survey, and 569 participants (47% of total participants) completed the survey, which included 300 from social media and 269 participants who were recruited from flyers. A total of 151 participants (13% of participants starting the survey) were screened out, and 494 participants (41% of participants starting the survey) did not complete the survey. Of 569 participants, 66% completed the survey in English, while the remaining 34% used Nepali. To remove potential fraudulent responses, I dropped responses based on the following criteria: 1) 20 responses (4% of completed responses) with a fraud score of more than 30, which is a built-in metric developed by Qualtrics to detect fraudulent and bot responses, 2) 46 responses (8% of completed responses) completed in less than 5 minutes (median survey completion time was 11 minutes), and 3) 71 responses (13% of completed responses) that included the same new travel mode for all six scenarios, indicating a straightlining effect. I retained 2,544 data points from 424 responses for the analysis.

4.3.3 Descriptive statistics

After the data cleaning process, 12% of choices were bikeshare, 11% of choices were e-bikeshare, and 9% of choices were shared e-moped. The remaining 68% of choices were to continue using existing travel modes. Figure 20 illustrates the choice among shared micromobility vehicles and existing travel modes (base mode) for different levels of attributes from the experimental design. The labels in the figure represent the percentage of choices of the specific vehicle (labeled on the left side) with all three attribute levels grouped vertically. Bikeshare was popular for a protected bike lane, while e-bike share was common for an unprotected bike lane. Most participants chose e-moped share for the scenario without a bike lane. Given the scenario with heavy rain, most participants did not choose any shared micromobility vehicles and had a slightly higher inclination towards using micromobility in sunny weather compared to light rain. Participants preferred normal and hot temperature conditions for bikeshare and e-bike share but had a higher preference for shared e-moped in scenarios with cold temperatures.

Figure 21 summarizes the key demographics aggregated by the recruitment method of study participants. According to the most recent National Population and Housing Census (Central Bureau of Statistics, 2014), the gender split of Kathmandu is 52.3% male and 47.7% female. Our sample had a much higher proportion of male respondents, likely due to males traveling more than females and a higher willingness of males to participate in the survey. The sample data oversampled the 19-30 age group while under-sampling higher age groups, possibly due to the younger generation being more familiar with navigating online surveys. Similar studies have also sampled younger, educated, and male demographics (Campbell et al., 2016; S. A. Shaheen, Zhang, Martin, & Guzman, 2011), likely due to the inherent selection bias problem with intercept surveys. Respondents recruited through social media were more educated, had higher household incomes, and had more representation of females than participants recruited through flyers.

4.3.4 Modeling framework

I used discrete choice modeling to explain the individuals' mode choice of shared micromobility, based on the assumption that an individual selects an alternative among given choices with maximum utility (Hensher & Johnson, 2018). Although the Multinomial Logit (MNL) model is the most popular discrete choice model for multiple alternatives, it assumes that the observed alternative components are independent and identical, which might be impractical in the real-world choice scenario. Mixed Logit (ML) relaxes the Independence of Irrelevant Alternatives (IIA) assumption of MNL by allowing random taste variation, unrestricted substitution patterns, and correlation between unobserved factors (Train, 2009). The ML model is also recognized as a random parameter model, Mixed Multinomial Logit (MML) model, or hybrid logit model. Furthermore, ML can incorporate the effect of multiple observations from the same individual while also controlling for heterogeneity in the parameter of an attribute across populations using a random coefficient (Hensher & Johnson, 2018; Train, 2009). Several studies have found that the ML modeling framework performs better for behavioral specification than other logit models (Farahmand et al., 2021; Ye & Lord, 2014).

The utility (U_{jtq}) of an alternative $j \in (1,..,J)$ in each choice t of choice set T by an individual q for the Mixed Logit (ML) model is provided in as follows (Farahmand et al., 2021):

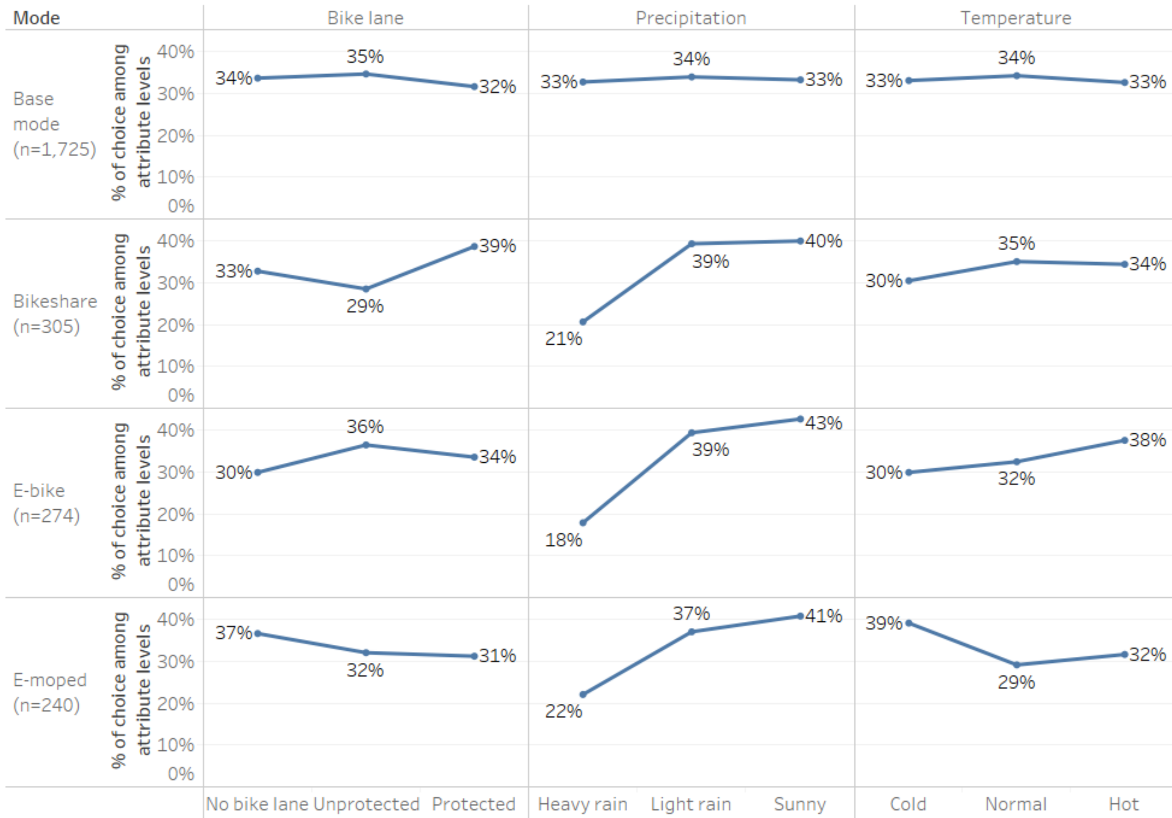
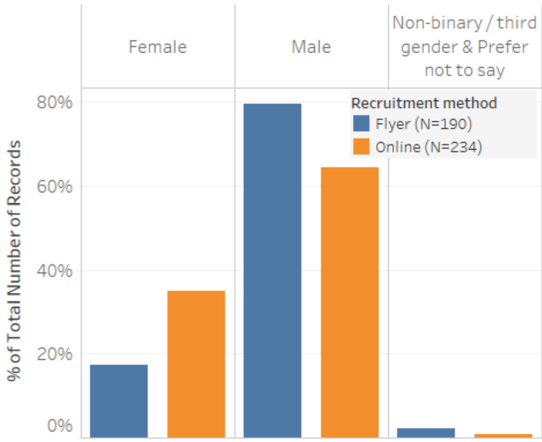
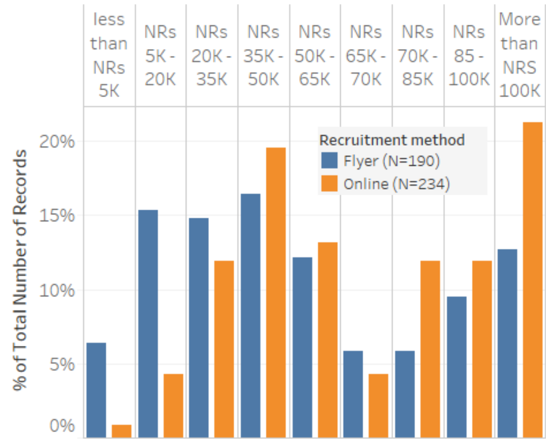


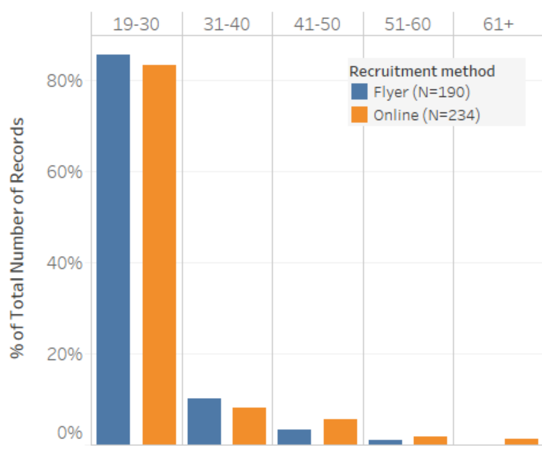
Figure 20 Choice of travel modes aggregated by attribute levels of the study



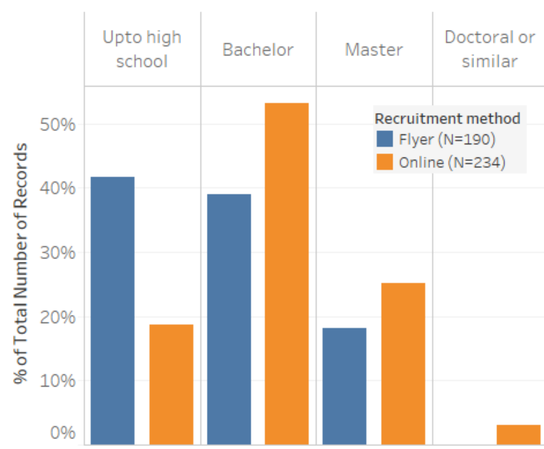
(a)



(b)



(c)



(d)

Figure 21 Demographics of survey respondents aggregated by recruitment method

a) Gender, b) Household income in Nepalese Rupees (NRs), c) Age group, and d) Education level

$$U_{jtq} = ASC + \sum_{k=1}^{k} \beta_{qk} x_{itqk} + \varepsilon_{itq}$$

Where, ASC is an alternative specific constant explaining the deterministic part of the utility of each alternative

k is the number of observed variables

x_{itq} is observed variables, including attributes of alternatives, sociodemographic of respondents, and context of decisions such as trip-specific components

β_q is a vector of coefficients of independent variables for individual q, and

ε_{itq} is an Independent and Identically Distributed (IID) random error term

The probability that the individual makes a sequence of choices among alternatives is calculated using the following equation:

$$L_{iq(\beta)} = \prod_{t=1}^{T} \left[\frac{e^{V_{iq}^{t}(\beta)}}{\sum_{j=1}^{J} V_{iq}^{t}(\beta)} \right]$$

Where, $V_{iq}^{t}(\beta)$ is the observed part of the alternative utility related to parameter β for choice t

I used the "cmxtmixlogit" command in STAT/SE 17 to estimate the panel data mixed logit model. I assigned travel time and travel cost variables as random parameters with normally distributed coefficients. I assigned the remaining variables as case-specific variables, including parameters that were the same for all alternatives in a given scenario (weather, precipitation, and bike lane availability), sociodemographic attributes of respondents (e.g., age, gender, and household income), and the context of the decision (e.g., original travel mode, and trip distance). Starting with a simple model with a few variables, I iterated models by adding/removing other variables to find the best model specification. I bootstrapped the standard error of parameter estimates by clustering estimates of each participant to control for possible heteroscedasticity and serial autocorrelation (Gonçalves, 2011).

4.4 Results

Table 9 summarizes the results of the final model specification, which is statistically significant, as indicated by the 0.000 p-values of the model test statistic. I retained the travel cost and time variable, although they were not statistically significant in the model, likely because there were insufficient observations for all levels of covariates. The precipitation variable has a positive coefficient and is statistically significant (p-value < 0.05) among all three shared micromobility modes. This means that light rain and sunny conditions are preferable compared to heavy rain for shared micromobility vehicles. The temperature variable is significant only for e-moped share, while the availability of bike lanes is statistically significant for e-bike share. I also explored the interaction of bike lane availability with other covariates, such as trip distance and gender, but still obtained statistically insignificant coefficient estimates for the bike lane availability variable.

The coefficient of trip distance is negative and statistically significant (p-value < 0.025) for e-moped share, indicating the choice of e-moped decreases with longer trip distance. The household income coefficient for e-moped share is positive and statistically significant (p-value < 0.025), suggesting higher income increases the use of shared e-moped. I dropped statistically insignificant variables collected in the survey, including trip purpose, a control for recruitment method, levels of education, and the number of household members and vehicles.

The marginal effects plot in Figure 22 complements the model results in Table 9 by visually summarizing the effect of attributes (represented on the x-axis of each figure) on the probability of choosing a travel mode (represented on the y-axis of each figure). I only included the choice for shared micromobility in the figures as they are the main focus of the study. Figure 22 (a) illustrates that the probability of choosing all shared micromobility modes is the least during heavy rain. Figure 22 (b) indicates that there is not much difference in normal and hot temperature, while the choice of e-moped share is high in cold temperature. Figure 22 (c) suggests that e-bike share is preferred for an unprotected bike lane, and bikeshare is popular if a protected bike lane is available. However, the effect of bike lane type is not statistically significant in the choice of shared micromobility vehicles. Despite the description and photograph, because bike lanes are uncommon in Kathmandu, the respondents likely had little experiential basis to judge their utility. Figure 22 (d) shows that e-moped share is preferred by females, while the choice of bikeshare is greater among male users. Figure 22 (e) indicates that the preference for e-moped share increases with higher household income, but there is no significant influence of household income on bikeshare and e-bike share. Figure 22 (f) suggests that modal shift from the existing travel mode varies depending on the type of shared

Table 9 Model results

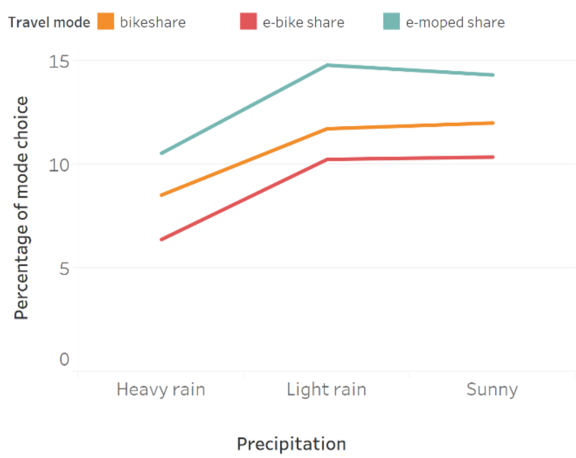
Parameter		Coefficient	Robust std. err.	P-value
Random Parameter	Travel time (minutes)	0.000	0.001	0.941
	Travel cost (NRs)	-0.007	0.005	0.207
	sd(Travel cost)	0.007	0.001	
	sd(Travel time)	0.042	0.006	
Continue using current mode		base alternative		
Bikeshare	Precipitation (base: heavy rain)			
	Light rain	0.590	0.208	0.005
	Sunny	0.603	0.203	0.003
	Temperature (base: cold (<10 °C))			
	Hot (10-25 °C)	0.183	0.163	0.262
	Normal (>25 °C)	0.184	0.148	0.215
	Bike lane availability (base: no bike lane)			
	Protected	0.161	0.181	0.374
	Unprotected	-0.127	0.152	0.404
	Gender (base: female)			
	Non-binary/prefer not to say	-0.138	0.967	0.886
	Male	0.652	0.225	0.004
	Trip distance (km)	-0.049	0.037	0.187
	Household income (NRs)	0.001	0.003	0.702
	Original travel mode (base: private two-wheeler)			
	Walk/bicycle	0.473	0.259	0.068
	Public transit	0.123	0.243	0.611
	Two-wheeler ride hailing	0.457	0.407	0.262
	Private four-wheeler	0.004	0.320	0.989
	Four-wheeler ride hailing	-0.934	0.522	0.074
	Others	1.497	1.072	0.163
	ASC	-2.799	0.408	0.000
E-bike share	Precipitation (base: heavy rain)			
	Light rain	0.722	0.197	0.000
	Sunny	0.731	0.196	0.000
	Temperature (base: cold (<10 °C))			
	Hot (10-25 °C)	0.216	0.161	0.180
	Normal (>25 °C)	0.053	0.170	0.758
	Bike lane availability (base: no bike lane)			
	Protected	0.145	0.167	0.385

Table 9 continued

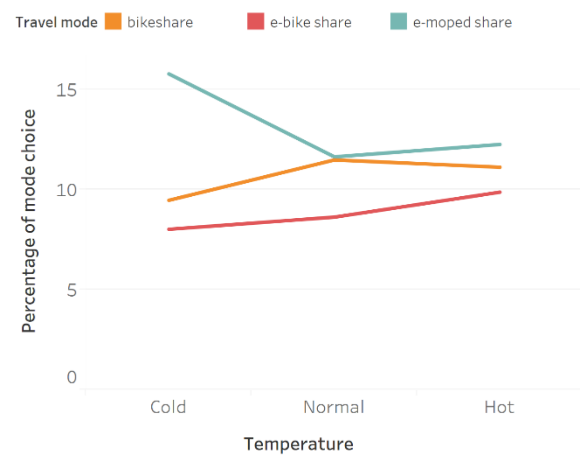
Parameter		Coefficient	Robust std. err.	P-value
	Unprotected	0.299	0.137	0.029
	Gender (base: female)			
	Non-binary/prefer not to say	-0.244	0.722	0.735
	Male	0.233	0.232	0.316
	Trip distance (km)	-0.026	0.037	0.481
	Household income (NRs)	0.003	0.003	0.292
	Original travel mode (base: private two-wheeler)			
	Walk/bicycle	-0.002	0.259	0.994
	Public transit	-0.329	0.222	0.138
	Two-wheeler ride hailing	0.184	0.394	0.640
	Private four-wheeler	-1.042	0.408	0.011
	Four-wheeler ride hailing	-1.027	0.513	0.045
	Others	0.147	1.235	0.905
	ASC	-2.604	0.443	0.000
E-moped share	Precipitation (base: heavy rain)			
	Light rain	0.599	0.242	0.013
	Sunny	0.560	0.239	0.019
	Temperature (base: cold (<10 °C))			
	Hot (10-25 °C)	-0.292	0.175	0.095
	Normal (>25 °C)	-0.379	0.169	0.025
	Bike lane availability (base: no bike lane)			
	Protected	-0.054	0.215	0.803
	Unprotected	-0.089	0.175	0.612
	Gender (base: female)			
	Non-binary/prefer not to say	-0.083	0.494	0.867
	Male	-0.362	0.255	0.155
	Trip distance (km)	-0.115	0.043	0.008
	Household income (NRs)	0.010	0.004	0.008
	Original travel mode (base: private two-wheeler)			
	Walk/bicycle	0.097	0.323	0.764
	Public transit	-0.346	0.313	0.270
	Two-wheeler ride hailing	1.686	0.344	0.000
	Private four-wheeler	-0.005	0.370	0.990
	Four-wheeler ride hailing	0.613	0.431	0.155
	Others	0.519	1.330	0.696
	ASC	-2.280	0.484	0.000

Table 9 continued

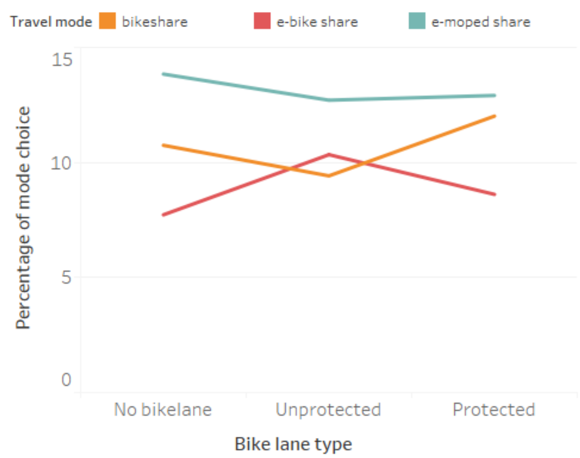
No of observations	10,176
Number of cases	2,544
Number of panels	424
Log simulated Likelihood	-2322.825
Wald chi2	162.43
Prob > chi2	0.0000



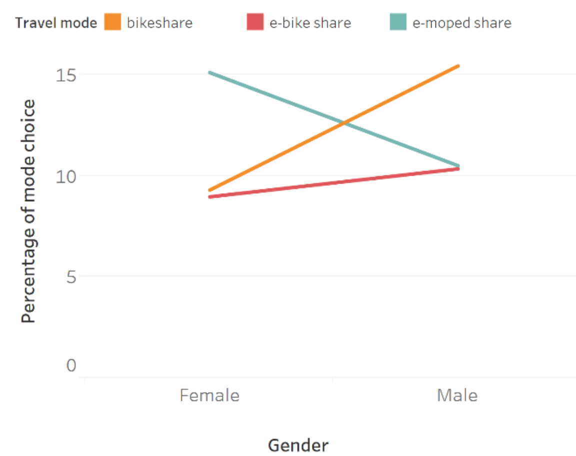
(a)



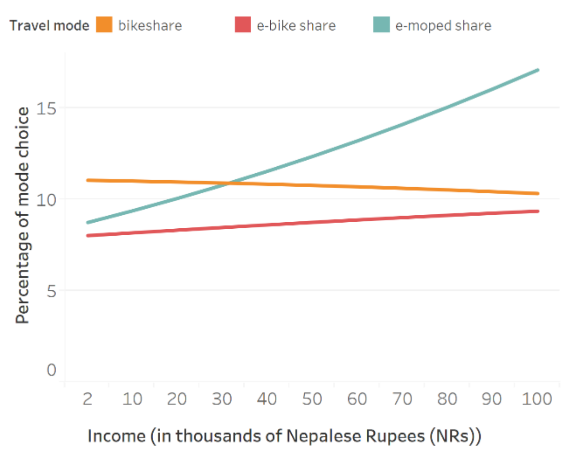
(b)



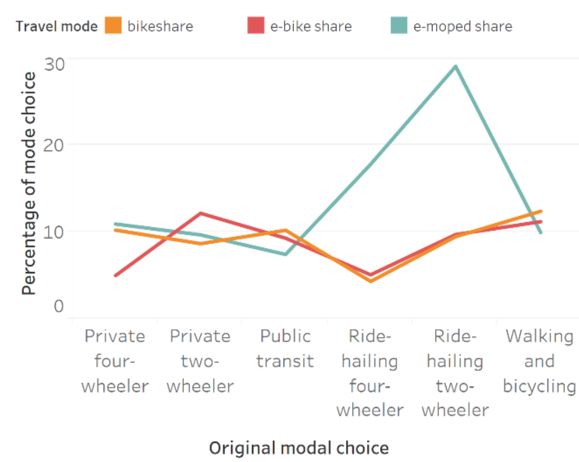
(c)



(d)



(e)



(f)

Figure 22 Marginal effects of choice of shared micromobility

a) Precipitation, b) Temperature, c) Availability of bike lane, d) Gender, e) Household income in thousands of Nepalese Rupees (NRs), f) Modal shift micromobility vehicles. Two-wheeler and four-wheeler ride-hailing users are more likely to choose e-moped share if this new mode was available.

4.5 Discussion

4.5.1 Factors influencing the choice of shared micromobility

The widespread adoption of innovative transportation technologies requires understanding how users choose to use these vehicles under various circumstances. Such information is helpful in successfully planning and budgeting for shared micromobility systems by estimating the demand and could help local governments prioritize infrastructure investments like bike lanes. The choice of e-moped share was highest among other shared micromobility vehicles during cold weather. Private two-wheelers are the predominant mode of travel throughout the year (Japan International Cooperation Agency (JICA), 2018) and are one of the fastest travel modes. People have likely adapted their travel behavior to cold weather, as Kathmandu has relatively cold climate conditions while indoor and vehicle air conditioning is not a standard. The effect of weather conditions should be interpreted with caution for other regions as travel behavior will likely be influenced by the general threshold of the local population.

Consistent with other studies (Campbell et al., 2016; Hosseinzadeh, Karimpour, et al., 2021; Kim, 2018), I found that "heavy rain" negatively impacts the use of bikeshare, e-bike share, and e-moped share. In the past decade, the number of rainy days (including light rain) in Kathmandu has been 175 days on average, with most of the rainy days occurring from June to September (Prajapati et al., 2021). I did not observe a statistical difference between the "light rain" and "sunny" weather condition. Users could further adapt their travel behavior around shared micromobility systems by improving weather predictions with high temporal and spatial accuracy (Weyn, Durran, & Caruana, 2020). However, extreme weather conditions due to climate change could be one of the challenges in the electrification of transportation through shared micromobility in developing countries (Markolf, Hoehne, Fraser, Chester, & Underwood, 2019). Transportation agencies should also consider micromobility systems in climate change resiliency strategies of transportation infrastructure and policy.

Despite weak evidence, I found that the availability of bike lanes promotes the choice of low-speed shared micromobility like bikeshare and e-bike share. It is possible that participants could not infer the implications of bike lane availability on their travel behavior because bike lanes are a relatively new concept in Kathmandu. A protected bike lane did not exist in Kathmandu while conducting the survey. Unprotected bike lanes have been constructed in a few street segments within the past few years (Ojha, 2021); however, entry of unauthorized two-wheelers into the bike lanes during congestion and motor vehicle parking has reduced the effectiveness of existing bicycling infrastructure (Khanal, 2021), influencing the perception of the usefulness of bike lanes among participants. Although not incorporated in this study, connectivity of bicycling infrastructure throughout the rider's travel route would be one of the critical factors influencing bicycling culture and the adoption of shared micromobility (Furth, Mekuria, & Nixon, 2016; Nitesh R Shah & Cherry, 2021),

4.5.2 Modal shift from traditional travel modes

Shared micromobility could be an inexpensive mobility solution for and hasten the electrification of transportation in mid-sized cities of developing countries, where the majority of trips are less than 10 km, which is within the practical range of shared and electric micromobility vehicles. Electrifying the two-wheeler fleet could result in significant urban air quality and greenhouse gas reduction improvements. Studies have found that shared micromobility can reduce the overall carbon footprint of the transportation sector through zero tailpipe emissions and modal shift from existing travel modes (Cazzola & Crist, 2020). I found that ride-hailing users (both two-wheeler and four-wheeler) had a higher inclination to use e-moped share and could be early adopters paving the way towards generating the critical mass needed to adopt these innovative mobility technologies (Chesbrough & Crowther, 2006). I found that introducing bikeshare and e-bike share would uniformly cause modal shift among private two-wheelers, public transit, ride-hailing two-wheelers, walking, and bicycling.

Similar to other studies, I found that the majority of shared micromobility adopters were younger people with a higher household income. Demographic factors also contribute to the choice among micromobility vehicles; for example, females preferred e-moped share more than bikeshare. Several studies have found a preference for motor-assisted vehicles among females, as such vehicles can mix with traffic better and are perceived as safer to ride. A combination of policy incentives to subsidize shared micromobility for low-income households, educational campaigns to highlight benefits, and investment in micromobility-friendly infrastructure could positively influence travel behavior to promote a broader modal shift from existing travel modes.

4.5.3 Limitations of the study and future research areas

Future research could address the following limitations of the study. First, I found weak evidence of the type of bike lanes influencing the propensity to use shared micromobility. It is likely that participants' response to the availability of bike lanes is correlated with other variables that were not captured in this study. Other experimental design methods, such as augmented reality techniques, could provide better context to aid the decision-making of participants. Second, the study used categorical descriptions for factors like heavy rain, and future studies could quantify such factors to avoid ambiguous interpretation. Third, this research did not assess emissions reductions from introducing shared micromobility modes. Future studies could build a comprehensive model to evaluate the net emission reductions for various scenarios and also include other sustainable and innovative travel technologies. I was surprised that price and travel time did not enter the model significantly. This could be because I did not introduce enough price or travel time variability into the choice experiment. Future studies should more carefully specify this important variable. Finally, I found a difference in sociodemographic in the recruitment method for the survey among social media and flyer distribution. Studies could compare and contrast such differences to address possible biases generated by the survey recruitment method in the context of shared micromobility in developing countries.

4.6 Conclusions

Micromobility modes could hold substantial promise for developing cities to pursue a low-carbon mobility pathway. Understanding how successful such programs can be is important, particularly in the context of weather, infrastructure, and social norms. This study sets out to parameterize several factors that could influence bikeshare, e-bike share, and e-moped sharing models. From this study, city governments could start with a small-scale pilot program by combining the findings of this study. Cities like Bogotá have produced lessons on successfully implementing shared micromobility. I also encourage the collection of usage and operation data during the pilot program so that a data-driven performance evaluation can inform decisions to improve and scale up shared micromobility systems. These data could also support transportation investment decisions, such as building bike lanes, promoting multimodal transportation systems, and adopting other innovative mobility solutions like Mobility-as-a-Service (MaaS). To realize the enormous potential of shared micromobility in promoting sustainable transportation in developing countries, I recommend a strategic partnership among local government and private entities with the technical support of non-profits and multilateral development banks.

Chapter 5. Usage-based clustering of e-scooter trips

This chapter is based on a research paper by Nitesh R Shah, Jing Guo, Han D Lee, and Christopher Cherry titled “Why Do People Take E-Scooter Trips? Insights on Temporal and Spatial Usage Patterns of Detailed Trip Data”. The paper is in review at the Transportation Research Part A: Policy and Practice. The paper was presented at Transportation Research Board 100th Annual Meeting 2021 in Washington, D.C. This research paper also received first place in the 2021 Annual Student Paper Competition, Tennessee Section Institute of Transportation Engineers, and second place in the 2021 Annual Student Paper Competition, Southern District Institute of Transportation Engineers.

Abstract

Electric scooters (e-scooters) are becoming one of the most popular micromobility options in the United States. Although there is some evidence of increased mobility, reduced carbon emissions, replaced car trips, and associated public health benefits, there is little known about the patterns of e-scooter use. This study proposes a framework for high-resolution analysis of micromobility data based on temporal, spatial, and weather attributes. As a case study, I scrutinized more than one million e-scooter trips of Nashville, Tennessee, from September 1, 2018, to August 31, 2019. Weather data and land use data from the Nashville Travel Demand Model data and scraping of Google Maps Point of Interest (POI) data complemented the trip data. The combination of Principal Component Analysis (PCA) and a K-means unsupervised machine learning algorithm identified five distinct e-scooter usage patterns, namely morning work/school, daytime short errand, social, nighttime entertainment district, and utilitarian trips. Among other findings, the most common use of e-scooters in Nashville was daytime short errand trips, contributing to 29% of all e-scooter trips. I found that 7% of all e-scooter trips resembled morning commuting to work or school. Only 16% of trips were classified as Nighttime Entertainment District trips. The average daily number of trips on a typical weekend was 81% higher than a typical weekday. I also found variation in e-scooter usage patterns over a year with high summer ridership patterns. The findings of this study can help city administrations, planners, and micromobility operators to understand when and where people are using e-scooters. Such knowledge can guide them in making data-driven decisions regarding safety, sustainability, and mode substitution of emerging micromobility.

5.1 Introduction

Cities have found themselves behind on managing and regulating e-scooter operations within their jurisdiction. Most e-scooter service providers distributed the devices in the street without any warning (Lazo, 2018), and the proprietary nature of these companies provide limited research opportunities (McKenzie, 2019). Although e-scooters can potentially increase mobility, reduce greenhouse gas emissions, decrease automobile use, and add health benefits (S. Shaheen & Cohen, 2019), there are several ongoing debates regarding their safety, operation, and actual impact on infrastructure and transportation systems.

This chapter offers a framework for analyzing micromobility trips based on temporal, spatial, and weather attributes. The study contributes to the literature by examining, with unprecedented resolution, the spatiotemporal usage of shared electric scooters in a mid-sized metropolitan city of the United States. The findings of this study complement the survey-based studies, which are based on the responses of a sample of e-scooter users over a short duration, by identifying the e-scooter usage patterns over a year.

The chapter is organized into the following sections. The remainder of this section provides a brief background on the usage characteristics of micromobility, factors influencing shared scooter trips, and the research hypothesis. Section two describes the methodology, followed by the results in section three. The discussion can be found in section four, while section five contains the conclusion.

5.2 Review of literature

5.2.1 E-scooter usage research approaches

Previous studies have taken a survey and micromobility data analysis approach to understand the usage of e-scooters as an emerging transportation technology. The Portland Bureau of Transportation (2019) accomplished one of the earliest survey-based studies, where 28% of survey respondents said that they would not have made the trip if e-scooters were not available, but 34% of e-scooter trips by local residents and 48% of e-scooter trips by travelers were the substitution of an automobile. Studies in other cities, like Austin, Texas, and Denver, Colorado, also reported approximately a third of e-scooter trips replacing private automobile trips (City of

Austin, 2019; Denver City Council, 2019). The e-scooter operator Lime reported that 55% of e-scooter trips in San Francisco, California, were related to work and school (Lime, 2018).

While user intercept survey studies are informative on mode substitution and trip purpose of e-scooter trips, the results might not necessarily be a complete representation of e-scooter usage. The location can be biased over e-scooter trip characteristics (Rayle, Dai, Chan, Cervero, & Shaheen, 2016); for instance, urban park areas could be overwhelmingly recreational, while e-scooter trips in downtown areas could be utilitarian, like work-related trips. The intercept survey results are also affected by the time of data collection, with under-representation during night-time and days with special events that result in a surge in e-scooter usage. Another limitation is the small sample size effect that influences the conclusion's reliability due to random error.

Many city governments also collect Global Positioning System (GPS) based trip summary datasets from micromobility operators, which provides a unique opportunity to evaluate usage characteristics of micromobility using regression models like negative binomial and spatial regression. Bai and Jiao (2020) found that downtown and university areas are the most common area for e-scooter use in Minneapolis, Minnesota, and Austin, Texas. Caspi et al. (2020) also found that e-scooters are popular among younger demographics, with higher e-scooter usage in low-income areas that have a high student population compared to low-income areas without student populations.

Although these studies incorporated spatial attributes of e-scooter usage using regression models such as Geographically Weighted Regression (GWR) and Generalized Additive Modeling (GAM) approaches, they lack an evaluation of detailed temporal characteristics and seasonal variations (Hosseinzadeh, Algomaiah, et al., 2021a). McKenzie (2019) evaluated both spatial and temporal attributes of shared e-scooter trips to compare with bikeshare trips in Washington, D.C. However, the author only used data from one e-scooter operator, although several operators provided service at the time. The study period was also less than five months. To our knowledge, a comprehensive spatiotemporal analysis of e-scooters lacks in the literature.

Researchers have combined data mining methods to combine GPS travel data with sociodemographic data to evaluate spatiotemporal travel patterns. Jiang, Ferreira, and González (2012) used eigendecomposition and K-mean clustering on an activity-based travel survey to identify activity patterns in Chicago. Several studies have used a similar approach to evaluate bikeshare usage. Xu et al. (2019) used the eigendecomposition method to understand the usage pattern of the dockless bikesharing system and its relationship with the built environment in Singapore. Bao, Xu, Liu, and Wang (2017) combined K-means clustering with Latent Dirichlet Allocation (LDA) to categorize the bikeshare trips in New York based on trip purpose.

This chapter is an exploratory study using existing spatiotemporal analysis techniques on the unique dataset of emerging micromobility that complements survey-based and micromobility data-based studies in the literature. The e-scooter usage patterns identified from the micromobility data provide knowledge on when and where people use e-scooters, while a yearlong study period captures the seasonal variation.

5.2.2 Factors influencing shared e-scooter trips

Understanding the factors that influence travel choices (modes and routes) helps inform transportation planning and policy decision making (Tu et al., 2018; Zhou et al., 2017). While there are limited studies on factors influencing dockless e-scooter trips, there is extensive research on docked bikeshare systems. The general trip pattern of dockless e-scooters resembles the trip pattern of casual users of docked bikeshare systems in Washington, D. C. (McKenzie, 2019) and dockless bikeshare systems in Indianapolis, Indiana, and Louisville, Kentucky (Mathew et al., 2019; Robert B Noland, 2019).

Previous studies have found socio-demographics, built environment, and weather condition factors to determine bikeshare use. Socio-demographic attributes such as gender, median household income, population density, and automobile ownership have an influence on micromobility ridership (Buck & Buehler, 2012; Faghih-Imani & Eluru, 2015). Built environment indicators, such as land use mixture, and proximity to transit stations, correlate with shared bikeshare use (Wang, Lindsey, Schoner, & Harrison, 2016; Xu et al., 2019; Y. Zhang, Thomas, Brussel, & Van Maarseveen, 2017). Several studies have also found extreme weather conditions (hot or cold temperatures, precipitation, and snowfall) to decrease the use of shared micromobility (El-Assi, Mahmoud, & Habib, 2017).

Some papers have explored the factors influencing shared e-scooter usage. The number of e-scooter trips has a significant correlation with the time of the day and day of the week (weekday vs weekend), with the peak use occurring on afternoon or evening of weekends (Bai & Jiao, 2020; Caspi et al., 2020; Hosseinzadeh, Algomaiah, et al., 2021a). E-scooters usage was observed mainly in high population density areas (downtown), university, and commercial areas. Hosseinzadeh, Algomaiah, et al. (2021a) also found a positive correlation between e-scooter use and urbanism indices, such as Walk Score, Bike Score, and Transit Score, in Louisville, Kentucky.

In a study of e-scooter use in Indianapolis, Mathew et al. (2019) found that the number of e-scooter trips reduced significantly during rain and snow, although the trip distance and duration decreased only slightly. Other related studies on e-scooter safety, operation optimization (Ciociola, Cocca, Giordano, Vassio, & Mellia, 2020), and charging optimization (Masoud et al., 2019) can also inform understanding of e-scooter usage.

5.2.3 Research objective

Some pilot studies rely on recall surveys, which are affected by response bias and small sample sizes. This study, on the other hand, takes a data-driven approach by examining all the e-scooter trips completed in a year to evaluate scooter use patterns.

The research questions of the study to examine the spatiotemporal usage characteristics are as follows:

1. What are the distinct e-scooter usage patterns based on temporal and spatial features and weather characteristics?
2. How can spatial and temporal visualization improve the understanding of the e-scooter usage patterns?

5.3 Methodology

The unprecedented spatial and temporal resolution, as well as the volume of micromobility data, requires state-of-the-art data analysis methods. This study proposes a conceptual framework for such research design in the first section of this chapter while presenting a case study of Nashville in the second section.

5.3.1 Research design

The integration of GPS-enabled smartphones with micromobility operations has allowed the collection of trip-level data. Figure 23 illustrates the conceptual framework of the research design that evaluates the micromobility trip data by adding contextual information like the built environment. The proposed method relies on an unsupervised machine learning approach, as the micromobility trip-level data does not have intrinsic usage-related information. However, knowledge of general micromobility usage is important for planning and policy-level decisions.

A brief description of each step in the research design is as follows:

5.3.1.1 Input data

The first step involves linking data on e-scooter trips and the built environment. The trip data collected by e-scooter operators include information such as distance, duration, location, and timestamp of origin and destination, and could also contain the GPS trace of the route. These scooter trip data, however, lack contextual information like built environment and weather attributes. The population, employment, parking, and intersection density, as well as land use mixture at origin and destination of the trip (measured by entropy) explain the built environment. The average daily temperature and precipitation on the day of the trip describe the weather attributes. Additionally, latent variables such as average trip speed and trip directness (ratio of route distance to Euclidian distance between origin and destination) explain the characteristics of trips.

5.3.1.2 Unsupervised Machine Learning

The second step entails unsupervised machine learning methods and associated pre-processing of the data. One advantage of an unsupervised approach is that it does not require a dependent variable and independently finds clusters within the data. As this study uses the K-means clustering algorithm, which utilizes distance-based optimization, I normalized the variables using the min-max technique to ensure the proportionate contribution of each variable in the cluster. The mathematical expression for min-max normalization is as follows:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

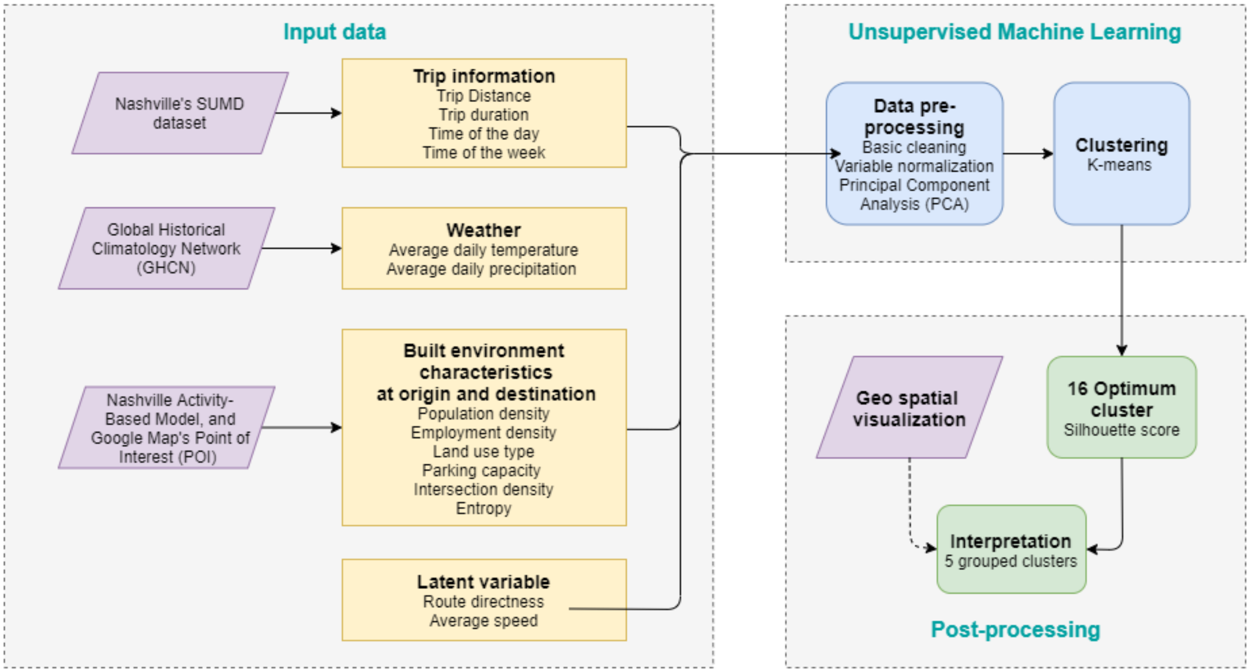


Figure 23 Research design framework

Where x' is the transformed value, and x is the actual value.

Next, the study used Principal Component Analysis (PCA) to reduce the number of variables of the input data for the K-means algorithm. PCA is a statistical tool that combines variables that could potentially be correlated into principal components that are linearly uncorrelated with each other (Jolliffe, 2011). Mathematically, for a given set of an input vector $x_t(t = 1, \ldots, l \; and \; \sum_{t=1}^{l} x_t = 0)$, where each input is of m dimension.

$$x_t = \left(x_t(1), x_t(2), \ldots, x_t(m)\right)^T \; for \; (m < l)$$

PCA transforms each vector x_t linearly into a new set of s_t by $s_t = U^T x_t$, where U is $m \; x \; m$ orthogonal matrix whose i^{th} column is u_i, which is the i^{th} eigenvector of the sample covariance matrix.

Some common clustering algorithms are K-means, Hierarchal clustering, and Gaussian Mixture Model (GMM). Using a subset of the data used in the paper, N. Shah (2020) found that using a combination of PCA and K-means clustering yields better clusters. The K-means algorithm clusters the data by separating observations into k groups of equal variance by minimizing a criterion known as the inertia or within-cluster sum-of square (MacQueen, 1967). The mathematical expression of the criterion is as follows:

$$J = \sum_{i=1}^{k} \sum_{j=1}^{n} \left(||x_i - v_j||\right)^2 = 1$$

Where, $||x_i - v_j||$ is the Euclidian distance between a point, x_i, and a centroid, v_j, iterated over all k points in the i^{th} cluster, for all n clusters.

To evaluate the performance of the K-means models, this study used the silhouette score, which measures how similar an observation is to its cluster. The silhouette coefficients range from -1 to +1, where a high value indicates a better match with its cluster and a poor match to neighboring clusters. Mathematically, the silhouette score is defined as the following:

$$Sil(i) = \frac{b(i) - a(i)}{max(b(i)a(i))}$$

Where, $a(i)$ is a measure of how well i is assigned to its own cluster, and $\mathrm{b}(i)$ is the measure of how dissimilar i is to its neighboring cluster.

5.3.1.3 Post-processing

In the final stage, the optimum clusters are interpreted through the aid of geospatial visualization. These maps of trip origin and destination of each cluster can explain the distribution of trip patterns across the city.

5.3.2 Case study

Using the aforementioned methodology, I conducted a case study analyzing all the e-scooter trips in Nashville, Tennessee for a year. The following sub-sections describe the study area, data sources, and data cleaning as well as preparation processes.

5.3.2.1 Study area

The study is based in Nashville, Tennessee, with a population of 1.9 million within the Nashville Metropolitan Area. According to a report published by INRIX, 51% of all trips taken in the United States during October 2018 were under 3 miles (Reed, 2019). The report ranked Nashville as the US city with the third-best potential for micromobility after Honolulu, Hawaii and New Orleans, Louisiana.

Bird first introduced 100 e-scooters without coordinating with the Metropolitan Government of Nashville and Davidson County, Tennessee in May 2018. After banning e-scooters for a few months, the Nashville Metropolitan Planning Organization (MPO) started an e-scooter pilot program by regulating the e-scooters operators in a permit-based system. Seven e-scooter operators, namely Bird, Lime, Lyft, Spin, Jump, Gotcha, and Bolt Mobility, provide service in Nashville.

5.3.2.2 Data source

All the permitted e-scooters in Nashville are required to submit a device's location and trip data sets as a condition of their permit, a Shared Use Mobility Device (SUMD) data standard was required by the city. This dataset is more detailed that the Mobility Data Specification (MDS) as it includes high-resolution GPS data along each trip. This analysis used the "Trip Summary" dataset, which contains trip information such as trip start time, end time, route distance, trip duration, and start and end location.

The study used land-use characteristics developed by the Nashville Activity-Based Model (RSG, 2016), as well as Point of Interest (POI) data from Google Maps. The travel demand model developed a land-use tool that used several inputs such as employment and household data in the Traffic Analysis Zone (TAZ) level, census block level employment and household information, school locations and enrollment by grade, census block geographies, and parking data. I obtained the shapefile of data from the Nashville Area MPO. I complemented the land use data by manually scraping 7,215 POI from Google Maps at the locations of scooter activity.

For weather data, this study used average daily precipitation and average daily temperature obtained from the Global Historical Climatology Network (GHCN). The GHCN is a database that contains historical daily temperature, precipitation, and snow records over global land areas. I extracted the subset of weather data from Nashville International Airport for the study period.

5.3.2.3 Data cleaning

Before preparing the data for analysis, I first cleaned the data for erroneous trips. Out of the 1,546,920 scooter trips extracted from September 1, 2018 to August 31, 2019, I first removed 25,711 trip records that had missing values. I also removed 17,857 trip records that had zero trip distance based on the GPS trace records. Next, I filtered out trip records that did not resemble usual scooter trips based on trip distance and duration. The median distance and duration of scooter trips is 0.21 miles and 10 minutes, respectively. I therefore removed 127,463 trips that were less than 60 seconds and greater than 180 minutes. I also deleted 182,529 trips that were less than 200 feet and greater than 10 miles.

Further, I calculated the route directness of the remaining trips, which equals the ratio of the Euclidean distance between the trip origin and destination to the actual distance travelled obtained from GPS trace data. As it is impossible for the actual distance traveled to be shorter than the Euclidian distance, I also removed 123,540 trips that had a route directness ratio greater than 1. After completing the initial cleaning, 1,072,430 scooter trips remained, having removed 474,490 trips (30% of the raw trip records).

5.3.2.4 Data preparation

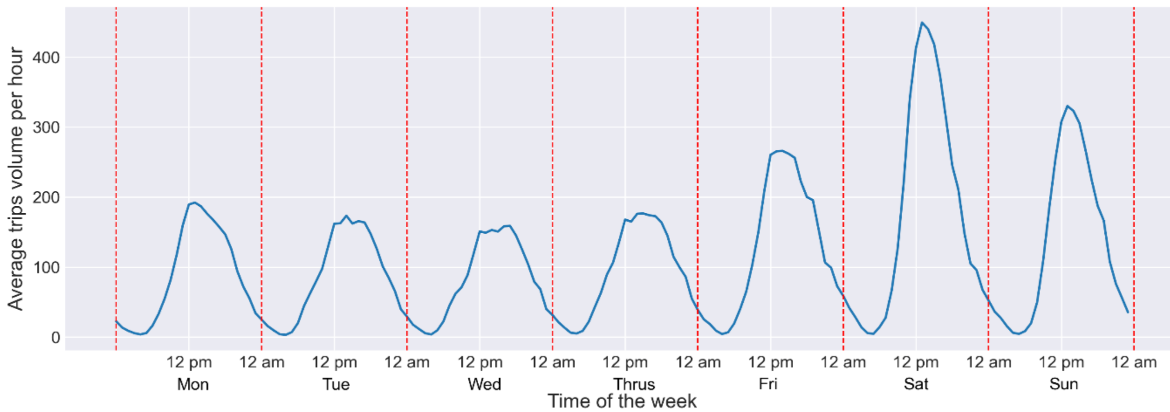
After the initial cleaning, I created a few latent variables from the trip records to describe trip characteristics. First, I calculated the average trip speed in miles per hour by dividing the trip distance by trip duration. I also added in average temperature and average precipitation data per date.

Next, I created dummy variables to indicate the trip start time throughout the day, as well as weekend trips. The dummy variable "AM Peak" indicates an e-scooter trip starting between 7 am and 10 am, and "Day" represents trips between 10 am and 4 pm. Similarly, "PM Peak" includes trips from 4 pm to 8 pm, while "Night" indicates trips between 8 pm to 7 am. Since significant e-scooter trips are completed between 4 pm on Friday and the end of the day on Sunday (see Figure 24 (a)), I also added a dummy variable to indicate weekend trips.

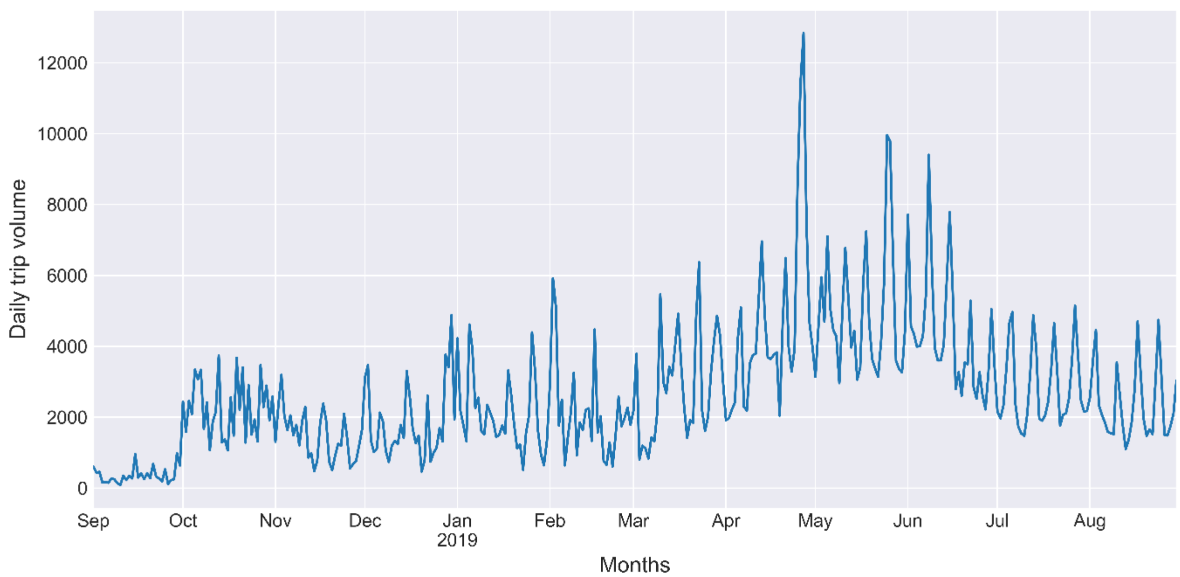
As seen in Figure 24 (b), the number of e-scooter trips increased in March, peaked in May, and gradually decreased in June. There are some high spikes in daily e-scooter trips between April and June 2019. For example, April 27, 2019, which coincides with the National Football League (NFL) draft, has the highest daily trip count in Nashville. As the 15 days with the highest daily trips account for 13.6% of all trips, I created a dummy variable indicating the trips during special events in Nashville.

After adding the latent variables, I used ArcGIS to create a grid of 250 m x 250 m squares (equivalent to 820 ft x 820 ft) for the Nashville area to link scooter trips with a built environment. First, I created an origin-destination (OD) matrix by intersecting the origin and destination location of scooter trips and cross tabulating on grid ID. Some of the squares had only a few scooter trip origins and destinations. Therefore, I removed squares with fewer than 2 origin and/or destination points (equal to the 25th percentile threshold of trip volume among all squares). In this process, I removed 22,389 additional scooter trips (1.4% of raw trip records), for a total number of trips for the analysis of 1,050,041.

Next, I calculated the average proportion of land-use type for each grid square, including central business district (CBD), urban, and suburban. These land-use variables were obtained from the MPO travel demand model aggregated at TAZ. I complemented the land use data by manually scraping POI data from Google Maps that I reclassified into eight categories: basic amenities,



(a)



(b)

Figure 24 Temporal usage pattern of scooter

(a) Scooter trips start time by time of day and day of the week and (b) Daily scooter trips over a year.

entertainment, government institutions and organizations, hotels, restaurants, bars, retails and services, and transportation. Then, I calculated the Shannon Entropy of each square to measure the land use diversity using the following equation:

$$H = -\sum_{i=1}^{n} (p_i) * \log_n(p_i)$$

Where, p_i is the percentage of POIs in i^{th} category and n is the total number of categories

In addition to land-use type, I added parking capacity, average population density, and average employment density for each square. I also estimated the intersection density per square mile for each square as a proxy of the road network. To do so, I made a query of roads within 500 m (equivalent to 1640 ft) from the center of the square using the OSMnx Python library (Boeing, 2017).

Table 10 presents the descriptive statistics of all the variables used in the study.

5.4 Results

The results of this case study of Nashville are organized into three sections. The first section presents the PCA decomposition of variables, while the second section describes the results of K-means clustering, including the grouping of K-means to simplify the segmentation of e-scooter usage. In the final section, I present the spatial and temporal characteristics of these grouped clusters.

5.4.1 PCA decomposition

This section presents the results of a principal component analysis, which indicates the significance of variables on the e-scooter trip data variance. Figure 25 illustrates the loading factor of 30 variables on the first ten principal components (PCs). While there is no specific consensus on what should be the correct number of PCs (Xu et al., 2019), I chose ten PCs, adopting the empirical rule proposed by Jolliffe (2011) to retain the number of PCs that explain at least 70% of the total variation in the data. The ten PCs in our study explained about 86% of the variation in the data.

Table 10 Descriptive statistics of variables used in the analysis

Variable Name	Type of variable	mean/ count	std	min	max
Route distance (miles)	Continuous	0.72	1.02	0.00	10.00
Trip duration (minutes)	Continuous	16.41	17.82	1.00	180.00
Route directness ratio	Continuous	0.55	0.30	0.00	1.00
Average trip speed (mph)	Continuous	2.97	2.97	0.00	304.29
Average daily precipitation	Continuous	0.14	0.35	0.00	4.00
Average daily temperature	Continuous	64.75	14.61	24.00	85.00
Proportion of CBD land use at origin	Continuous	0.66	0.33	0.00	0.90
Proportion of urban land use at origin	Continuous	0.23	0.33	0.00	0.90
Proportion of suburban land use at origin	Continuous	0.00	0.01	0.00	0.60
Proportion of rural land use at origin	Continuous	0.00	0.00	0.00	0.00
Average population density at origin (per sq. miles)	Continuous	8137.08	4665.16	0.00	18555.69
Average employment density at origin (per sq. miles)	Continuous	74560.58	70045.31	24.54	229577.11
Average parking density at origin (per sq. miles)	Continuous	12622.29	16216.93	0.00	53492.32
Intersection density at origin (per sq. miles)	Continuous	536.47	144.46	20.72	808.08
Entropy at origin	Continuous	0.66	0.25	0.00	0.93
Proportion of CBD land use at destination	Continuous	0.66	0.33	0.00	0.90
Proportion of urban land use at destination	Continuous	0.23	0.33	0.00	0.90
Proportion of suburban land use at destination	Continuous	0.00	0.01	0.00	0.60
Proportion of rural land use at destination	Continuous	0.00	0.00	0.00	0.00
Average population density at destination (per sq. miles)	Continuous	8039.68	4619.75	0.00	18555.69
Average employment density at destination (per sq. miles)	Continuous	75594.81	70944.77	24.54	229577.11
Average parking density at destination (per sq. miles)	Continuous	12901.98	16402.38	0.00	53492.32
Intersection density at destination (per sq. miles)	Continuous	535.63	145.50	20.72	808.08
Entropy at destination	Continuous	0.64	0.27	0.00	0.93
Trips on special event	Dummy	142668 (13.6%)			
Weekend trips	Dummy	265020 (25.2%)			
AM Peak trips (7 am to 10 am)	Dummy	72813 (6.9%)			
Daytime trips (10 am to 4 pm)	Dummy	508505 (48.4%)			
Evening Peak trips (4 pm to 8 pm)	Dummy	298641 (28.4%)			
Night trips (8 pm to 7 am)	Dummy	170538 (16.2%)			

These PCs are listed in descending order of proportion of variance. The color scale in the figure indicates the loadings, which is a measure of the contribution of variables in each of the principal components. A positive value of loading indicates a positive correlation between the variable and principal component, whereas a negative value indicates a negative correlation. A large value (either positive or negative) indicates that a variable has a strong effect on the corresponding principal component.

The PCs are combinations of loadings of almost all variables except suburban and rural land-use variables. There is a strong correlation between e-scooter use and start time (hours of the day and day of the week) as well as the proportion of land use (CBD and urban). The route directness and average daily temperature also explain the pattern of trips. Furthermore, the loadings of PCA indicate contributions of population, employment, parking density, and land use mixture of origin and destination in e-scooter usage. I removed the intersection density variable since it did not add a meaningful interpretation of the clusters.

5.4.2 Clustering

The PCs described above were used to identify clusters of micromobility trips using the K-means algorithm. This section presents the evaluation of various K-means models, interpretation of the optimum model, and grouping of clusters for meaningful e-scooter trip characteristics.

5.4.2.1 Evaluation of K-means models

I evaluated 18 K-means models that ranged in the number of clusters between 2 to 19 and an increment of one. A K-means model with a low Davies-Bouldin (DB) Index and high silhouette score is desirable for the optimal model. The DB Index had one of its lowest troughs at 15 K-means of clusters (as illustrated in the figure of Appendix A4.1 Clustering quality metrics). On the other hand, the silhouette score was highest at four K-means clusters, with subsequent peaks at 11 K-means clusters and 15 K-means clusters. Although the clustering performance indexes showed better values at higher numbers of K-means clusters, these additional clusters might not be practically distinct from others and would lead to higher computing costs (Naghizadeh & Metaxas, 2020). Therefore, I decided to select the model with 15 K-means clusters for interpretation, considering the values of both the DB Index and the silhouette score.

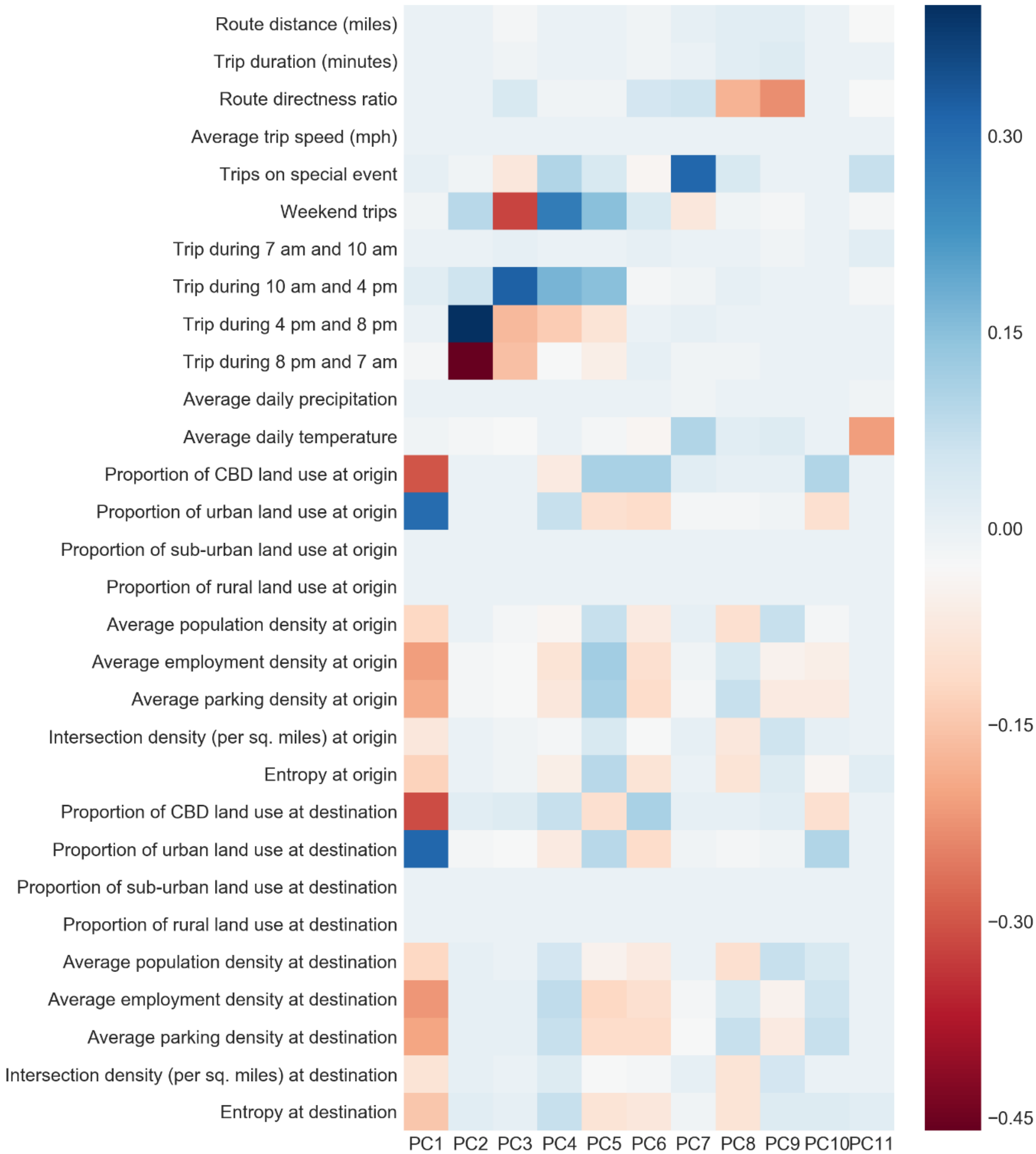


Figure 25 Loadings on the first eleven principal components of the scooter trip

5.4.2.2 Interpreting clusters

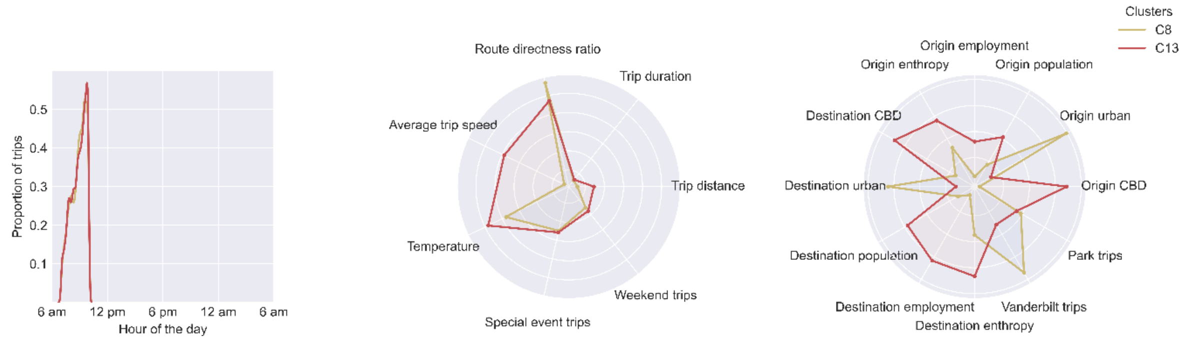
Figure 26 summarizes the results of the optimum model selected for interpretation. Some K-means clusters of the optimum model have similar origins and destinations, as well as trip start times and characteristics. Therefore, I combined clusters from the K-means analysis into five usage-grouped clusters to simplify the interpretation of e-scooter travel behavior in Nashville. These usage-grouped clusters are morning work/school trips, daytime short errand trips, social trips, nighttime entertainment district trips, and utilitarian trips.

Each usage-grouped cluster has three subplots: a temporal attribute indicating trip start time in a day, a radar plot of trip attributes describing trip characteristics, and a radar plot of spatial attributes summarizing the built environment of origins and destinations. The values in the radar plot are normalized between 0 and 1 to make a comparison among clusters.

Based on the attributes, I can describe the general trip characteristics of each K-means cluster. Trips in Cluster C8, for instance, were completed during the morning (7 am to 10 am), as shown by the temporal attribute plot. These trips are mostly on weekdays, have short distances, and have a direct route between the origin and destination (indicated by the high route directness ratio), as illustrated in the trip attributes plot. The origin and destination of these trips were mainly at Vanderbilt University and areas outside downtown Nashville, indicated by the higher values of urban land use and CBD, as shown in the spatial attributes plot. Therefore, e-scooter trips in Cluster C8 are morning trips mainly in Vanderbilt University and outside downtown Nashville resembling morning work/school trips. The remaining K-means clusters follow a similar interpretation.

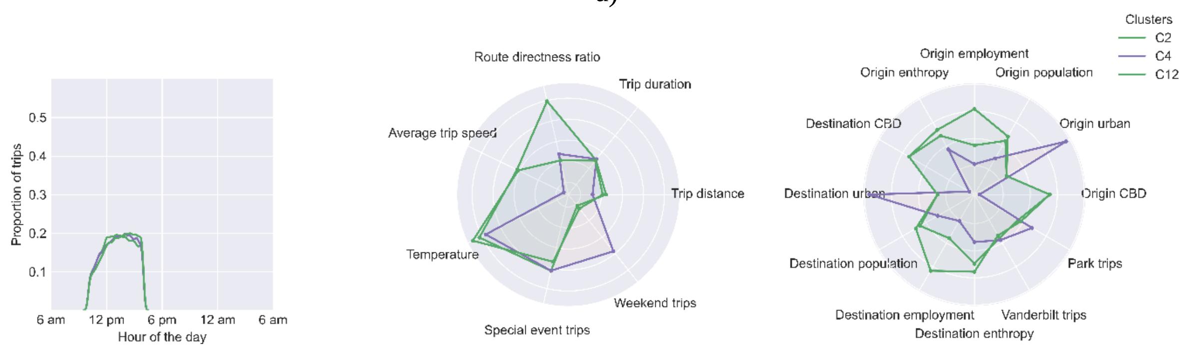
Table 11 presents the aggregated value of the spatiotemporal attributes and summary statistics of the five usage-grouped clusters. The values are color-coded such that shades of blue represent higher mean values among groups, whereas shades of red indicate lower values. The white background of the cell indicates mid values. Darker shades of red and blue indicate extreme values, whereas lighter shades represent less-extreme values.

Based on Table 11, Figure 26, and heat map of origin and destination (included in the Appendix A4.2 Heat maps of origin and destination), a brief description of each usage-grouped cluster, including the list of K-means clusters, are as follows:



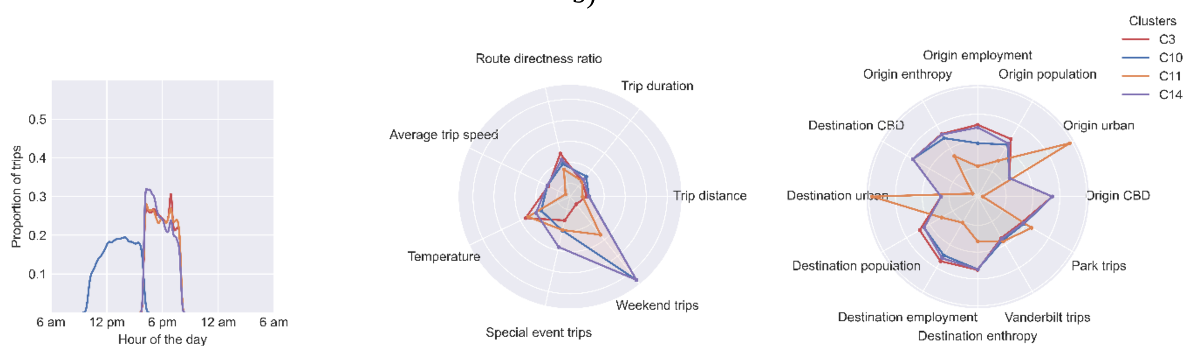
Temporal attribute *Trip attributes* *Spatial attributes*

a)



Temporal attribute *Trip attributes* *Spatial attributes*

b)

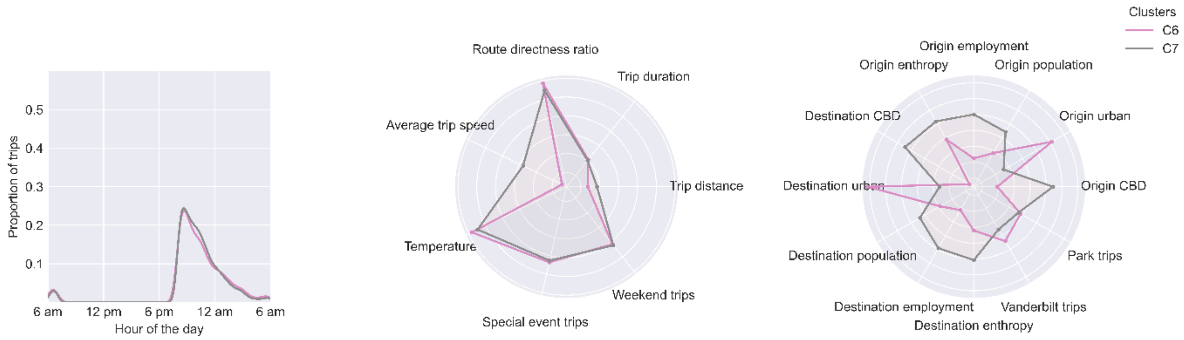


Temporal attribute *Trip attributes* *Spatial attributes*

c)

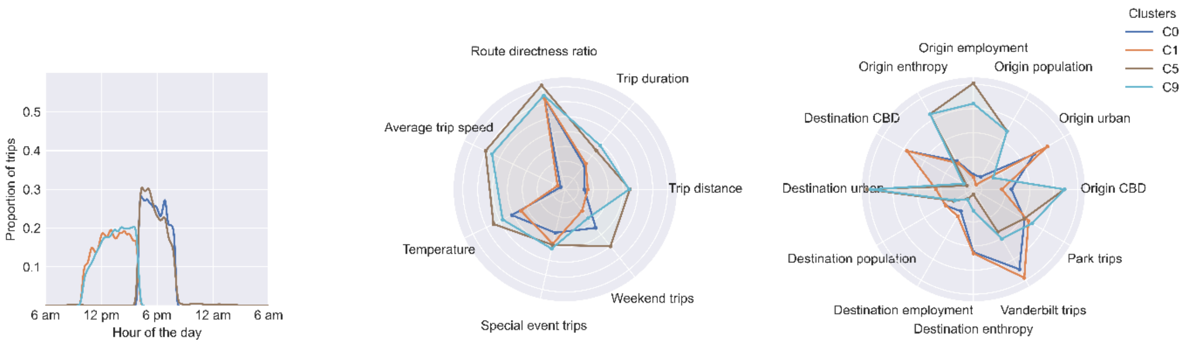
Figure 26 Clustering results grouped by usage

a) Morning work/school trips, b) Daytime short errands, c) Social



Temporal attribute *Trip attributes* *Spatial attributes*

d)



Temporal attribute *Trip attributes* *Spatial attributes*

e)

Figure 26 continued

d) Nighttime entertainment districts, e) Utilitarian

Table 11 Aggregated values of spatiotemporal attributes and summary statistics of usage-grouped clusters

Variables	**Usage-grouped cluster name** **Morning work/school**	**Daytime short errand**	**Social**	**Nighttime entertainment districts**	**Utilitarian**
Route distance (miles)	0.68	0.71	0.68	0.67	0.86
Trip duration (minutes)	13.07	17.13	16.53	15.07	17.36
Route directness ratio	0.60	0.49	0.52	0.57	0.64
Average trip speed (mph)	3.62	2.76	2.75	2.97	3.27
Average daily temperature	65.55	64.63	65.22	65.41	63.40
Proportion of CBD land use at origin	0.65	0.66	0.71	0.67	0.62
Proportion of urban land use at origin	0.25	0.24	0.18	0.22	0.27
Average population density at origin	7475.39	8983.54	9197.89	8310.11	5866.55
Average employment density at origin	59800.97	79228.37	87626.72	80251.17	53642.39
Average parking density at origin	9114.48	13559.66	15135.34	13708.41	8761.92
Entropy at origin	0.63	0.69	0.70	0.67	0.56
Proportion of CBD land use at destination	0.70	0.66	0.72	0.64	0.60
Proportion of urban land use at destination	0.20	0.24	0.17	0.25	0.29
Average population density at destination	8021.85	9037.09	9281.62	7909.03	5381.02
Average employment density at destination	79262.92	85090.22	92812.85	74195.29	42925.37
Average parking density at destination	13712.36	15033.61	16305.78	12265.58	6344.97
Entropy at destination	0.66	0.68	0.70	0.63	0.52
Percentage of weekend trips within cluster group	13.69	7.74	55.49	26.88	15.30
Percentage of special day trips within cluster group	10.49	13.54	14.65	15.59	11.89
Trip distribution among cluster group					
Percentage of trips by count	6.92	29.03	25.78	16.17	22.10
Percentage of trips by Vehicle-Miles Travelled (VMT)	6.48	28.24	24.20	14.86	26.21
Percentage of trips by travel duration	5.51	30.30	25.97	14.84	23.38

Note: Red color indicates lower values while blue color indicates higher values among clusters

Morning work/school trips: These e-scooter trips were made during the morning (7 am to 10 am), mainly during the weekdays, with origin and destinations in downtown Nashville and Vanderbilt University. These trips have shorter route distances than most of the usage-grouped clusters and have a direct route between the origin and destination, as indicated by a higher-value route directness ratio. Such trips contribute to 7% of all e-scooter trips in Nashville and are likely for the purpose of commuting to work in downtown Nashville or going to class at Vanderbilt University. The individual K-means clusters included in the morning work/school usage-grouped cluster are as follows:

- C8: Short trips during AM peak outside downtown Nashville including Vanderbilt University
- C13: Short trips during AM peak in downtown Nashville

Daytime short errand trips: These e-scooter trips were completed during the daytime (10 am to 4 pm) in downtown Nashville mainly on the weekdays. These trips have the lowest route distance on average among all usage-grouped clusters. The low average travel speed of trips in this cluster, as compared to other usage-grouped clusters, indicates that e-scooter riders may have spent more time stopped at traffic signals. The average daily temperature of trips is also low among all usage-grouped clusters, which suggests that these trips were made on days with cooler temperatures. These trips make up 30% of all e-scooter trips in Nashville and resemble errand trips like going to lunch. The individual K-means clusters within this usage-group clusters are as follows:

- C2: Trips in the commercial area nearby downtown Nashville, mostly on weekdays
- C4: Daytime trips outside the downtown Nashville area
- C12: Trips in downtown Nashville, mostly on weekdays

Social trips: These trips exhibited characteristics that might be affiliated with social activities. The majority of these trips are completed during the weekend, mainly in the evening (4 pm to 8 am), with some trips during the daytime. The origin and destination of these trips are the commercial areas of downtown and nearby Vanderbilt University, which have high entropy values indicating high diversity in land use. Social trips contribute to 26% of all e-scooter trips in Nashville. The individual K-means clusters in the social usage-grouped cluster are as follows:

- C3: Trips in downtown Nashville in the evening, mostly on weekdays
- C10: Trips in the commercial area nearby downtown Nashville, mostly on weekends
- C11: Evening weekend trips outside the downtown Nashville area, including areas like Centennial Park
- C14: Trips in downtown Nashville in the evening, mostly on weekends

Nighttime entertainment districts trips: These trips were completed at nighttime (8 pm to 6 am), with origin and destinations nearby entertainment services, like bars. Compared to some usage-grouped clusters, these trips have a more direct path between origin and destination and are made on warmer days. Such trips make up 16% of all trips in Nashville. The individual K-means clusters in this usage-grouped cluster are as follows:

- C6: Trips outside downtown Nashville at night, mostly on weekends
- C7: Trips in downtown Nashville at night, mostly on weekends

Utilitarian trips: These trips were longer in route distance and had the highest value of route directness, indicating that these trips utilized shorter paths between origin and destination compared to other groups. These trips were completed throughout the day. The built environment of the origin and destination had different land-use types. For example, if the origin had a high proportion of CBD land use, then the destination was more likely to be urban land use. The utilitarian trips are likely to travel from origin to destination with the shortest route possible, as indicated by the highest route directness ratio among all usage-grouped clusters. Utilitarian trips make up 22% of all trips in Nashville. The individual K-means clusters in the utilitarian usage-grouped cluster are as follows:

- C0: Trips starting at Vanderbilt University or outskirts and traveling within Vanderbilt University or towards the downtown Nashville
- C1: Trips in downtown Nashville in the evening, mostly on weekends

- C5: Trips originating in downtown Nashville and traveling towards outskirts in the evening
- C9: Trips from downtown Nashville to an outside area during the daytime, mostly on weekdays

5.4.3 Characteristics of Usage-grouped clusters

The following two subsections go into more detail on the spatial and temporal distribution of these usage-grouped clusters.

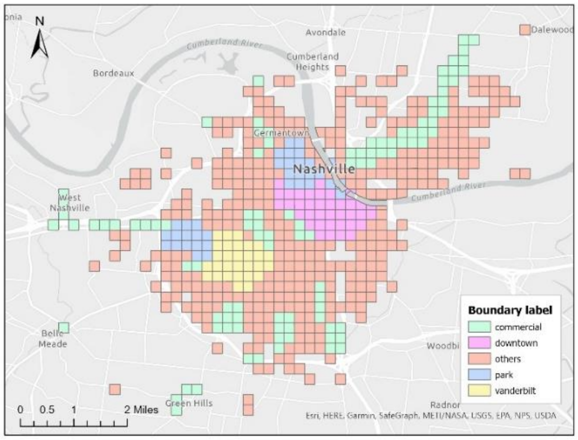
5.4.3.1 Spatial distribution

A big part of the e-scooter usage story is related to the spatial distribution of those trips. I can identify the origin and destination of trips, revealing a large component of the trip patterns. Figure 27 illustrates the spatial distribution of usage-grouped clusters in Nashville through chord diagrams. Figure 27 (a) represents the area within Nashville that I used to describe the spatial distribution; for instance, the "commercial" category includes the areas along the major commercial corridors, and the "park" category contains areas like Centennial Park. Figure 27 (b) - (f) summarize the origin and destination of each usage-grouped cluster among the areas represented in Figure 27 (a). The color of the arrow represents the starting location of a trip, and the direction of the arrow represents the ending location. The width of the arrow represents the volume of trips, with the units indicating the number of trips in thousands.

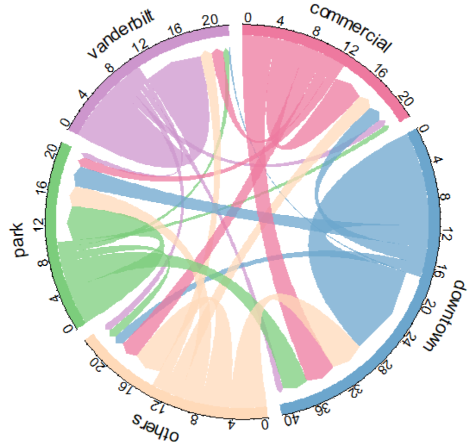
Furthermore, the origin and destination of the e-scooter trips can be associated with specific usage-groups. For instance, trips starting and ending at Vanderbilt University are predominantly morning work/school and utilitarian. Additionally, the starting and ending locations of morning work/school and utilitarian trips are relatively evenly distributed among the area categories. In contrast, a large portion of daytime short errand, social, and nighttime entertainment districts trips start and end in downtown Nashville.

5.4.3.2 Temporal distribution

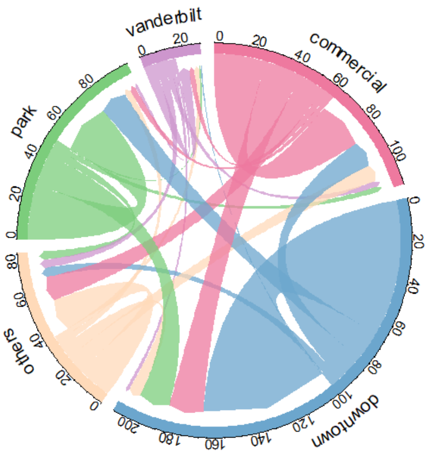
Analyzing a full year of e-scooter trip data enables us to understand e-scooter usage patterns based on time of the day, time of the week, and time of the year. Figure 28 (a) illustrates the



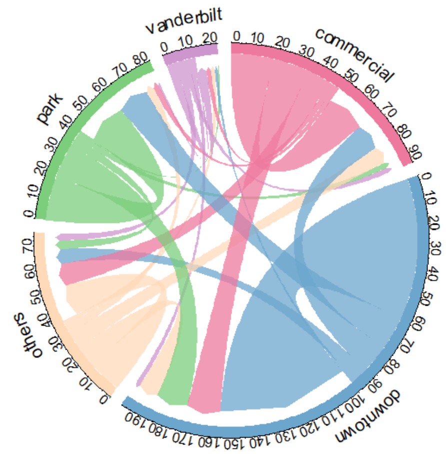
a) Boundary for chord diagram



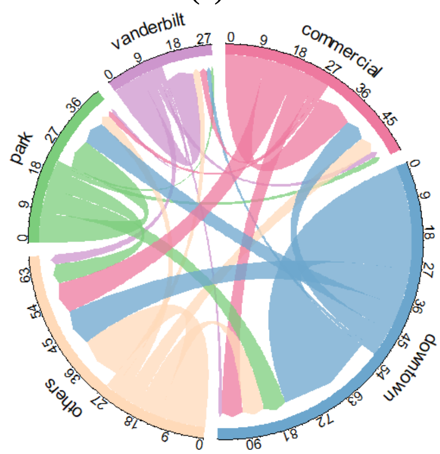
(b)



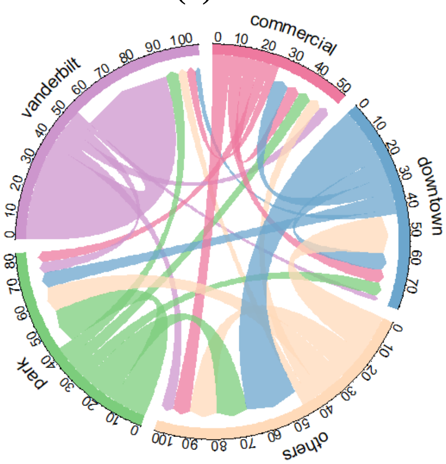
(c)



(d)



(e)



(f)

Note: The unit of the value on the axis is thousands.

Figure 27 Spatial distribution of usage-grouped clusters

(a) Boundary for chord diagram (b) Morning work/school trips (c) Daytime short errands trips (d) Social trips (e) Nighttime Entertainment District trips, and (f) Utilitarian trips average trip start times of the usage-grouped clusters throughout the day and week, while Figure 28 (b) presents the daily usage pattern over the year. I used a 21-day rolling average to get a smoother trend over the yearly pattern, as the daily e-scooter trips have a high level of variation during weekends and special events in Nashville.

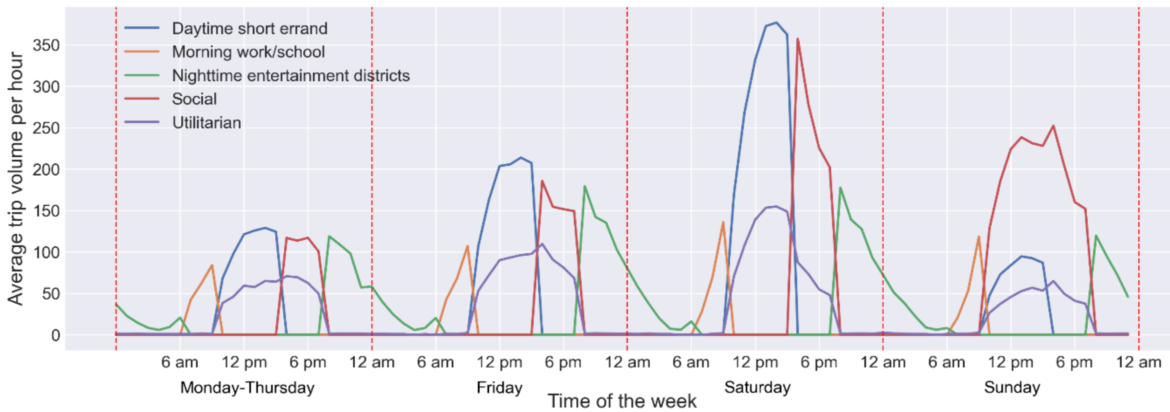
Except for the utilitarian and morning work/school trips, all the other e-scooter usage-grouped clusters significantly increased during the weekends, as indicated in Figure 28 (a). The peak of social trips on the weekends is almost twice the peak of that on the weekdays. Similarly, the peak of the nighttime entertainment district trips is higher on Friday and Saturday than other days of the week.

All usage-grouped clusters' daily average trips increased during the summer months, as illustrated in Figure 28 (b), indicating higher e-scooter usage during warm weather. The number of e-scooter trips for all usage-grouped clusters is also higher at the end of September 2019 than at the beginning of September 2018 with increasing average daily trips, which suggests an increase in popularity of e-scooters after the first year of their launch in Nashville.

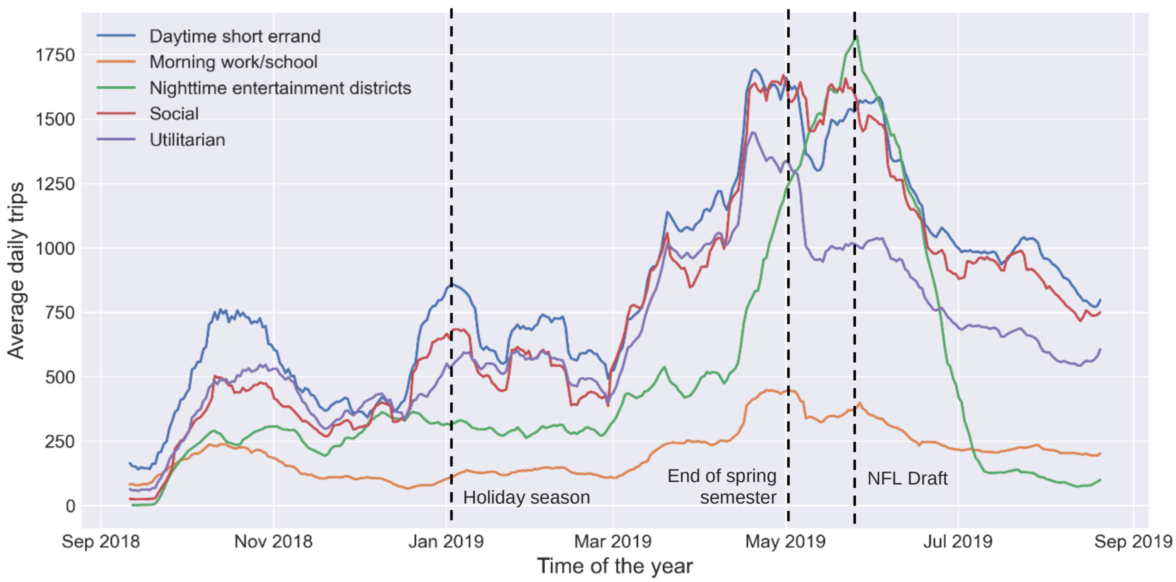
Events in Nashville, like holidays and the NFL draft, also drive up the trip volume of specific usage-grouped clusters. There was a prominent surge in nighttime entertainment district trips during the NFL draft week in Nashville, while the trip volume of other usage-grouped clusters also increased during this period. During the Christmas and New Year holidays, there was an increase in the number of trips for daytime short errand, social and utilitarian trips, suggesting people visiting Nashville use e-scooters to get around the city. The Spring semester period (January to May) at Vanderbilt University also corresponds to the increasing number of utilitarian trips, which entails a significant number of trips starting and ending at the university area.

5.5 Implications

The following section presents a discussion based on the analysis of the case study. The first section describes the value of the proposed framework, whereas the second section discusses the key findings of e-scooter usage patterns in Nashville. The last section identifies future research areas based on this study.



(a)



(b)

Figure 28 Temporal pattern of usage-grouped clusters of e-scooter

(a) Trip start time of usage-grouped clusters over day and week and (b) Trip distribution of usage-grouped clusters over months

5.5.1 High-resolution method to classify micromobility data

When e-scooters were launched in the streets of the United States, many cities imposed a ban on these emerging vehicles as their impact on the transportation system was unknown. Cities eventually permitted micromobility service providers to operate under their jurisdiction with regulations, including data sharing. The data generated by micromobility devices is unprecedented to date, and has not been leveraged to its full potential to answer questions relevant to transportation stakeholders. The understanding of e-scooter usage can inform questions regarding safety, sustainability, and mode substitution of such emerging vehicles. A similar analytical framework could also be applicable for future transportation technologies like automated vehicles.

To understand how people use e-scooters, transportation policymakers have adopted a combination of recall surveys from users and descriptive statistics of micromobility data (Portland Bureau of Transportation, 2019). However, the results of recall surveys have limited sample sizes and could also be affected by response bias, while descriptive statistics do not fully explain the usage patterns. The method presented in this study provides a framework that complements micromobility data with land use and weather datasets to add contextual information about usage. The unsupervised machine learning approach identifies distinct patterns of e-scooter usage to explain the segmentation of where and when people use e-scooters.

I propose the use of the route directness ratio, in addition to essential trip information like trip start time, to classify various e-scooter usage patterns. For instance, utilitarian trips have a higher route directness ratio that indicates paths closer to the shortest distance. This analysis is only possible with route-level trace data. I also recommend that micromobility data standards, such as Mobility Data Specification (MDS), should allow storing and sharing of disaggregated location data as well as trace data with secured access to analysts and researchers. This information is essential for the high-resolution analysis of micromobility data.

5.5.2 Nashville application

Several temporal and spatial variables can explain the e-scooter usage pattern in Nashville. The trip start time in terms of the time of the day and day of the week has distinct patterns. The route directness ratio, which represents the difference between the shortest possible path and actual route, is critical in explaining the variation in trip patterns. Furthermore, the land use type (CBD vs. urban) and mixture (homogenous vs. heterogeneous) are associated with e-scooter usage. Population, employment, and parking density also contribute to the spatial distribution of origin and destination. The effect of these variables on e-scooter usage is similar to previous studies of e-scooters (Bai & Jiao, 2020; Caspi et al., 2020) and bikeshare (Bachand-Marleau, Lee, & El-Geneidy, 2012; Faghih-Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014).

These temporal and spatial attributes can be used to identify distinct usage patterns of e-scooters. I found that 7% of e-scooter trips in Nashville were completed during morning peak hours, which might be for commuting purposes to work or school. Survey-based studies (Lime, 2018) and research analyzing micromobility data (Caspi et al., 2020) have also found some evidence of e-scooters being used for commuting. Utilitarian trips to travel between two locations contribute to 22% of all trips, indicating that e-scooters are not solely used for recreation purposes. The most common usage-grouped clusters in Nashville are daytime short errands like getting lunch, making up 29% of e-scooter trips. Social trips contribute to 26% of all e-scooter trips, while nighttime entertainment district trips make up 16% of e-scooter trips in Nashville. It is noteworthy to mention that there may be some overlap between social and nighttime entertainment district trips as trip origin and destination are similar for these usage but trip start times vary. Most of the e-scooter trips were observed in the downtown area and Vanderbilt University, similar to the findings of other studies (Bai & Jiao, 2020; M. Liu, Seeder, & Li, 2019).

The revealed-preference approach of e-scooter usage can supplement the stated-preference approach of trip purpose questionnaires in e-scooter pilot evaluations. While studies based on surveys evaluate the responses of users at specific times (Portland Bureau of Transportation, 2019), this study of all micromobility trips throughout the year allowed us to examine the weekly as well as yearly change in usage patterns. The number of trips in all usage-grouped clusters peaked during the summer and increased over the analysis period in general. Several large-scale events in the city and outdoor activities attract more e-scooter users in the summer, while increasing usage indicates the popularity of e-scooters over time. During holidays like Christmas and New Year, the number of daytime short errand, social and utilitarian trips increased. Similarly, I observed a prominent surge in nighttime entertainment district trips during the NFL draft period. These peaks suggest that e-scooters could be popular among tourists visiting Nashville for these events.

Additionally, the trips peaked in the early afternoon on both weekends and weekdays. The average daily number of trips on a typical weekend is 81% higher than a typical weekday, with the highest peak on Saturday early afternoon. These findings are consistent with previous research of e-scooter use peaking in the afternoon (Bai & Jiao, 2020; Caspi et al., 2020; McKenzie, 2019).

5.5.3 Limitations and future research

Further studies can improve this analysis in several ways. First, the results of this method can be compared with survey results for validation. Another approach could be to use survey data in combination with micromobility data through semi-supervised machine learning methods, which classify clusters by combining a small subset of labeled data (obtained from surveys) with a larger subset of unlabeled data (micromobility data). Second, additional research can improve upon the data and modeling of the approach used in this analysis. The GPS trace data of e-scooter trips could be linked with transportation network data to understand more nuanced travel behavior, like the average traffic volume of certain road segments. Spatial-based clustering algorithms, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), could generate robust models for outliers. Future models could also account for e-scooter device availability, which influences the use of these vehicles.

Third, the analysis framework of this paper can be applied to data standards, like MDS, to compare micromobility usage patterns across cities, and evaluate the impacts of various policies and regulations related to micromobility. Finally, the findings in this analysis are based on the e-scooter activity in Nashville, Tennessee, which might not necessarily be the same in other cities. Future studies can compare e-scooter usage findings from different cities to develop a comprehensive summary of e-scooter use characteristics.

5.6 Conclusion

This study proposes a novel approach to analyze high-resolution micromobility data based on unsupervised machine learning, which is further applied to the Nashville SUMD dataset as a case study. Using a combination of PCA and a K-means clustering algorithm, I found five types of distinct e-scooter usage patterns: morning work/school, daytime short errand, social, nighttime entertainment district, and utilitarian trips. These usage-grouped clusters showed temporal and spatial characteristics that contribute to understanding e-scooter usage in Nashville across a year of study.

The findings of this study can be useful to city administrations, planners, and micromobility operators. Decision-makers can use this information to make policies to ensure the safe and efficient operation of shared electric e-scooters. Transportation planners and designers can take a data-driven approach, such as the one described in this study, to better design and develop infrastructure and regulations to accommodate these emerging vehicles. The understanding of e-scooter usage patterns can also help micromobility operators optimize e-scooter distribution and maximize revenues.

Chapter 6. Estimating energy usage and emissions from micromobility data

This chapter is based on a research paper by Nitesh R Shah, Yi Wen, and Christopher Cherry titled "Estimating energy use and emissions of shared e-scooters from micromobility data."

Abstract

While shared micromobility data can be used to evaluate energy use and emissions of e-scooter systems, very few studies, have leveraged the full potential of the detailed data. I used a year-long Shared Urban Mobility Device (SUMD) dataset to deconstruct the usage and operational phases of shared e-scooter systems in Nashville, Tennessee. Using Information Complexity (ICOMP) to identify the distribution of key variables of the usage and operational phases, I used Monte Carlo simulation to evaluate the overall energy use and emission per vehicle per km traveled as well as energy use and emissions estimates for the usage and operation phases. I found that the estimates were higher than other existing studies, and the energy use and emissions vary among service providers. The findings could be helpful for city governments and service providers to inform strategies for reducing overall emissions, like increasing the lifespan of e-scooter vehicles and the utilization rate.

6.1 Introduction

The shared micromobility system is one of the fastest-growing businesses globally, with the potential to impact the environmental sustainability of urban mobility through 1) the reduction of operation emissions and 2) modal shift. In combination with high-density modes, such as transit and pooled car-sharing, micromobility can reduce car dependency by filling the gaps in mobility. Meanwhile, the integration of Smartphones and GPS technologies in micromobility services has allowed us to generate almost real-time vehicle location and detailed trip-level usage data. The adoption of Mobility Data Specification (MDS) has standardized such data across operators and cities.

This study proposes a framework to implement standardized micromobility data, such as MDS, to evaluate the energy and emission impacts of the shared e-scooters. The proposed methodology complements the existing studies evaluating the emission of shared e-scooter systems by estimating the usage and operational parameter of the Life Cycle Assessment (LCA) using Big Data. The findings of the proposed analysis are expected to help city governments to understand the overall environmental impact of shared e-scooters for data-driven strategies to manage their transportation-related sustainability impacts.

This chapter is organized into the following sections. The review of the literature section provides an overview of existing studies, highlighting key findings. The methodology section describes the study area, data, and analytical framework. The result section includes the analysis results, while the implication and future research provide an interpretation of the results. The conclusion section concludes the chapter.

6.2 Review of literature

6.2.1 Overview of prior studies

Chester (2019), a consultant, assessed one of the early Life Cycle Assessment (LCA) of shared e-scooters using generic data and basic assumptions to find emissions between 198.9 g CO_2e per passenger-km and 416.6 gm of CO_2e per passenger-km. The author found that manufacturing contributed to most emissions, followed by the collection and redistribution of e-scooters. Hollingsworth et al. (2019) published a first peer-reviewed LCA analysis to find that the average emission of shared e-scooters in Raleigh, North Carolina to be 125.5 gm CO_2e per passenger-km. Material and manufacturing contributed to 50% of the emission, while daily collection and charging contributed 43% of the emission. The authors found modal shift emission of shared e-scooters to be 93.2 gm CO2 per passenger-km, assuming one e-scooter mile travelled displaces 0.34 miles of personal cars, 0.11 miles of bus, and 0.08 miles of bicycle.

In a study in Brussels, Moreau et al. (2020) found that shared e-scooters systems emitted 131 gm CO_2-e per passenger-km, with material and manufacturing driving the majority of emissions. The authors estimated modal shift-related emission to be 110 gm CO2e, which is higher than the study by (Hollingsworth et al., 2019). Moreau et al. (2020) argued that a large extent of e-scooter trips replaced public transit trips in Brussels, while more car trips were replaced by e-scooters in the United States, contributing to larger modal shift emission. Similarly, Severengiz, Finke, Schelte, and Wendt (2020) simulated emission impacts for a longer lifespan of scooters, various collection and distribution strategies, and battery charging methods.

Pierpaolo Cazzola (2020) compared the emission and energy impact of shared e-scooters with other modes to find that shared e-scooters have a lower footprint than private cars but higher than public transit and shared e-bikes. This study also considered the infrastructure component of the shared e-scooter systems, which was overlooked by previous studies. Furthermore, de Bortoli and Christoforou (2020) applied the Consequential Life Cycle Assessment (CLCA) approach to assess the broader environmental impact of shared e-scooter systems, such as rebound effects due to the system disruption.

Most of these studies found that material and manufacturing drive most emissions of shared e-scooter systems followed by collection and redistribution (shared e-scooter system operation). These studies made numerous assumptions in various phases of shared e-scooter systems, including the lifespan of e-scooters that influence emission related to material and manufacturing as well as distance traveled by service vehicles that influence shared e-scooter system operations. Few of these studies also considered various scenarios to account for the lack of available data and uncertainties of assumptions. The following sub-section provides a detailed overview of usage and operational phase assumptions better estimated from the shared micromobility data.

6.2.2 Review of usage and operational phase assumptions

The use of shared e-scooter systems depends upon the lifetime distance traveled and/or lifespan of e-scooters. The operational phase depends on the pick-up method and strategies of e-scooters for charging and redistribution, and charging frequency, location, and time of the day. Figure 29 illustrates various usage and operational phase. Table 12 summarizes the average value of these parameters and ranges of values for the scenario analysis from the leading studies evaluating emission impacts of shared e-scooter systems.

6.2.2.1 Usage phase

Most of the LCA studies considered the average lifespan of the e-scooters between six months to one year as baseline. Few studies considered the minimum lifespan of e-scooters as one month based on the open data of Louisville, Kentucky (Griswold, 2019). E-scooters often have a short lifespan because of poor design of e-scooters, theft, vandalism, and use in deteriorated infrastructure like uneven pavements (Hollingsworth et al., 2019; Moreau et al., 2020). The maximum e-scooter lifespan varied between 2 and 2.5 years among studies, based on the battery cycle lifespan and assumption on improved design of e-scooters (Hollingsworth et al., 2019; Pierpaolo Cazzola, 2020).

The average daily distance traveled by e-scooters is another essential usage phase parameter in the LCA analysis. Based on the interviews with service providers, the studies assumed the average daily distance traveled by e-scooters was between 6 and 11 km, while different scenarios assumed the e-scooters traveled between 1 and 20 km daily on average. These studies estimated the average lifetime distance of e-scooters as the product of average lifespan and average daily traveled distance.

6.2.2.2 E-scooter collection and redistribution phase

Based on the interviews with service providers, the LCA studies considered gasoline and diesel-powered vehicles as service vehicles for collecting and redistributing e-scooters, as shown in Figure 30. Depending on the location of the study, the tailpipe emission of these vehicles is assumed to be between 245 and 337 g CO_2 equivalent per km. The scenario simulations assumed cleaner service vehicles, like electric vehicles and cargo e-bikes, to evaluate the emission impacts of using different service vehicles (Pierpaolo Cazzola, 2020; Severengiz et al., 2020).

Studies also made assumptions on distance traveled by the service vehicles and the number of e-scooters served each service vehicle per day. The assumed values varied between 4.4 and 13.7 km per day per e-scooters served (Pierpaolo Cazzola, 2020). The route of the service vehicles is not likely optimized to minimize the emission impacts and distance/duration traveled. E-scooter service providers could also use several e-scooter pick-up and charging strategies, including battery swapping and mobilizing gig-workers.

6.2.2.3 Battery charging phase

Previous studies estimated the energy and emission impacts of battery charging based on the total energy required to charge e-scooters throughout the lifetime using two methods. The first group of studies assumed the energy demand for a full battery charging cycle to divide by average distance traveled per charge and multiplied average lifetime mileage (Hollingsworth et al., 2019; Moreau et al., 2020; Severengiz et al., 2020). On the contrary, Pierpaolo Cazzola (2020) assumed the electricity use per distance traveled by e-scooters and multiplied the average lifetime mileage.

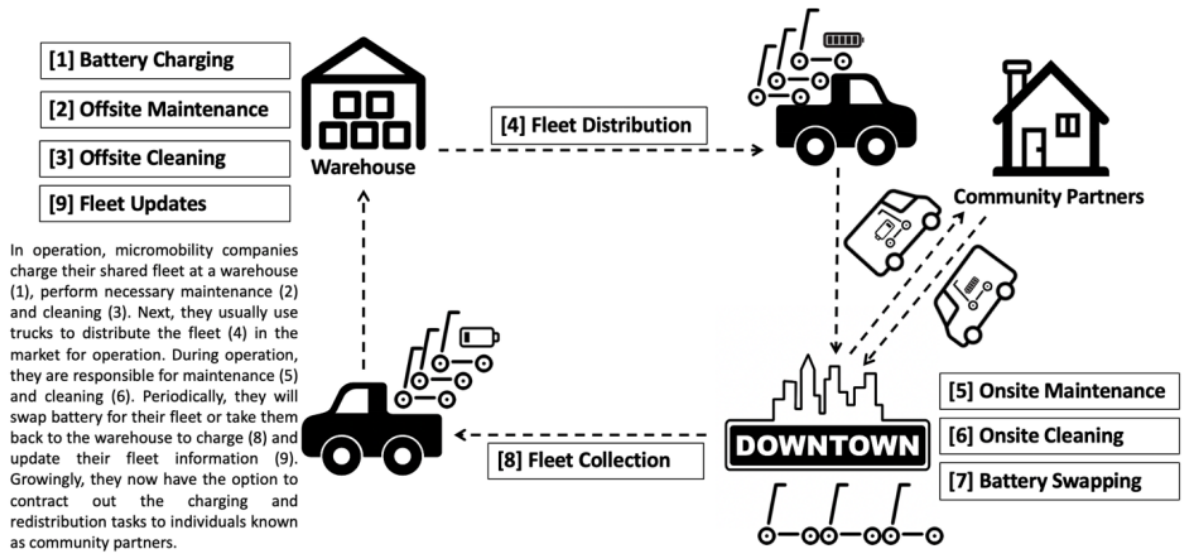


Figure 29 Micromobility Service Operation (Source: Yi Wen)

Table 12 Usage and operational phase assumptions from leading LCA studies of shared e-scooter systems

Variable	Unit	*Hollingsworth et al. (2019)*		*Moreau et al. (2020)*		*Pierpaolo Cazzola (2020)*		*Severengiz et al. (2020)*	
		Average value	**Range of values**	**Average value**	**Range of values**	**Average value**	**Range of values**	**Average value**	**Range of values**
Use phase									
Daily distance travelled by e-scooters	km per day	10.1	-	6.39	1.2 - 20	7.9	4 - 11.9	10.2	-
Lifespan of e-scooters	months	0.9	6 – 24	1	1 - 30	9.6	6 - 24	24	6 - 24
Operation phase									
Vehicle used for collection/distribution	-	Van - ICE	-	Van - ICE	-	Van - ICE	Van – ICE,	Van - ICE	-
Emission of operation vehicle	g CO2 e per km	245.26	-		-	245.26	0 - 245.26	337	-
No of e-scooters served	per van per day	21.9				10	5.6 - 11.3	200	100 - 200
Distance travelled by collection vehicle	km per day e-scooter		0.96 - 4.0		6.39 - 20	11.25		0.25	
Battery charging									
Battery capacity (Energy demand)	kWh	0.335		0.334		0.335		0.015	
E-scooter mileage with full charge	km			20	6.39 - 20				
Emission of grid mix	g CO2 eq/kWh					563.7	0 - 1061.8	568	

The energy and emission impact of battery charging is influenced by the electricity mix of the local grid system, which depends on the location and time of charging (Zivin, Kotchen, & Mansur, 2014). The study location of the previous studies was Raleigh, North Carolina (Hollingsworth et al., 2019), Brussels (Moreau et al., 2020), Germany (Severengiz et al., 2020), while Pierpaolo Cazzola (2020) used the global average emission of the electricity mix. Only Hollingsworth et al. (2019) considered the time of the day for charging e-scooters. Some of these studies considered the effect of renewable energy sources for charging e-scooters like solar that would reduce charging-related emissions.

6.2.3 Research objective

The existing Life Cycle Assessment (LCA) studies found that manufacturing, material, and collection, and redistribution of e-scooters are significant contributors to the emission and energy of shared e-scooters systems. In the absence of accurate data, most of these studies made assumptions related to LCA usage and operational phases that can be better estimated from the micromobility data. This study takes the Big Data approach to propose a framework for evaluating emission and energy use of shared e-scooter systems, with the following research question:

Q10: What is the operational related emission and energy use of the shared e-scooter system in Nashville, Tennessee, based on the Big Data (micromobility data)?

Q11: Is there a difference between operational and usage emission and energy use between shared e-scooter service providers?

6.3 Methodology

6.3.1 Study area

This research evaluates the sustainability impacts of shared e-scooter systems in Nashville, Tennessee, with a population of 1.9 million (U.S. Census Bureau). Renowned as the center of country music, Nashville attracts thousands of tourists every year (Music City). The downtown area includes diverse land use for entertainment, dining, cultural, and high-rise offices, and the metropolitan area has one of the highest growth in urban housing. According to INRIS, Nashville

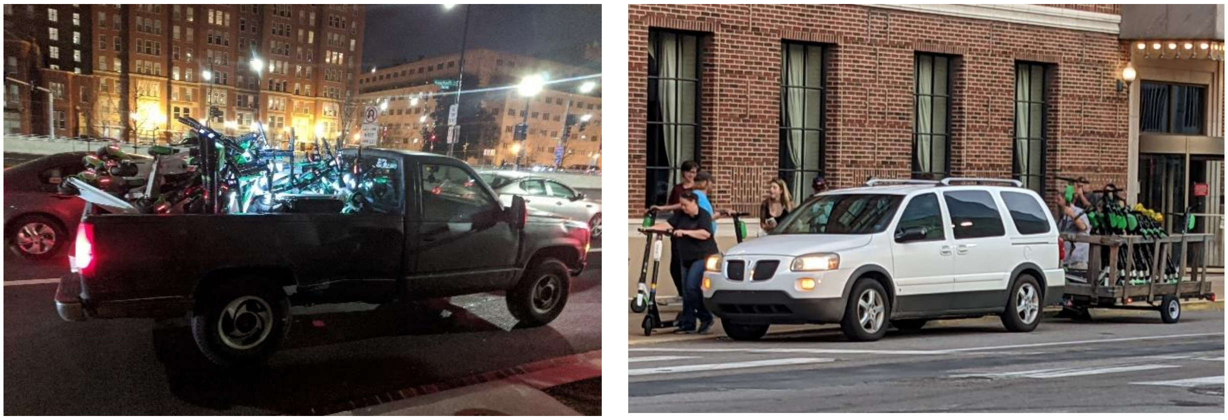


Figure 30 Old and polluting truck used for micromobility collection and rebalancing (Credit: Chris Cherry)

is the third-best city in the United States for the potential success of micromobility, based on average trip distance, topography, and climate (Reed, 2019). The mode share of the Nashville metropolitan area is mostly driving alone (80.8%), followed by carpool (9.4%), public transit (1%), and walking (1%) (American Community Survey, 2019).

The City of Nashville started a pilot program in the summer of 2018 to manage the shared e-scooters, while the study period of this research is from September 1, 2018, to February 28, 2020. The start of the study period is a few months after the shared e-scooters launch since the data is available. The study period ends before the COVID-19 pandemic, so the data is representative of the usual e-scooter usage and operation. Six service providers (Bird, Jump, Bolt, Gotcha, Lime, Lyft, and Spin) operated in Nashville during the study period.

6.3.2 Data Source and processing

I used the Trip Summary and Device Availability dataset of Shared Urban Mobility Device (SUMD) data acquired from the City of Nashville to identify the usage and operational phase of the shared e-scooter systems. The Trip Summary dataset includes trip-related information, such as trip distance, trip duration, timestamp, and geolocation of trip origin and destination. The Device Availability dataset includes timestamped geolocations of each deployed e-scooters with information about battery charge level. This dataset is updated every five minutes, which allows tracking of the location and charge level of each e-scooters to identify operational phases like charging and relocation. The "sumdID" variable, which is unique for deployed e-scooters, was used to merge these two datasets as well as estimate vehicle-level parameters such as the lifespan of each e-scooters and the total distance traveled.

I only included e-scooter vehicles whose last day of operation was before February 1, 2022 (one month prior to the end of the study period) so that the e-scooter vehicles that were still active would be included in the analysis. I also dropped trip records that did not represent a typical e-scooter trip record. By tracking the location and battery charge level over time in the Device Availability dataset, I identified three events for each e-scooters during the shared e-scooter operations as follows: 1) *e-scooter vehicle pick up for charging:* if the battery level increased more than 20% following timeframe, 2) *trip:* if the location of the e-scooter vehicle changed more than 60 meters between timeframe and the trip record was matched in Trip Summary dataset for same "sumdID" and timeframe, 3) *redistribution:* if the location of e-scooter vehicles changed more 60 meters, battery level didn't decrease more than 5%, and no trip record was found in Trip Summary dataset. The dataset for four service providers was not complete; therefore, I dropped them from the studies. The study includes two of the major service providers operating in Nashville during the analysis period.

6.3.3 Analytical framework

The ISO standard of LCA includes goal and scope, inventory analysis, impact assessment, and interpretation. The functional unit of the analysis is one e-scooter vehicle per passenger-km traveled. This study will only focus on the usage and operational phase of the LCA, which is a significant contributor to emissions based on previous studies(Hollingsworth et al., 2019; Moreau et al., 2020; Pierpaolo Cazzola, 2020). Emission estimates for other LCA phases were based on the findings of the existing LCA studies (Pierpaolo Cazzola, 2020). I used the grid emission data of Nashville obtained from the city government of Nashville. Nashville has a grid emission of 562 lb CO2/MWh, which is lower than the national average of 884 lb CO2/MWh2 (City of Nashville, 2022). I used the conversion factor from EPA to convert grid emission into the metric system (EPA, 2022).

I identified the distribution of key usage and operational-related variables for each service provider using ICOMP (Bozdogan, 2000), which scores the model selection by also including the structural complexity that controls for risks of both insufficient and over parameterized models. ICOMP results are attached in Appendix A5. Then, I used the Simulink model builder to create the LCA model to estimate usage, operational emission, and energy following the framework illustrated in Figure 31. Using the "Sensitivity Analysis" plugin, I created 2000 randomly sampled data points with the distribution obtained and performed a Monte Carlo simulation.

6.4 Results

6.4.1 Exploratory analysis of shared e-scooter usage and operation

Figure 32 illustrates the usage-related variables among the three service providers included in the analysis. Figure 32 a) includes the distribution of lifespan (in months), and Figure 32 b) provides the distribution of daily mileage (in km). The mean lifespan of e-scooter vehicles for service providers #1, #2, and #3 is 6.5, 10.0, and 4.5 months respectively. The distribution of lifespan for each service provider is also different, likely due to the operational strategy of fleet among each service provider and usage of e-scooter vehicles. On the other hand, the distribution of each service provider's average daily mileage of e-scooter vehicles is similar but has different parameter values for the distribution. The mean value of the average daily mileage of e-scooter vehicles of all three service providers is below 1 km per day. This finding suggests that the actual e-scooter vehicle lifetime and daily mileage are not uniform, as assumed by previous studies (Hollingsworth et al., 2019).

Figure 33 summarizes the operational-related variables of shared e-scooter operations. Figure 33 a) illustrates the distribution of charge of e-scooter vehicles during pick-up for charging, indicating that service providers tend to pick up e-scooters mostly below 50% of battery level, except in the case of service provider #3. Figure 33 b) includes the distribution of frequency of charging of e-scooter vehicles (in days), which suggests that most of the shared e-scooters vehicles are charged every one-two day. Figure 33 c) illustrates the average daily rebalancing distance of e-scooter vehicles (in km), indicating the majority of e-scooters vehicles are redistributed about 0.5 km per day. The frequency of charging of e-scooter vehicles and average daily redistribution distance are similar among the three service providers. In contrast, the distribution of charge levels during pick-up for charging is different.

Table 13 supplements Figure 32 and Figure 33 by summarizing the distribution and its parameters for the key usage and operational-related variables included in the analysis. I used piecewise distribution for variables that did not have specific distributions shape and included the cumulative distribution function (cdf) values. The table also includes the distribution of assumptions for operation vehicles used during recharging and redistribution of shared e-scooter vehicles.

6.4.2 Monte Carlo simulation

Figure 34 summarizes three service providers' total energy usage (per vehicle per km) and emissions (per vehicle per km). Figure 35 and Figure 36 illustrate the energy use and emissions for the usage and operational phase of shared micromobility operations. The usage phase energy use is greater than the operational phase. However, the operational emission is greater than the

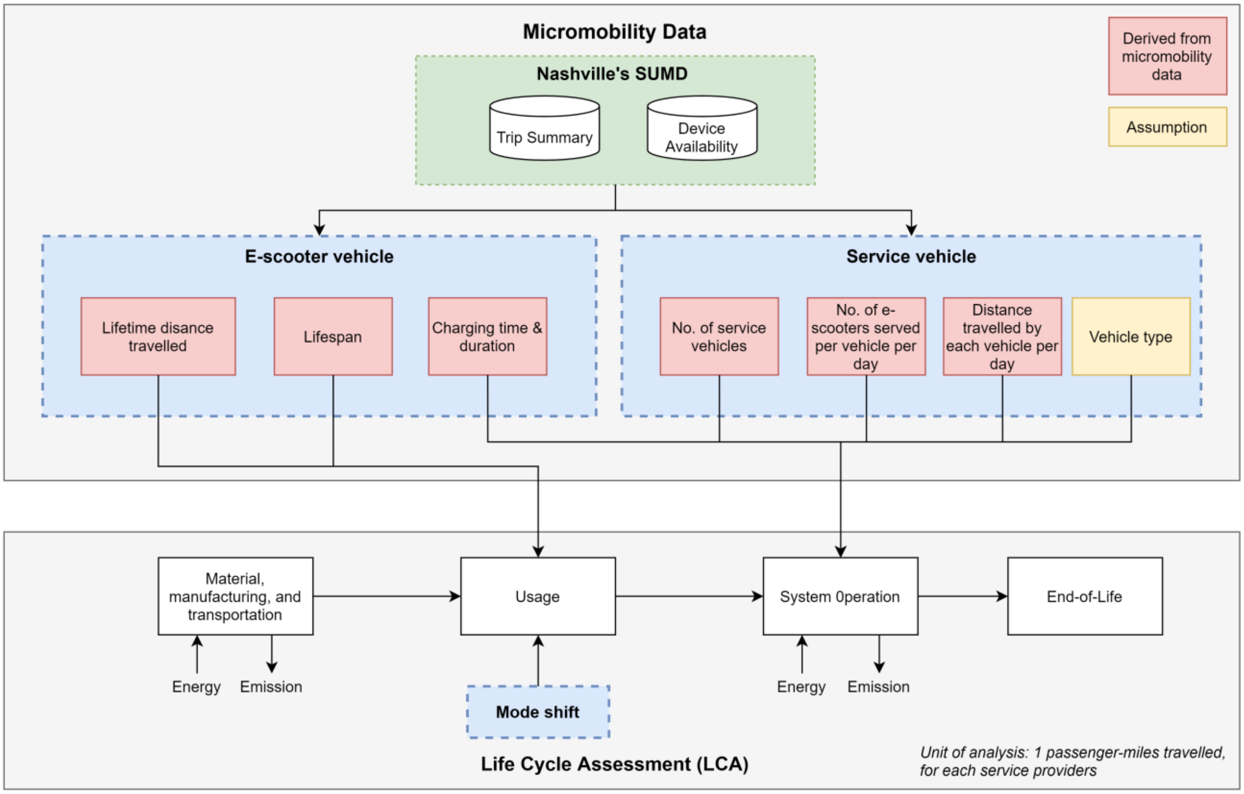
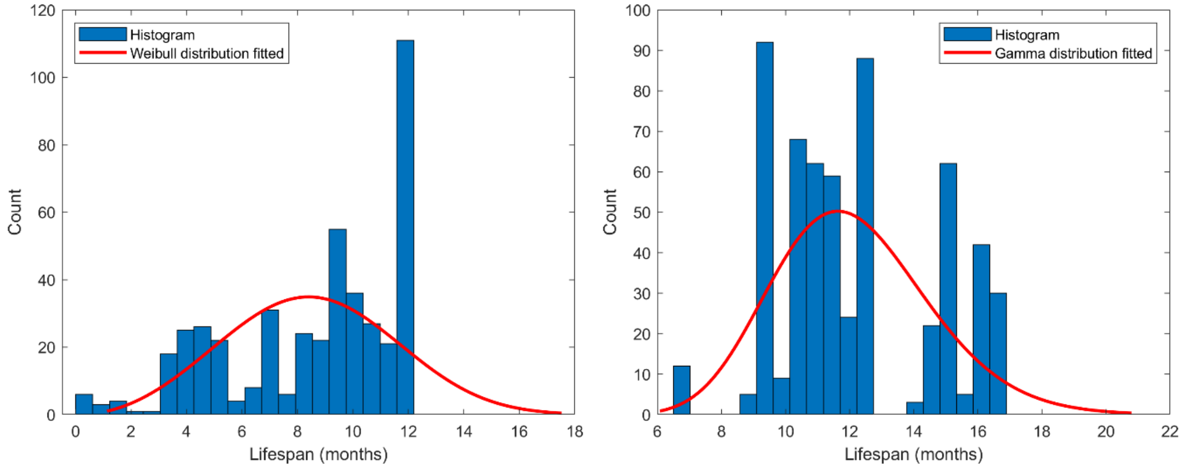
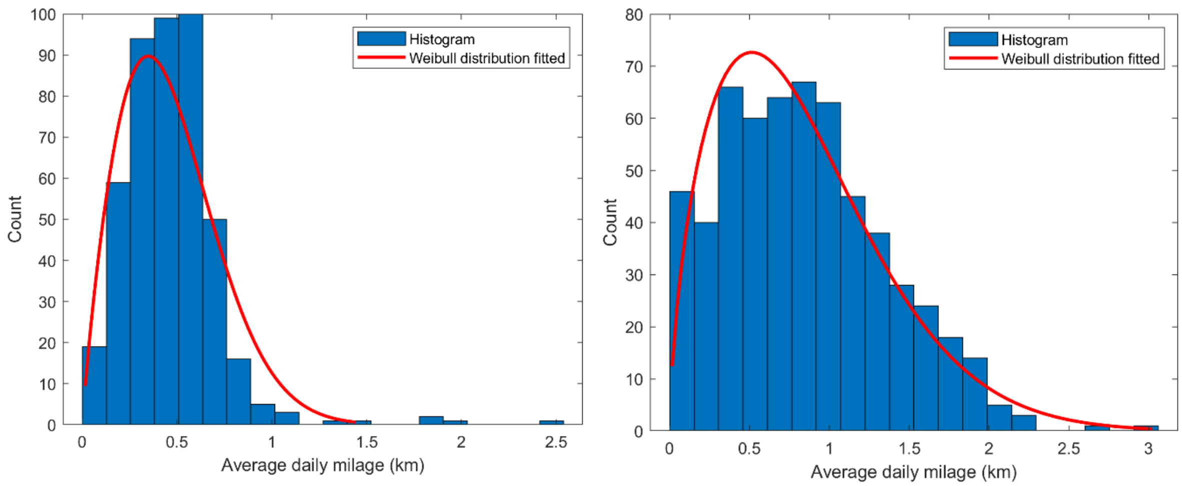


Figure 31 Analytical framework to estimate energy use and emissions



Service provider #1 Service provider #2

a)

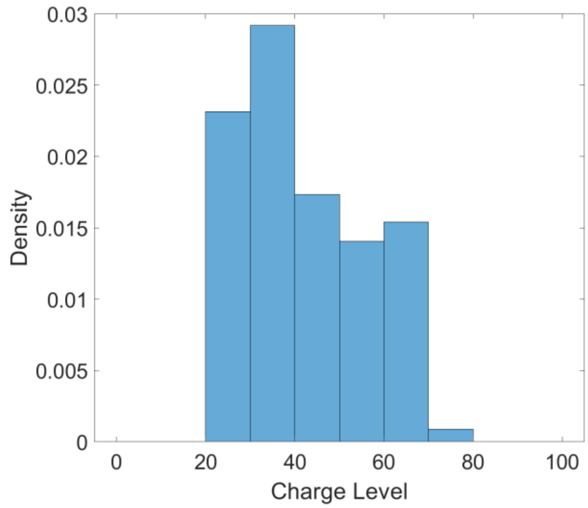


Service provider #1 Service provider #2

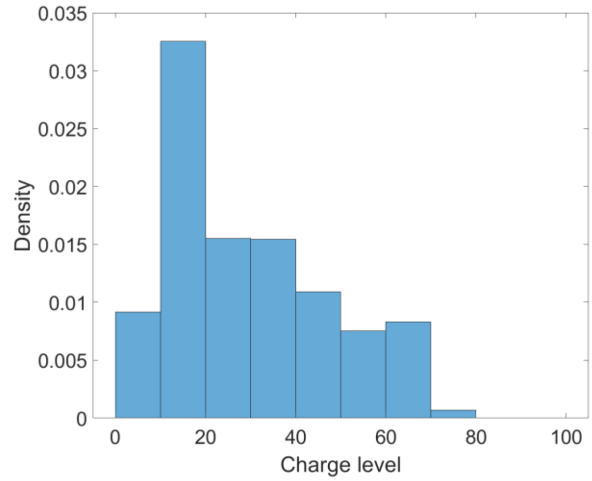
b)

Figure 32 Distribution of usage-related variables

a) Lifespan (in months), and b) Daily mileage (in km)

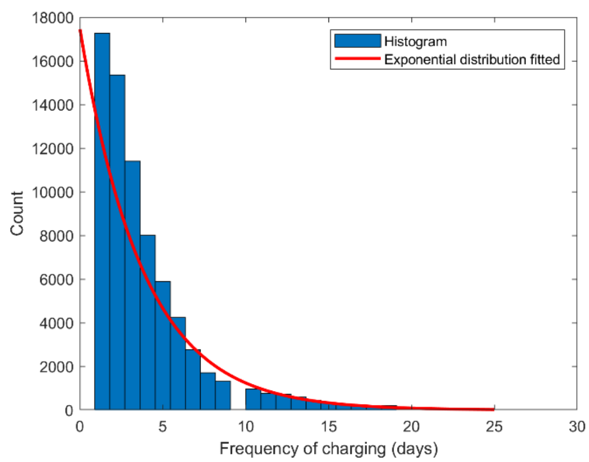


Service provider #1

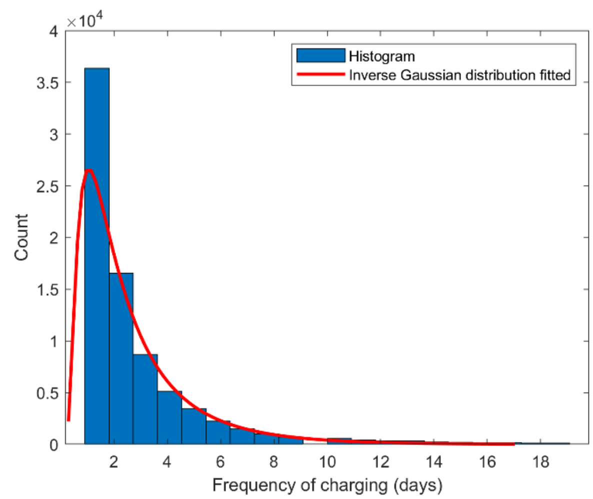


Service provider #2

a)



Service provider #1

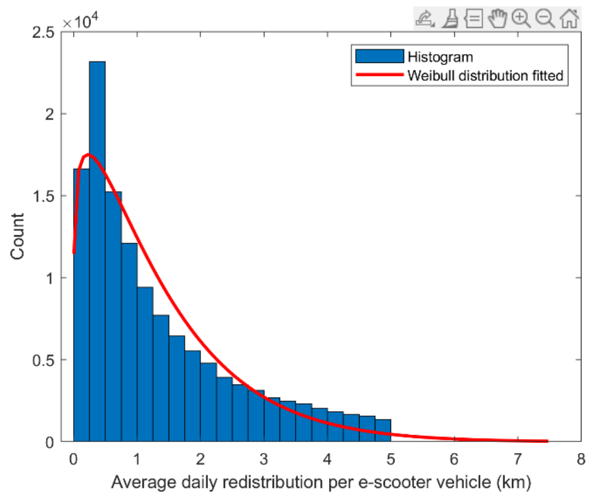


Service provider #2

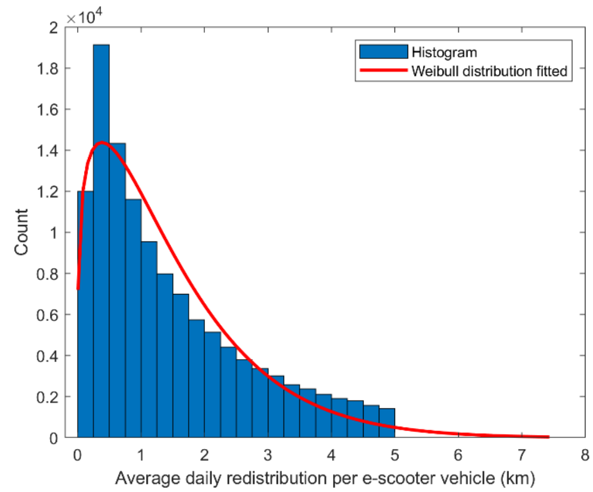
b)

Figure 33 Distribution of operational-related variables

a) Battery charge level (percentage) during a pick-up, b) Frequency of pick-up for charging (days)



Service provider #1



Service provider #2

c)

Figure 33 continued

c) Daily average redistribution distance per e-scooter vehicle (km) usage phase. Using high emissions vehicles to pick up and distribute e-scooter vehicles and redistribute contributes to higher operational emissions.

Table 14 summarizes the mean values of the total and the energy use and emissions phases.

6.5 Implications and future research

I found that energy use and emissions value are higher than existing LCA studies of shared e-scooters(Hollingsworth et al., 2019; Moreau et al., 2020; Pierpaolo Cazzola, 2020). The estimates from my analysis are higher for two main reasons as follows: 1) the distribution obtained from micromobility data is different from the assumptions made from existing studies, such as life span and daily mileage, that increased the estimate values, 2) the micromobility data includes the first generation e-scooter vehicles that had a lower lifespan and the deployed fleet had lower utilization rates as reflect in daily mileage. I also found that energy use and emissions differ among shared micromobility service providers, mainly due to their vehicle design reflecting the lifespan value and operational strategies' differences.

This study deployed the probabilistic framework to estimate the energy use and emission of shared micromobility systems using the micromobility data. These estimates better reflect the actual energy use emissions. City governments can adopt the framework used in the study to set emissions goals as well as track the real-time progress of service providers. Furthermore, the variable used in the framework can also be related to other policy goals, such as the utilization rate of e-scooter vehicles, that could inform city governments to make a data-driven decision on shared micromobility systems.

Future studies can improve the analysis in several ways. First, studies can identify key factors influencing higher emissions, such as lifespan and daily usage, to perform sensitivity analysis. Such information can inform decision-makers to develop targeted policy goals. Second, other studies can evaluate hypothetical scenarios to evaluate the effect of new strategies on energy use and emissions. For instance, battery swapping and extended battery life could affect energy use and emissions differently. Finally, studies can implement other methods, such as Agent-Based Modelling (ABM), to test various operational strategies incorporating the behavior of people (demand) and operations (supply).

Table 13 Summary of distribution of usage and operational-related variables

Variable /Service providers	**Bird**	**Lime**	**Data source**
Usage phase			
Lifespan (months)	Weibull (9.5296, 3.0990)	Gamma (24.5513, 0.4940)	SUMD
Daily mileage (km)	Weibull (0.5245, 1.8683)	Weibull (0.9372, 1.6125)	SUMD
Operational phase			
Battery charge level during pickup (Edge values (10 20 30 40 50 60 70 80 90 100)	Stepwise cdf (0 0 0.2315 0.5232 0.6964 0.8370 0.9911 1.0000 1.0000 1.0000)	Stepwise cdf (0.0917 0.4169 0.5720 0.7263 0.8353 0.9104 0.9933 1.0000 1.0000 1.0000)	SUMD
Frequency of pick-up for charging (days)	Exponential (3.7840)	Inverse Gaussian (2.66316, 3.7292)	SUMD
Average daily redistribution distance per e-scooter vehicle (km)	Weibull (1.4222, 1.1376)	Weibull (1.5739, 1.2163)	SUMD
Operational vehicle distance travelled from base to pick up location and back (km)	Uniform (20, 40)	Uniform (20, 40)	Assumption
Operational vehicle distance travelled between each scooter vehicle pick-up (km)	Normal (0.5, 0.15)	Normal (0.5, 0.15)	Assumption
Operational vehicle occupancy (percent)	Normal (0.5, 0.15)	Normal (0.5, 0.15)	Assumption
Operational vehicle capacity	Uniform (40, 60)	Uniform (40, 60)	Assumption
Distance between e-scooters during pickup (km)	Normal (0.5,0.15)	Normal (0.5,0.15)	Assumption

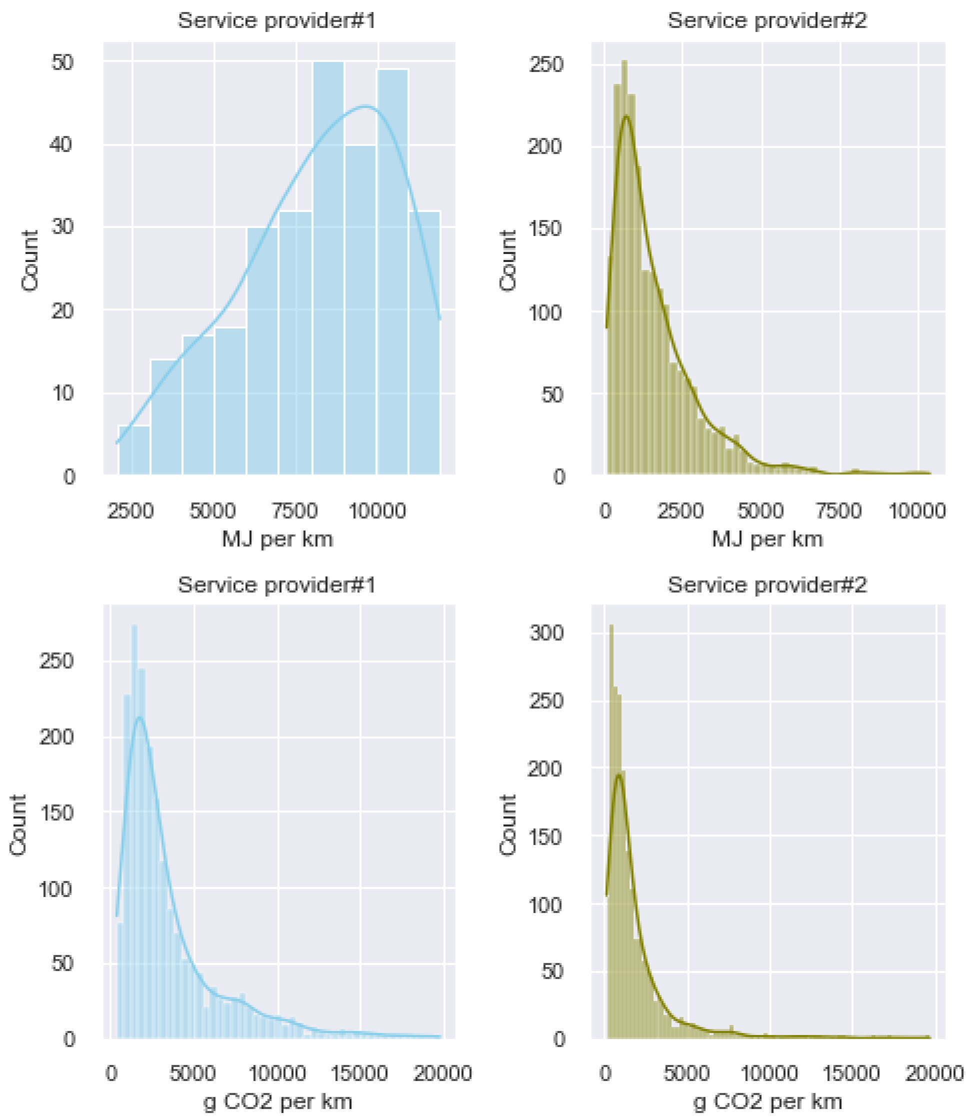


Figure 34 Total energy and emission of shared e-scooter operations

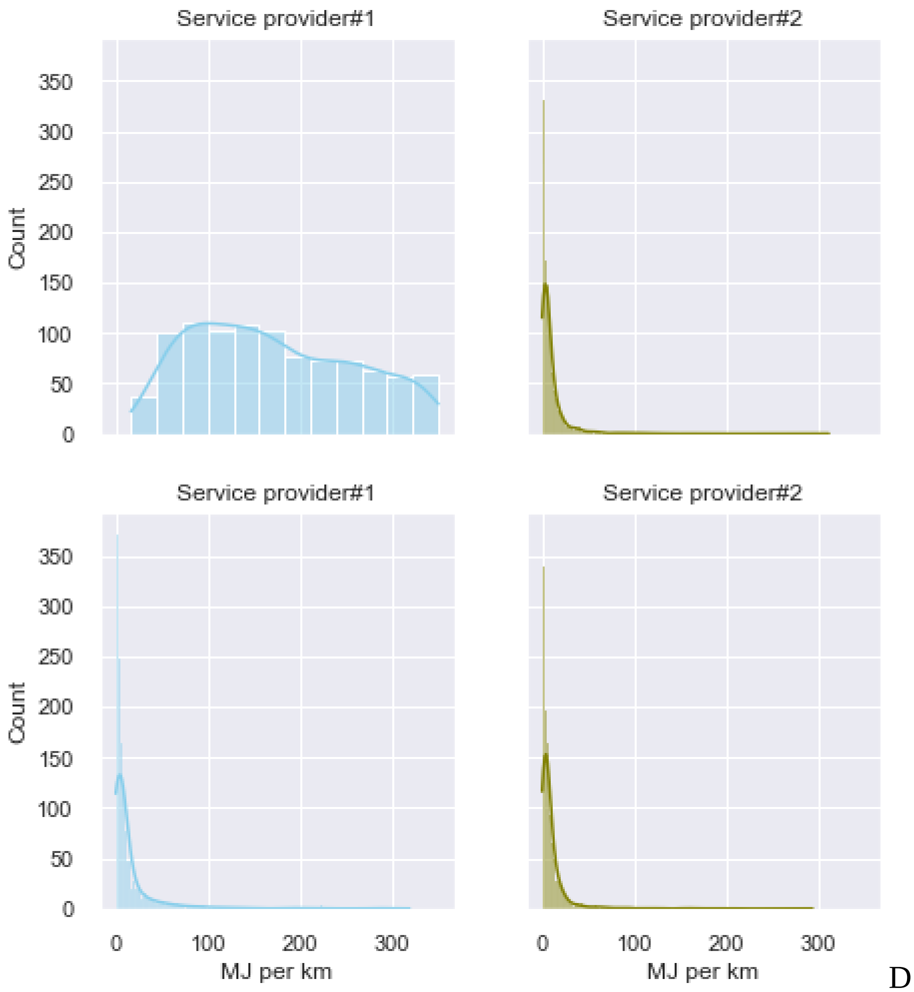


Figure 35 Energy usage by phase of shared e-scooter operations

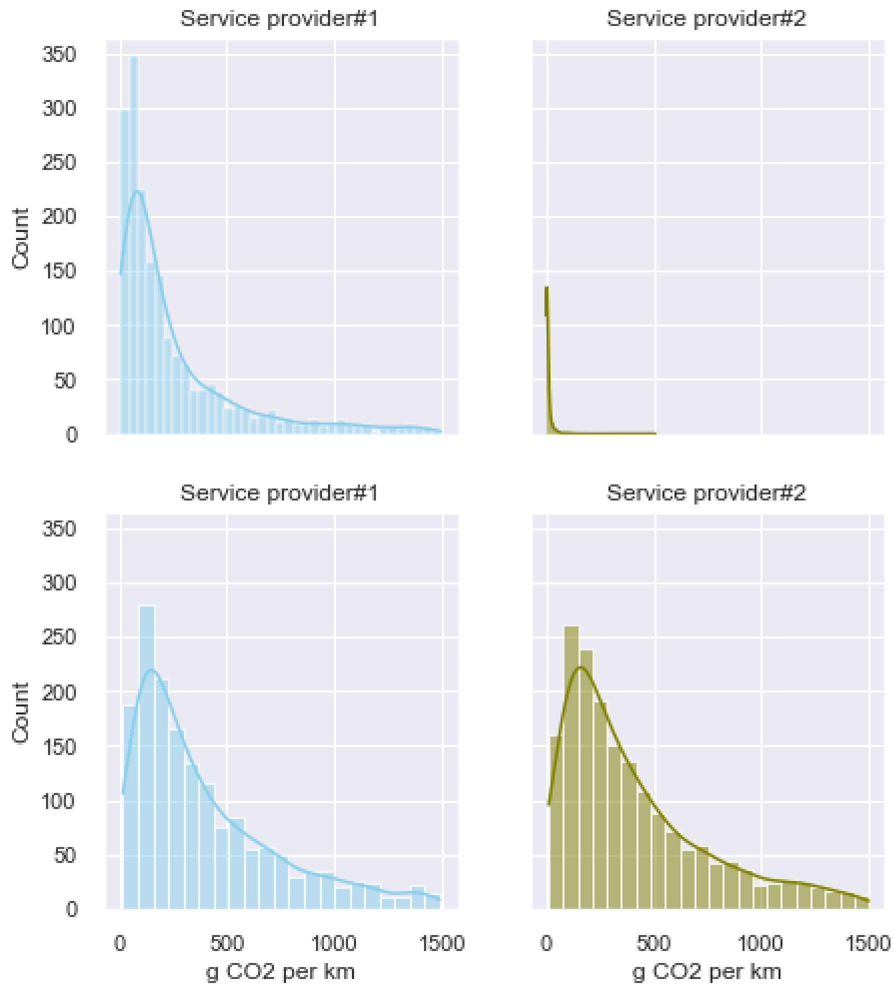


Figure 36 Emissions by phase of shared e-scooter operations

Table 14 Mean emissions and energy by phase and service provider

Measures	**Service provider #1**	**Service provider #2**
Total energy per vehicle per km (MJ/km)	166844.4	1595.46
Total usage phase energy per vehicle (MJ/km)	1967.628	11.2403
Total operational phase energy per vehicle (MJ/km)	27.21043	11.45184
Total emissions per vehicle per km (g CO2/km)	5419.638	2371.113
Total usage phase emissions per vehicle (g CO2/km)	866.4295	11.2403
Total operational phase emissions per vehicle (g CO2/km)	1967.628	793.6135

6.6 Conclusion

Using the micromobility data and Monte Carlo simulation, I estimated the energy use and emissions of shared micromobility systems in Nashville, Tennessee. I found that the estimates were higher than other existing studies, and the energy use and emissions vary among service providers. City governments and service providers can use the findings of this study to inform strategies to reduce overall emissions, like increasing the lifespan of e-scooter vehicles and the utilization rate. Furthermore, the probability framework of the study can be helpful in decision-making to incorporate uncertainties in the real world. For example, city governments can introduce the policy that a certain percentage of e-scooter fleets should have a longer life span than specific values to meet the emission goals.

Chapter 7. Main findings, recommendations, policy implications, and conclusion

The popularity of shared micromobility has grown exponentially in the past few years, further accelerated due to social distancing measures during the COVID-19 pandemic. On the other hand, city governments have struggled to regulate and manage these innovative mobility technologies, partly due to limited understanding of these new travel technologies. This chapter summarizes the key findings of the dissertation and provides several recommendations with policy implications.

7.1 Main findings

In this section, I summarize the main findings of the impacts of shared e-scooters from the perspective of sustainable transportation (Chapter 2-6). While each chapter has an in-depth discussion of its results, this section highlights key findings centered around sustainable transportation principles.

7.1.1 Scrutinizing e-scooter crashes and crash risk

Evaluating police crash reports of e-scooters and bicycles in Nashville, Tennessee, over two years, I found notable differences between e-scooter and bicycle crashes in temporal and spatial crash locations, crash distance from home, demographics of riders, crash characteristics, crash risk, and maneuver of motorist and e-scooter riders or bicyclist before the crash. Most crashes of both modes occurred during the summer months. E-scooter crashes were mainly around downtown Nashville and Vanderbilt University, while bicycle crashes were spread outside the core part of the city. Over 70% of bicyclists involved in a crash lived within three miles of the crash location, whereas 33% of e-scooter crashes occurred more than 50 miles away from the home of the e-scooter rider. Although males are highly representative in bicycle and e-scooter crashes with a motor vehicle, female riders represent a higher rate of e-scooter crashes (31% vs. 13%) when comparing the proportion of females involved in crashes among both modes. E-scooter riders colliding with motor vehicles were younger than bicyclists crashing with motor vehicles. 13% of e-scooter riders crashing were below 18 years old, although the legal age to ride an e-scooter in Nashville is 18 years.

Most e-scooter and bicycle crashes involving motor vehicles occurred in daylight and clear weather conditions, without any statistical significance between the two modes. However, the crash risk for e-scooter at nighttime is twice as much as at daytime when controlling for exposure. Most e-scooter riders and bicyclists (>90%) were not intoxicated during crashes. While most of the motorist was also not intoxicated, one-in-five motorists fled the crash scene, and their intoxication status was unavailable. When comparing crash locations based on roadway characteristics, the majority of e-scooter and bicycle crashes with motor vehicles occurred at an intersection (>65% of all crashes). Only a few PBCAT crash typologies based on the maneuver of riders and motorists explained most of the e-scooter crashes in Nashville. In contrast, bicycle-motor vehicle crashes were distributed among several crash typologies. Generalized engineering, education, and enforcement strategies to reduce and prevent e-scooter and bicycle crashes, injuries, and fatalities might not result in equal outcomes for each mode. More rigorous enforcement could be implemented to deter e-scooters riders under the age of 18 years, and e-scooter safety campaigns could target female riders

7.1.2 Demand elasticity of e-scooter vehicles deployment

I evaluated the demand and supply aspects of shared e-scooter systems in Nashville, Tennessee, to estimate the demand elasticity of e-scooter vehicles deployed, segmented by land use and weekday type. I found that the demand for e-scooter vehicles deployed is 0.55, which is inelastic and similar to other transportation modes. The demand elasticity estimates of e-scooters deployed are slightly higher during the weekend than on weekdays (0.59 vs. 0.55), indicating that trips would increase at a higher rate when increasing e-scooter vehicle deployment during the weekend than on weekdays. When segmenting by the size of the service providers, the demand elasticity of e-scooter vehicles deployed for a large service provider (fleet size more than 500) is 2.5 times more than mid-sized service providers (fleet size between 250 to 500) and 36 times more than small service providers (fleet size below 250). Service providers with large fleet sizes have a competitive advantage over others.

The demand elasticity of e-scooter vehicles deployed varies by land use type. Deploying e-scooter vehicles at the university and park & waterfront will increase e-scooter trips at a higher rate than in other land use areas. E-scooter trips increase at a higher rate during weekends than on weekdays in Central Business District (CBD) & commercial, and park & waterfront land use types. I found that the demand elasticity estimates of e-scooter vehicles deployed by large service providers are higher and likely drive the overall demand elasticity estimate. The weekday and land use types demand elasticity estimates of large, medium, and small service providers do not follow the same patterns, indicating that each service provider category has its own market based on location and day of the week.

7.1.3 Shared micromobility as the first wave of the decarbonizing transport sector in developing countries

Using a dynamic and online pivoting stated preference survey design, I evaluated the users' propensity to adopt shared micromobility (bikeshare, e-bike share, and e-moped share) in the context of developing countries with Kathmandu, Nepal, as a case study. I found that weather factors influence the propensity to use shared micromobility, and heavy rain is a deterrent to using shared micromobility vehicles. Bikeshare and e-bike share are preferred during warm and normal temperatures, whereas e-mopeds have a high preference during cold weather. I found that the availability of bike lanes promotes the use of shared micromobility, despite weak statistical evidence. Protected bike lanes did not exist during the study period, and unprotected bike lanes were constructed in a few places. It is likely that survey respondents could not infer the implications of bike lanes availability, although pictures were included in the questionnaire, indicating the necessity of investment in bicycling (active transportation) infrastructure along with the public promotion of its benefits.

Most shared micromobility adopters were younger demographics with a higher household income. Gender had an effect on the choice of micromobility vehicles; females preferred e-moped, which is likely due to motor assistance to navigate better in mixed traffic and perceived as safer to ride. Ride-hailing users (both two-wheeler and four-wheeler) had the highest inclination to use shared micromobility vehicles, likely due to familiarity with technologies to find the ride and make a payment. These groups could be early adopters of shared micromobility in developing countries. Shared micromobility could be an inexpensive option to lead the electrification of transport sector in emerging economies, paving ways to further electrification of other travel modes.

7.1.4 Usage-grouped clustering of e-scooter trips

Using unsupervised machine learning techniques, I found five usage-grouped clusters of e-scooter trips in Nashville, Tennessee. These clusters are as follows: 1) daytime short errand trips, 2) utilitarian trips, 3) evening social trips, 4) nighttime entertainment district trips, and 5) recreational trips. The nighttime entertainment district trips (in downtown Nashville and nearby Vanderbilt University) were the most popular e-scooter use in Nashville, contributing to 26% of all e-scooter trips. Several factors contributed to e-scooter trip patterns, including usage time (hour and day of the week), average daily temperature, population density, employment and parking density, and land use types. The route directness ratio, which represents the difference between the shortest possible path and the actual route, is critical in explaining the variation in trip patterns.

Each of these groups has distinct spatial and temporal patterns. The majority of starting and end points of evening social and nighttime entertainment district trips were in downtown Nashville. In contrast, the origin and destinations of daytime short errand and utilitarian trips were somewhat evenly distributed in the city. The e-scooter usage rate of the usage-grouped clusters increased in general over the analysis period, peaking during the summer months. Several events in Nashville, such as the NFL draft and Christmas holiday, increased e-scooter trips indicating e-scooters are popular among tourists visiting the city. Such big data and machine learning methods can supplement the stated-preference approach of understanding shared e-scooter usage to help the city manage and regulate shared e-scooter programs.

7.2 Recommendations and policy implications

Based on the main findings of my research in the context of the transportation literature, I developed recommendations for decision-makers, transportation practitioners, and researchers for integrating emerging travel technologies, like shared e-scooters, into the existing transportation systems. Although a few datasets used in my analysis are a few years old, the key findings still apply in the present context. Shared micromobility ridership has recovered relatively more quickly than other travel modes like transit after COVID-19 disrupted general travel behavior (NABSA, 2022). While my research findings are based in Nashville, Tennessee, and Kathmandu, Nepal, these recommendations are generalizable across other cities and should be interpreted considering the local context. The recommendations are as follows:

1. **Decision makers should be proactive in incorporating new travel technologies like shared micromobility:** Decision-makers should make unprecedented decisions to embrace these new mobility technologies in the existing transportation systems and

benefit from enormous potential to solve current issues of urban mobility. Legislative amendments might be necessary to redefine existing laws, and emerging travel modes should be incorporated in transportation master plans to regulate the new technologies to maximize the benefits while reducing unintentional consequences. Decision makers can adopt sustainable transportation approaches, such as Shared Mobility Principles for Livable Cities promoted by the New Urban Mobility Alliance (NUMO) (Chase, 2017), and learn from the best practices of shared micromobility from existing programs.

2. **City governments should leverage shared micromobility usage and operation data to empower the decision-making process**: The integration of the Global Positioning System (GPS) enabled smartphones with shared micromobility allows collection of vehicle usage (e.g., trip starting and ending locations) and system operation (e.g., parked vehicle locations) data. I recommend city governments adopt data standards, such as Mobility Data Specification (MDS) and General Bikeshare Feed Specification (GBFS), that help cities to better manage shared micromobility operations within their jurisdictions, as well as help to integrate shared micromobility into multimodal trip planning. Data collected from shared micromobility systems should adhere to the data privacy rules, such as Managing Mobility Data compiled by the National Association of City Transportation Officials (NACTO), for responsible use of data and protection of individual privacy (NUMO, NABSA, & OMF, 2020). The historical and real-time data can help city governments plan and manage shared micromobility systems that are safe, equitable, and sustainable.

3. **Each shared micromobility vehicle type should be approached uniquely to improve road safety:** While shared micromobility vehicles have many similarities, the user demographics, vehicle features, and user travel behavior might have different implications on road safety. I recommend that the safe system approach be taken to reduce fatalities and serious injuries through engineering, planning, and policy tools that accommodate human mistakes and injury tolerance. Although shared micromobility vehicles are inherently low-speed and cause less impact during a crash than other vehicles, there is a complex interaction between new mobility users and other road users. Shared micromobility provides technological tools to enhance road safety, such as

geofencing and sidewalk riding, but it should be complemented with other safety tools of the safe system approach.

4. **City governments should consider regulating the number of service providers and their fleet sizes**: I recommend that the city government consider permitting fewer number of shared micromobility service providers with larger fleet sizes. Deploying a larger fleet size would also allow service provider to expand their service area and meeting the city's equity goals while increasing profits and not fragmenting the market between service providers. However, fewer service providers could limit innovation and competition. I recommend city governments adopt dynamic fleet sizing based on the system-wide performance metrics that encourage service providers to improve the system's efficiency and meet the policy goals set by city governments.

5. **Decision makers should prioritize expanding shared micromobility in emerging economies as one of the first efforts to decarbonize the transportation sector:** Shared micromobility is one of the affordable options for users, does not require huge investments, and has enormous potential to reduce transportation emissions. I found that people are willing to use shared micromobility in mid-sized cities of developing countries (with more than 500,000 and less than 5 million in population), which make up a majority of the world's cities and have the highest population growth (DESA, 2011). Early adopters are users who are familiar with technologies such as smartphone apps and online payment systems. Weather, bicycling infrastructure, and demographic factors influence the choice of shared micromobility vehicles. Such knowledge, coupled with the best practices of successful programs in developed countries and megacities of developing countries, could make this innovative transportation technology a potential leapfrogging alternative in mid-sized cities of developing countries.

The policy implications of the recommendations mentioned above are as follows:

7.2.1 A proactive approach to regulating shared micromobility

Since the initial deployment of shared micromobility vehicles, many authorities have slowly adopted a regulatory framework to integrate these new travel technologies within the existing transportation systems. One of the fundamental discussions is whether to regulate shared micromobility vehicles in urban spaces similar to other private and public vehicles or use public spaces similar to street vendors like food trucks (ITF, 2021). There is a need to regulate shared micromobility systems with a focus on building infrastructures to move people and goods and to improve accessibility, equity, sustainability, and safety. While the mobility requirements differ from city to city, a common rule should apply across (US) states or nations while being flexible enough to adapt to the local context. Such a law should identify micromobility as a vehicle class based on their similar operation characteristics such as speed and size.

Shared micromobility regulations should target broader environmental, safety, and socioeconomic goals, driven by sustainable transportation principles and outcome-based metrics. Several agencies, including the NACTO and the International Transport Forum (ITF), have compiled best practices of shared micromobility programs to identify several policy goals that can be somewhat transferable across cities and nations (ITF, 2021; NACTO, 2019). As an illustration of the proactive approach to regulating shared micromobility, France replaced its transportation law with a mobility law called Loi d'orientation des mobilités (LOM) (French Government, 2019). The updated law provides the authority to regulate e-scooters to the city government beyond the conventional transportation law (Highway Code). The regulations framework is included in Box 1.

7.2.2 Data-driven decisions for managing and integrating shared micromobility

Shared micromobility is an innovative technology that allows cities to manage public space digitally as well as provide users with real-time data to make decisions for completing a multimodal trip seamlessly. Agencies can adopt data standards to consistently collect and implement data for planning, regulating, and integrating shared micromobility systems with other travel modes. These data standards can be broadly grouped into two categories as follows: 1) agency-facing data standards, such as Mobility Data Specification (MDS), that provides system-level data like historical trip and fleet locations for managing shared micromobility systems, and 2) user-facing data standards, such as General Bikeshare Feed Specification (GBFS), that enables information sharing across platforms for multimodal trip planning for users.

Box 1: Regulation of micromobility in France

In France, users of electric scooters must comply with the requirements of the Code de la Route (Highway Code). In urban areas, users must use bicycle paths when available or roads limited to 50 km/h or less. The maximum speed limit for scooters is set at 25 km/h. In addition:

- E-scooters are not allowed on sidewalks (fine of EUR 135) unless authorized by the mayor. In this case, the maximum speed is 6 km/h only for non-electric vehicles
- Users must be at least 12 years old
- Carrying additional passengers is prohibited
- The use of headphones is prohibited
- Parking on the sidewalks is authorized, provided it does not obstruct pedestrians. The mayor can decide to forbid it. For instance, in Paris, parking of shared e-scooters on the sidewalks is illegal and subject to a fine of EUR 49 for users

The 2019 Loi d'orientation des mobilités (LOM) is a national framework that accounts for public space occupation by free-floating services. Operators require a permit from local authorities through tender or expression of interest. Article 41 of the law instructs authorities on regulating free-floating services:

1. Data sharing: Public authorities can ask operators to share data (General Data Protection Regulation (GDPR) format) to ensure compliance with licensing criteria. The number of available vehicles, number, duration and length of trips, origin destination, and the number of unique users, are among the most common data required.
2. Fleet size: The LOM allows public authorities to cap fleet sizes. Caps must take into account the minimum fleet size required for a service to be economically viable, and the maximum fleet size should not flood the public space with shared vehicles. Public authorities can choose to leave fleet sizes and number of operators unregulated or to deliver a limited number of permits via the competitive tender procedure.
3. Spatial conditions for vehicle deployment: The law allows local authorities to define the operational area (including parking and no-ride zones) after consultation with operators.
4. Compliance with riding and parking rules: In addition to the Highway Code, the LOM allows public authorities to implement additional rules, especially in places of potential conflicts with other road users. Operators have to use technical means such as GPS solutions to enforce safety rules.

Box 1 continued

5. Removal of unavailable vehicles: Permits can set requirements and deadlines for removal of any out of order vehicle to avoid impeding access in public spaces. It also allows for removal requirements for specific situations, such as for operators withdrawing from a city. A good practice is set at between 24 and 48 hours for light vehicles situations, such as for operators withdrawing from a city.
6. Polluting emissions and greenhouse gases: Electric vehicles are preferred and full-lifecycle costs are to be considered.
7. Advertising restrictions on the vehicles: Local authorities are authorized to ban advertising, other than for the shared mobility service itself, on the shared vehicles.
8. Respecting neighborhood tranquility: Public authorities need to take into account noise pollution impacts (including maintenance, charging, removal of vehicles, or vehicles' alarms).

Adapted from French Government (2019) and ITF (2021)

Several applications of the agency-facing and user-facing data standards in managing the new travel technologies are illustrated in Box 2. MDS data standard uses Application Programming Interfaces (API) protocols to safely transfer data between service providers and cities as well as allows consistency across systems within and across cities. City governments have leveraged usage and operations data to achieve broader policy goals, such as equity and safety, using the data collected through MDS. The MDS is also working to expand its scope to manage imminent mobility technology, such as autonomous fleets digitally. Similarly, GBFS includes a real-time data of locations of available vehicles with information of service provider's information, cost of using the vehicles, and policy information like speed limits and parking zones. This data specification is a foundation for the (multimodal) trip planning and Mobility-as-a-Service (MaaS), including integrated trip planning and payment components.

7.2.3 Safety approach to shared micromobility

In a safe systems approach to transportation safety, travel behavior is critical to reducing fatalities and serious injuries. People using micromobility vehicles interact with other road elements based on the characteristics of the vehicle (e.g., motor assistant, the position of riding, etc.), infrastructure available (e.g., bike lane, an average speed of motor vehicles, etc.), and demographics of rider (e.g., younger demographics for shared e-scooters compared to bicycle share). New mobility, like shared e-scooters, also opens technological tools to enforce and encourage better riding behaviors and parking compliance to improve micromobility safety. For instance, sidewalk riding of shared e-scooters is illegal in most cities, mainly due to speed differential with pedestrians leading to conflict; however, many e-scooter riders feel safer riding on the sidewalk than on road lanes. Several shared e-scooter operators have developed sidewalk detection technology that recognizes riding on the sidewalk and slows the rider's speed to reduce speed deferential with pedestrians (Hellman, 2022). Similarly, augmented reality technology can improve parking compliance by using a smartphone camera to identify the e-scooter parking location at the end of the ride as well as verify the parking compliance rules (Bellan, 2022).

While technology aids in enforcing safe riding behaviors, educating users on how to ride safely is also necessary. Although there might be some familiarity with some of the features of shared micromobility, they are new technologies, and users might not be able to comprehend the safety features and safe riding behavior fully. Several cities require shared micromobility service

Box 2: Applications of MDS and GBFS data

The Open Mobility Foundation (OMF) is developing Mobility Data Specification (MDS) for data governance and creating urban mobility management tools to help transportation agencies achieve their mobility goals. Some of the case studies of MDS applications highlighted by the OMF are listed as follows:

Vehicle Caps: Determine the total number of vehicles per operator in the right of way

Distribution Requirements: Ensure vehicles are distributed according to equity requirements

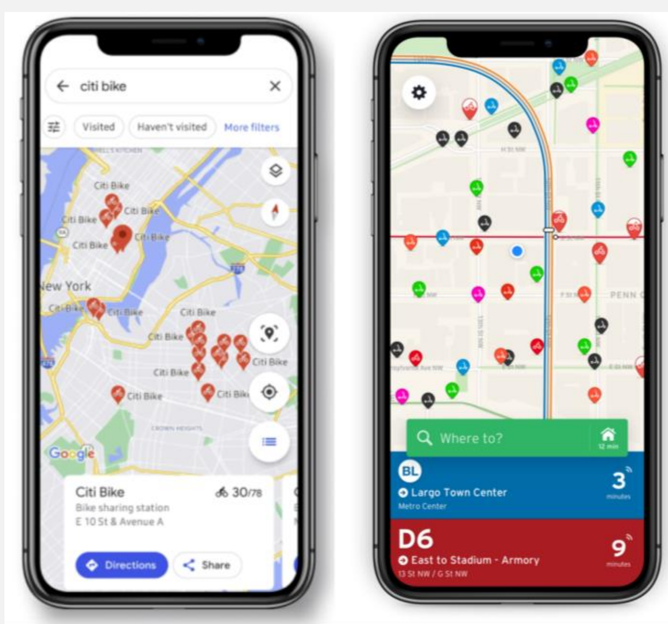
Injury Investigation: Investigate injuries and collisions with other objects and cars to determine roadway accident causes

Restricted Area Rides: Find locations where vehicles are operating or passing through restricted areas

Resident Complaints: Investigate and validate complaints from residents about operations, parking, riding, speed, etc., usually reported through 311

Infrastructure Planning: Determine where to place new bike/scooter lanes and drop zones based on usage and demand, start and end points, and trips taken

General Bikeshare Feed Specification (GBFS), first introduced by the North American Bikeshare and Scootershare Association (NABSA) in 2015, is the major data standard for real-time micromobility data across systems from more than 45 countries. The following figure illustrates the integration of micromobility in trip planning on Google Maps and Transit App.



GBFS application in Google Maps and Transit App (Picture Credit: NABSA)

Adapted from OMF (2022) and NABSA (2021) providers to educate first-time users on riding rules and provide proof of driving license. Some service providers have also launched websites for comprehensive education on safe road behavior with e-scooters (Vio, 2020). On the other hand, educating the differences of safe riding among shared micromobility vehicles is also necessary. For instance, motor-assisted vehicles such as e-scooter and e-bikes have different riding patterns and risk-taking behavior than bicycles, leading to different crash mechanisms. An educational campaign should incorporate such patterns to promote safe riding. Box 3 illustrates a comparative safety campaign from the Los Angeles county office for shared e-scooters and bikeshare, where messaging incorporates difference in vehicle features and general riding behavior (Los Angeles County, 2022).

7.2.4 Public space and regulating shared e-scooter service providers and their fleet size

Several studies have highlighted the disproportionate urban and infrastructure investment for cars compared to other transportation modes and their relative mode share (ITF, 2022), as illustrated in Figure 37. To achieve mobility goals, cities need to prioritize other sustainable transportation modes, including micromobility. City planners should reimagine the use of public space and allocate equitable space to micromobility vehicles by building dedicated bike lanes, sidewalks, and parking spaces. Although the initial deployment of shared e-scooters caused issues like improper parking and blocking sidewalks, city governments investing in micromobility-friendly infrastructures, like Paris and London, have significantly improved parking compliance. A combination of expanding designated e-scooter parking areas and in-app parking enforcement increased parking compliance from 35% to 97% in Paris (Dott, 2021).

On the other hand, the relatively cheaper unit cost of e-scooter vehicles encourages service providers to increase the deployment of e-scooters exponentially. City governments should regulate the number of service providers and their fleet size so that the deployed vehicles improve mobility in the city without oversupplying. Fewer service providers with larger fleet sizes avoid market fragmentations and improve service provider’s profitability. However, this strategy could reduce competition among service providers and stifle innovation. A dynamic fleet size of service providers based on performance metrics could allow expansion and equitable operation across cities and provide incentives for service providers to improve service quality

Box 3: Educating about e-scooter and bicycle safety

The same rules for helmet and rider safety apply to all modes of personal transportation – including skateboards, roller skates, rollerblades, bicycles, and scooters.

Report Safety Issues – If you see something, say something. If you see debris in the bike lane, blocked lanes, or other safety hazards, let the County know by calling (800) 675-HELP. If there's something wrong with your bike/scooter, stop riding and report the problem to the rental company.

	
Age guideline: Shared Electric Scooters are for riders aged 18+ ONLY.	**Under 10? Supervision may be needed:** Young children should NOT ride at night or in the street unsupervised. Young children riding on the sidewalk should ride slowly and be prepared to stop quickly, especially at driveways and intersections.
Practice before the ride: Find a safe place to practice before you ride for the first time. The practice place should have little to no car traffic.	**New at this? Take a bike riding class!** Ask your local bike coalition or nearest bike shop for resources: la-bike.org
Wear a helmet that fits properly EVERY time you ride: A properly fitted helmet is the best way to prevent death and serious injuries in a crash.	**Protect your head:** Wear a helmet that fits properly EVERY time you ride. A properly fitted helmet is the best way to prevent death and serious injuries in crashes. If you are under 18, it's the law.
Adjust the scooter for your body: Scooter handlebars should be around the height of your waist when standing on the deck.	**Adjust the bike for your body and don't carry anyone else:** Change the seat height with your foot on the pedal, your fully extended legs should have a slight bend. Don't carry anyone else.
Don't ride on the sidewalk and go with the flow: Ride in the bike lane, if available. If riding in the street, ride as far to the right as you can. Go with the flow. Always ride in the direction of traffic.	**Be visible and go with the flow:** Wear bright-colored clothes in the daytime and light-colored or reflective clothing at night; and don't ride where it's dark or poorly lit unless your bike has a front light and rear reflector. Go with the flow. Always ride in the direction of traffic.

Box 3: continued

	
Make sure the scooter is in good condition: Before riding, check the brakes are working and tires are properly inflated. If you're riding at night, make sure you have a light on the front and a red rear reflector on the back.	**Make sure the bike is in good condition:** Before riding, check that brakes are working and tires are properly inflated. If you're riding at night, make sure you have a light on the front and a red reflector on the back.
Stay focused, sober, and alert: Stay aware of the traffic around you, watch for an obstacle in your path, and avoid gravel, potholes, cracks, and other hazards that could make you fall. Remember, alcohol and drugs will impair your ability to scoot safely and stay alert, just like driving.	**Stay focused, sober, and alert:** Stay aware of the traffic around you, watch for an obstacle in your path, and avoid gravel, potholes, cracks, and other hazards that could make you fall. Remember, alcohol and drugs will impair your ability to bicycle safely and stay alert, just like driving.
Obey all traffic laws, watch for pedestrians, and keep your eyes and ears open: All the rules of the road apply to scooters, too – obey traffic signs, signals, and lane markings. Slow down and/or stop when you approach pedestrians. Dismount in crosswalks and walk your scooter across the street. Give pedestrians priority. Keep your eyes and ears open. Put away your phone while riding, and never wear headphones that cover both ears and earplugs in both ears (except hearing aids).	**Obey all traffic laws and don't ride on the sidewalk, unless you're under 10:** All the rules of the road apply to bicyclists, too – obey traffic signs, signals, and lane markings. Ride in the bike lane, if one is available. If riding in the street, ride as far to the right as you can. If you're on a bike and the lane is narrow, it may be safer to "take" the lane by riding in the middle, rather than "share" the lane with a vehicle. Watch out for pedestrians. Slow down and/or stop when approaching pedestrians. Dismount in crosswalks and walk your bike across the street. Give priority to pedestrians.

Box 3: continued

	
Don't carry anyone else and park responsibly: Scooters should always be ridden alone; and could tip over if someone else rides with you! Park responsibly. When you're done with your ride, be considerate and park the scooter where it won't block the sidewalk, building entrances, or ADA ramps.	**Keep your eyes and ears open:** Put away your phone while riding, and never wear headphones that cover both ears and earplugs in both ears (except hearing aids).
Be visible, predictable, and ride in a single file: Help drivers know what you are about to do. Signal before changing lanes or before making a turn by raising and pointing your arms in the direction you intend to go. Ride straight and do not swerve in and out of traffic. Ride in single file. This will help vehicles navigate safely around you and the people you are riding with. Be visible. Wear bright-colored clothes in the daytime and light-colored or reflective clothing at night; and don't ride where it's dark or poorly lit unless your scooter has a front light and rear reflector.	**Be predictable, and ride in a single file:** Help drivers know what you are about to do. Signal before changing lanes or before making a turn by raising and pointing your arms in the direction you intend to go. Ride straight and do not swerve in and out of traffic. Ride in single file. This will help vehicles navigate safely around you and the people you are riding with.

Adapted from Los Angeles County (2022) and operational efficiency. Box 4 highlights some of the performance metrics for dynamic fleet sizing proposed by NACTO (NACTO, 2019).

7.2.5 Expanding shared micromobility in emerging economies

Shared micromobility can be the first wave of electrification in the mid-sized cities of emerging economies. However, the modal substitution of shared micromobility is critical to reducing the net transportation emissions. The modal shift needs to happen from vehicles with higher emissions. Meanwhile, shared micromobility must be easily accessible to widespread users so that these new travel technologies are common travel modes. Shared micromobility systems should adapt to the local context (such as culture, travel behavior, technological and road infrastructures, and political/institutional conditions) and promote the benefits of new travel technologies to reach broader users.

One approach to introducing shared micromobility would be proactively integrating these new travel modes into the existing transportation systems. Such integration would promote multimodal transportation through physical infrastructure (e.g., building bicycling lanes and docking stations), payment (e.g., online transactions), informational (e.g., access to the location of nearby vehicles), and institutional (e.g., cooperation between agencies). Box 5 lists the recommendations from the Institute for Transportation and Development Policy (ITDP) on integrating shared micromobility in the context of developing countries (ITDP, 2021).

7.3 Areas of future research

This section provides a high-level overview of future research on shared micromobility, while the individual chapter provides an in-depth discussion of the specific topics. First, researchers can use standardized micromobility data to develop policy tools that support data-driven decisions on managing and improving shared micromobility systems. The data collected from the shared micromobility can support broader goals, such as carbon emission reduction, accessibility, and safety. While shared micromobility data includes more detail than many other travel modes, several critical information, such as the actual lifespan of e-scooter vehicles and operations-related data, are still missing. Future research could develop tools to incorporate this information into the micromobility data to provide a comprehensive dataset.

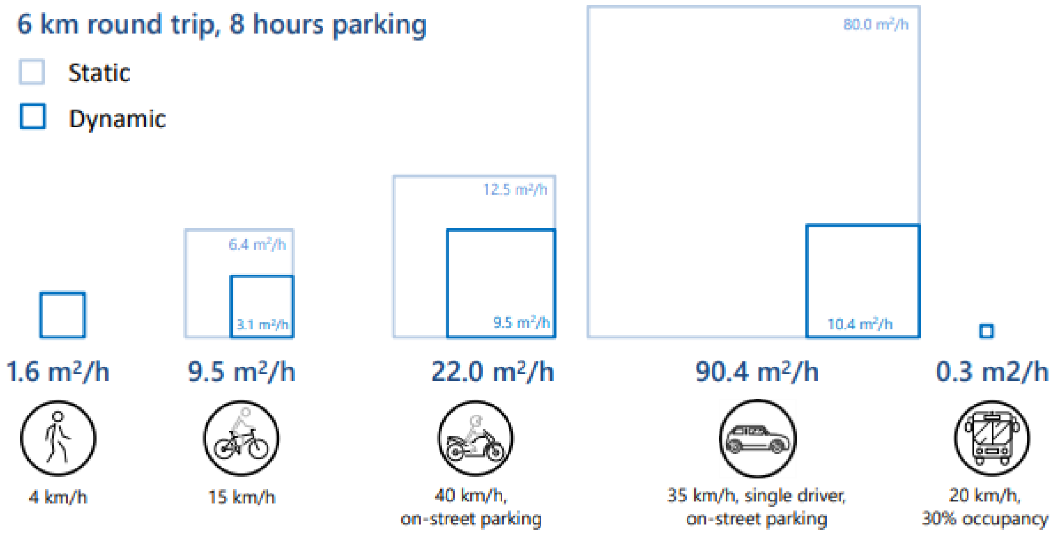


Figure 37 Space occupied by different travel modes (m^2 per hour) (Credit: ITF (2022)

Box 4: Performance metrics for dynamic fleet sizing

- **Number of trips per scooter per day measured over an identified time frame**: If a service provider meets this performance measure, they are allowed to increase their fleet size, but should decrease fleet size if they fail to meet the service performance measures.
- **Number of trips per scooter per day originating or ending in city-identified targeted service areas**: If a service provider meets/exceeds performance standards for available vehicles in areas with poor transit access and/or low rates of car ownership, they are permitted to increase their fleet size. If an operator fails to meet performance measures, the allowed fleet size decreases.
- **Strategies that address barriers to use:** Service providers may increase the fleet size if they meet targets for providing services to target groups such as unbanked populations or providing adaptive vehicles.
- **Strategies that encourage preferred parking or riding behaviors**: If a service provider demonstrates actions to meet the city's goals for parking and use, they are permitted to increase their fleet size.
- **Permit compliance**: Cities could adjust the allowed fleet size to reflect compliance infractions, measured in the number of infractions per established timeframe.

Adapted from NACTO (2019) and ITF (2021)

Box 5: Integrating micromobility in developing countries

- Ignite momentum for integration and developing strong working relationships with private operator(s)
- Move beyond operational regulation and toward intermodal integration
- Explicitly link integration to a goal of expanded access, especially by sustainable transport modes
- Consider integration in steps, starting with physical integration
- Identify shifts in travel demand (due to COVID-19 or other major events), internal factors such as contracts up for renewal, or similar opportunities that could help facilitate integration

Adapted from ITDP (2021)

Second, future studies can explore the equity impacts of shared micromobility and identify barriers to low-income demographics using these new mobility solutions. Several cities have identified equity zones and capped minimum service requirements for service providers in these areas. Future research could evaluate the efficacy of such policies as well as explore targeted policies that increase mobility and accessibility to opportunities for the minority population through micromobility. The research findings could support policy decisions like subsidized payments, while micromobility data could supplement the performance evaluation to promote equity goals.

Third, there is a limited understanding of the impacts of recent-generation micromobility vehicles, which are sturdily built and have a longer lifespan than first-generation e-scooters. The vehicle design has also been evolving, such as three-wheeled e-scooter, battery-swapping designs, and seated e-scooters. Researchers can evaluate the effect of recent designs on various aspects, including safety, sustainability, user experience, and overall system performance. Future research could also focus on improving the system efficiency of the shared micromobility, reducing the overall energy use and emissions.

7.4 Conclusion

Shared micromobility vehicles are low-speed vehicles that are affordable, low-emission, and efficient systems for urban mobility. While the worldwide popularity and deployment of shared micromobility have increased in the past few years, little is known about its impacts on the existing transportation systems. Decision makers, planners, and engineers can use the recommendations based on the dissertation's key findings to improve shared micromobility systems and achieve broader policy goals, including safety, accessibility, equity, and sustainability.

References

Abduljabbar, R. L., Liyanage, S., & Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. *Transportation Research Part D: Transport and Environment, 92*, 102734. doi:https://doi.org/10.1016/j.trd.2021.102734

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. doi:https://doi.org/10.1016/j.trd.2021.102821

Aguilera-García, Á., Gomez, J., & Sobrino, N. (2020). Exploring the adoption of moped scooter-sharing systems in Spanish urban areas. *Cities, 96*, 102424. doi:https://doi.org/10.1016/j.cities.2019.102424

Allem, J.-P., & Majmundar, A. (2019). Are electric scooters promoted on social media with safety in mind? A case study on Bird's Instagram. *Preventive medicine reports, 13*, 62-63.

Aman, J. J., Smith-Colin, J., & Zhang, W. (2021). Listen to E-scooter riders: Mining rider satisfaction factors from app store reviews. *Transportation Research Part D: Transport and Environment, 95*, 102856.

American Community Survey. (2019). 2015—2019 ACS 5-Year Data Profile. Retrieved from https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2019/

Anselin, L., Syabri, I., & Kho, Y. (2010). GeoDa: an introduction to spatial data analysis. In *Handbook of applied spatial analysis* (pp. 73-89): Springer.

Austin Public Health. (2019). *Dockless Electric Scooter-Related Injuries Study*. Retrieved from https://austintexas.gov/sites/default/files/files/Health/Epidemiology/APH_Dockless_Electric_Scooter_Study_5-2-19.pdf

Bachand-Marleau, J., Lee, B. H., & El-Geneidy, A. M. (2012). Better understanding of factors influencing likelihood of using shared bicycle systems and frequency of use. *Transportation research record, 2314*(1), 66-71.

Badeau, A., Carman, C., Newman, M., Steenblik, J., Carlson, M., & Madsen, T. (2019). Emergency department visits for electric scooter-related injuries after introduction of an urban rental program. *The American journal of emergency medicine, 37*(8), 1531-1533.

Bai, S., & Jiao, J. (2020). Dockless E-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. *Travel Behaviour and Society, 20*, 264-272.

Bao, J., Xu, C., Liu, P., & Wang, W. (2017). Exploring bikesharing travel patterns and trip purposes using smart card data and online point of interests. *Networks and Spatial Economics, 17*(4), 1231-1253.

Beck, S., Barker, L., Chan, A., & Stanbridge, S. (2019). Emergency department impact following the introduction of an electric scooter sharing service. *Emergency medicine Australasia*.

Bellan, R. (2021, June 23, 2021). Ford micromobility subsidiary Spin launches first in-house-built e-scooter. Retrieved from https://techcrunch.com/2021/06/23/ford-micromobility-subsidiary-spin-launches-first-in-house-built-e-scooter/

Bellan, R. (2022). Bird, Lime use Google's ARCore to power scooter parking solution. Retrieved from https://techcrunch.com/2022/05/11/bird-lime-to-use-googles-arcore-to-power-scooter-parking-solution/

Berrebi, S. J., Joshi, S., & Watkins, K. E. (2021). On bus ridership and frequency. *Transportation Research Part A: Policy and Practice, 148*, 140-154.

Berrebi, S. J., & Watkins, K. E. (2020). Who's ditching the bus? *Transportation Research Part A: Policy and Practice, 136*, 21-34.

Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. *Computers, Environment and Urban Systems, 65*, 126-139.

Bozdogan, H. (2000). Akaike's information criterion and recent developments in information complexity. *Journal of mathematical psychology, 44*(1), 62-91.

Buck, D., & Buehler, R. (2012). *Bike lanes and other determinants of capital bikeshare trips.* Paper presented at the 91st Transportation research board annual meeting.

Burchell, R. W., & Shad, N. A. (1998). The evolution of the sprawl debate in the United States. *Hastings W.-Nw. J. Envtl. L. & Pol'y, 5*, 137.

Bureau of Transportation Statistics. (2021). Bikeshare and E-scooter Systems in the U.S. Retrieved from Bikeshare and E-scooter Systems in the U.S.

Button, K., Frye, H., & Reaves, D. (2020). Economic regulation and E-scooter networks in the USA. *Research in transportation economics*, 100973.

Cai, Q., Lee, J., Eluru, N., & Abdel-Aty, M. (2016). Macro-level pedestrian and bicycle crash analysis: Incorporating spatial spillover effects in dual state count models. *Accident; analysis and prevention, 93*, 14-22. doi:10.1016/j.aap.2016.04.018

Campbell, A. A., Cherry, C. R., Ryerson, M. S., & Yang, X. (2016). Factors influencing the choice of shared bicycles and shared electric bikes in Beijing. *Transportation Research Part C: Emerging Technologies, 67*, 399-414.

Caspi, O., Smart, M. J., & Noland, R. B. (2020). Spatial associations of dockless shared e-scooter usage. *Transportation Research Part D: Transport and Environment, 86*, 102396.

Cazzola, P., & Crist, P. (2020). Good to go? Assessing the environmental performance of new mobility.

Central Bureau of Statistics. (2014). *National Population and Housing Census 2011*. Retrieved from https://unstats.un.org/unsd/demographic-social/census/documents/Nepal/Nepal-Census-2011-Vol1.pdf

Chang, A. Y., Miranda-Moreno, L., Clewlow, R., & Sun, L. (2019). TREND OR FAD?

Chase, R. (2017). Shared Mobility Principles for Livable Cities. Retrieved from https://www.sharedmobilityprinciples.org/

Cherry, C., & Cervero, R. (2007). Use characteristics and mode choice behavior of electric bike users in China. *Transport policy, 14*(3), 247-257.

Chesbrough, H., & Crowther, A. K. (2006). Beyond high tech: early adopters of open innovation in other industries. *R&d Management, 36*(3), 229-236.

Chester, M. (2019). It's a Bird…It's a Lime…It's Dockless Scooters! But Can These Electric-Powered Mobility Options Be Considered Sustainable Using Life-Cycle Analysis? Retrieved from https://chesterenergyandpolicy.com/2019/01/28/its-a-bird-its-a-lime-its-dockless-scooters-but-can-these-electric-powered-mobility-options-be-considered-sustainable-using-life-cycle-analysis/

Ciociola, A., Cocca, M., Giordano, D., Vassio, L., & Mellia, M. (2020). *E-Scooter Sharing: Leveraging Open Data for System Design.* Paper presented at the 2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT).

City of Austin. (2019). *Dockless Mobility Community Survey Report*. Retrieved from https://austintexas.gov/sites/default/files/files/Transportation/Dockless_Mobility_Community_Survey_Report_2-28-19.pdf

City of Cambridge. (2014). *Bicycle Crash Fact Sheet*. Retrieved from https://www.cambridgema.gov/-/media/Files/CDD/Transportation/Bike/bicyclesafetyfacts_final_20140609.pdf

City of Chicago. (2020). *E-Scooter Pilot Evaluation*. Retrieved from https://www.chicago.gov/content/dam/city/depts/cdot/Misc/EScooters/E-Scooter_Pilot_Evaluation_2.17.20.pdf

City of Nashville. (2022). *FAQs About Electricity in Nashville*. Retrieved from https://www.nashville.gov/sites/default/files/2022-02/FAQs-About-Electricity-in-Nashville.pdf?ct=1645216618

City of Santa Monica. (2019). *Shared Mobility Pilot Program Summary Report*. Retrieved from https://www.smgov.net/uploadedFiles/Departments/PCD/Transportation/SantaMonicaSharedMobilityEvaluation_Final_110419.pdf

Clewlow, R. R. (2019). *The Micro-Mobility Revolution: The Introduction and Adoption of Electric Scooters in the United States*. Retrieved from

Cross, K. D., & Fisher, G. (1977). A Study of Bicycle/Motor-Vehicle Accidents: Identification of Problem Types and Countermeasure Approaches. Volume 1. (DOT-HS-803-315).

Curl, A., & Fitt, H. (2019). Attitudes to and use of Electric Scooters in New Zealand Cities. In: Figshare.

de Bortoli, A., & Christoforou, Z. (2020). Consequential LCA for territorial and multimodal transportation policies: method and application to the free-floating e-scooter disruption in Paris. *Journal of Cleaner Production, 273*, 122898.

De Ceunynck, T., De Smedt, J., Daniels, S., Wouters, R., & Baets, M. (2015). "Crashing the gates"– selection criteria for television news reporting of traffic crashes. *Accident Analysis & Prevention, 80*, 142-152.

DeMaio, P. (2009). Bike-sharing: History, impacts, models of provision, and future. *Journal of public transportation, 12*(4), 3.

Denver City Council. (2019). *Electric scooter data & survey results*. Retrieved from https://www.denvergov.org/content/denvergov/en/denver-city-council/council-members/at-large-2/news/2019/electric-scooter-data---survey-results-.html

Department of Transport Management. (2017). Details of Registration of Transport up to Fiscal Year 2046/47 - 073/74: Registration in Bagmati Zone, Nepal. Retrieved from https://www.dotm.gov.np/Files/NoticePDF/bagmati0730742020-01-17_04-43-33-560.pdf

DESA, U. (2011). Population Division (2018) World Urbanization Prospect: the 2018 revision. In: ST/ESA/SER. A/366). UN Department of Economic and Social Affairs, New York.

Didier, T., Feyen, E., Montanes, R. L., & Alper, O. A. (2021). Global patterns of fintech activity and enabling factors. *World Bank Group Fintech and the Future of Finance report*.

Dott. (2021). First Paris, now London – micromobility parking gets smart. Retrieved from https://ridedott.com/blog/global/first-paris-now-london---micromobility-parking-gets-smart

Dutzik, T., Inglis, J., & Baxandall, P. (2014). Millennials in motion: Changing travel Habits of young Americans and the implications for public policy.

Eccarius, T., & Lu, C.-C. (2020b). Adoption intentions for micro-mobility – Insights from electric scooter sharing in Taiwan. *Transportation Research Part D: Transport and Environment, 84*, 102327. doi:https://doi.org/10.1016/j.trd.2020.102327

El-Assi, W., Mahmoud, M. S., & Habib, K. N. (2017). Effects of built environment and weather on bike sharing demand: a station level analysis of commercial bike sharing in Toronto. *Transportation*, *44*(3), 589-613.

Elmashhara, M. G., Silva, J., Sá, E., Carvalho, A., & Rezazadeh, A. (2022). Factors influencing user behaviour in micromobility sharing systems: A systematic literature review and research directions. *Travel Behaviour and Society*, *27*, 1-25. doi:https://doi.org/10.1016/j.tbs.2021.10.001

EPA. (2022). Greenhouse Gases Equivalencies Calculator - Calculations and References. Retrieved from https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references

Eren, E., & Uz, V. E. (2020). A review on bike-sharing: The factors affecting bike-sharing demand. *Sustainable cities and society, 54*, 101882. doi:https://doi.org/10.1016/j.scs.2019.101882

Faghih-Imani, A., & Eluru, N. (2015). Analysing bicycle-sharing system user destination choice preferences: Chicago's Divvy system. *Journal of Transport Geography, 44,* 53-64.

Faghih-Imani, A., Eluru, N., El-Geneidy, A. M., Rabbat, M., & Haq, U. (2014). How land-use and urban form impact bicycle flows: evidence from the bicycle-sharing system (BIXI) in Montreal. *Journal of Transport Geography, 41,* 306-314.

Farahmand, Z. H., Gkiotsalitis, K., & Geurs, K. T. (2021). Mobility-as-a-Service as a transport demand management tool: A case study among employees in the Netherlands. *Case Studies on Transport Policy, 9*(4), 1615-1629.

Fawcett, C. R., Barboza, D., Gasvoda, H. L., & Bernier, M. D. (2018). Analyzing Rideshare Bicycles and Scooters.

Fenn, J., & Time, M. (2007). Understanding Gartner's hype cycles, 2007. *Gartner ID G, 144727*.

Ferenchak, N. N., & Abadi, M. G. (2021). Nighttime pedestrian fatalities: A comprehensive examination of infrastructure, user, vehicle, and situational factors. *Journal of Safety Research, 79*, 14-25.

Figueroa, B. G. 8. Financing And Business Models. *The road forward: Cost-effective policy measures to decrease emissions from passenger land transport*, 119.

Fishman, E., & Allan, V. (2019). Bike share. *Advances in Transport Policy and Planning, 4*, 121-152.

French Government. (2019). *Loi d'orientation des mobilités (LOM)* Retrieved from https://www.ecologie.gouv.fr/loi-dorientation-des-mobilites#:~:text=La%20loi%20d'orientation%20des%20mobilit%C3%A9s%20a%20%C3%A9t%C3%A9%20publi%C3%A9e%20au,moins%20co%C3%BBteux%20et%20plus%20propres.

Fry, R. (2013). Young adults after the recession: Fewer homes, fewer cars, less debt. *Pew Research Center. February, 21*.

Furth, P. G., Mekuria, M. C., & Nixon, H. (2016). Network connectivity for low-stress bicycling. *Transportation research record, 2587*(1), 41-49.

Garikapati, V. M., Pendyala, R. M., Morris, E. A., Mokhtarian, P. L., & McDonald, N. (2016). Activity patterns, time use, and travel of millennials: a generation in transition? *Transport Reviews, 36*(5), 558-584.

Gautam, N., Sapakota, N., Shrestha, S., & Regmi, D. (2019). Sexual harassment in public transportation among female student in Kathmandu valley. *Risk management and healthcare policy, 12*, 105.

Gonçalves, S. (2011). The moving blocks bootstrap for panel linear regression models with individual fixed effects. *Econometric Theory, 27*(5), 1048-1082.

Greater Nashville Regional Council (GNRC). (2021). *Traffic Analysis Zones*. Retrieved from: https://data-gnrc.opendata.arcgis.com/datasets/1d17ae3a9b834125b2b09a83e01f8230_0/explore?location=36.029266%2C-86.693560%2C9.75

Griswold, A. (2019). Shared scooters don't last long. Retrieved from https://qz.com/1561654/how-long-does-a-scooter-last-less-than-a-month-louisville-data-suggests/

Guzman, L. A., Beltran, C., Bonilla, J. A., & Cardona, S. G. (2021). BRT fare elasticities from smartcard data: Spatial and time-of-the-day differences. *Transportation Research Part A: Policy and Practice, 150*, 335-348.

Haas, B., Doumouras, A. G., Gomez, D., De Mestral, C., Boyes, D. M., Morrison, L., & Nathens, A. B. (2015). Close to home: an analysis of the relationship between location of residence and location of injury. *The journal of trauma and acute care surgery, 78*(4), 860.

Hamal, P., & Huijsmans, R. (2022). Making markets gendered: Kathmandu's ride-sharing platforms through a gender lens. *Gender, Place & Culture*, *29*(5), 670-692.

Harkey, D. L., Tsai, S., Thomas, L., & Hunter, W. W. (2006). *Pedestrian and bicycle crash analysis tool (PBCAT): version 2.0 application manual*. Retrieved from

Hausman, J. A., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. In: national bureau of economic research Cambridge, Mass., USA.

Hellman, S. (2022). Scooter Sidewalk Riding Detection Technology Demonstration. Retrieved from https://www.sfmta.com/blog/scooter-sidewalk-riding-detection-technology-demonstration

Hensher, D. A., & Johnson, L. W. (2018). *Applied discrete-choice modelling*: Routledge.

Herbert, K. (2020). Spin Is Undergoing Major Restructuring. Retrieved from https://betterbikeshare.org/2022/01/14/spin-is-undergoing-major-restructuring/

Hertach, P., Uhr, A., Niemann, S., & Cavegn, M. (2018). Characteristics of single-vehicle crashes with e-bikes in Switzerland. *Accident Analysis & Prevention, 117*, 232-238. doi:10.1016/j.aap.2018.04.021

Hollingsworth, J., Copeland, B., & Johnson, J. X. (2019). Are e-scooters polluters? The environmental impacts of shared dockless electric scooters. *Environmental Research Letters*, *14*(8), 084031. doi:10.1088/1748-9326/ab2da8

Hosseinzadeh, A., Algomaiah, M., Kluger, R., & Li, Z. (2021a). E-scooters and sustainability: Investigating the relationship between the density of E-scooter trips and characteristics of sustainable urban development. *Sustainable cities and society*, *66*, 102624.

Hosseinzadeh, A., Algomaiah, M., Kluger, R., & Li, Z. (2021b). Spatial analysis of shared e-scooter trips. *Journal of Transport Geography, 92*, 103016. doi:https://doi.org/10.1016/j.jtrangeo.2021.103016

Hosseinzadeh, A., Karimpour, A., & Kluger, R. (2021). Factors influencing shared micromobility services: An analysis of e-scooters and bikeshare. *Transportation Research Part D: Transport and Environment, 100*, 103047. doi:https://doi.org/10.1016/j.trd.2021.103047

Hu, W., & McCartt, A. T. (2016). Effects of automated speed enforcement in Montgomery County, Maryland, on vehicle speeds, public opinion, and crashes. *Traffic injury prevention, 17*(sup1), 53-58.

Huang, H., Song, B., Xu, P., Zeng, Q., Lee, J., & Abdel-Aty, M. (2016). Macro and micro models for zonal crash prediction with application in hot zones identification. *Journal of Transport Geography*.

ITDP. (2021). *Maximizing Micromobility*. Retrieved from http://www.itdp-china.org/media/publications/pdfs/MaximizingMicromobility.pdf

ITF. (2021). *Micromobility, Equity and Sustainability: Summary and Conclusions,* . Retrieved from Paris: https://www.itf-oecd.org/sites/default/files/docs/micromobility-equity-sustainability.pdf

ITF. (2022). *Streets That Fit: Re-allocating Space for Better Cities*. Retrieved from https://www.itf-oecd.org/streets-fit-re-allocating-space-cities

James, O., Swiderski, J., Hicks, J., Teoman, D., & Buehler, R. (2019). Pedestrians and e-scooters: An initial look at e-scooter parking and perceptions by riders and non-riders. *Sustainability, 11*(20), 5591.

Janssen, C., Barbour, W., Hafkenschiel, E., Abkowitz, M., Philip, C., & Work, D. B. (2020). City-to-city and temporal assessment of peer city scooter policy. *Transportation research record, 2674*(7), 219-232.

Japan International Cooperation Agency (JICA). (2018). *The Project on Urban Transport Improvement for Kathmandu Valley in Federal Democratic Republic of Nepal* Retrieved from https://openjicareport.jica.go.jp/pdf/12289674.pdf

Jermakian, J., & Zuby, D. (2011). Primary pedestrian crash scenarios: factors relevant to the design of pedestrian detection systems. *Insurance Institute for Highway Safety, Arlington, VA.*

Jiang, S., Ferreira, J., & González, M. C. (2012). Clustering daily patterns of human activities in the city. *Data Mining and Knowledge Discovery, 25*(3), 478-510.

Jolliffe, I. (2011). *Principal component analysis*: Springer.

Kadir, N. A., Ghee-Thean, L., & Law, C. H. (2019). An interim evaluation of Penang's first bike-share scheme. *Geografia, 15*(3).

Kathait, N., & Agarwal, A. (2021). *Genealogy of Shared Mobility in India.* Paper presented at the 8th International Conference on Transportation Systems Engineering and Management (CTSEM 2021).

Kaviti, S., Venigalla, M. M., & Lucas, K. (2019). Travel behavior and price preferences of bikesharing members and casual users: A Capital Bikeshare perspective. *Travel Behaviour and Society, 15*, 133-145. doi:https://doi.org/10.1016/j.tbs.2019.02.004

Kennedy, S. (2020). Astral v2.2. Retrieved from https://astral.readthedocs.io/en/latest/

Khanal, P. (2021). How urban design and planning failed cycling in Kathmandu. *The Record*. Retrieved from https://www.recordnepal.com/how-urban-design-and-planning-failed-cycling-in-kathmandu

Kim, K. (2018). Investigation on the effects of weather and calendar events on bike-sharing according to the trip patterns of bike rentals of stations. *Journal of Transport Geography, 66*, 309-320. doi:https://doi.org/10.1016/j.jtrangeo.2018.01.001

Kobayashi, L. M., Williams, E., Brown, C. V., Emigh, B. J., Bansal, V., Badiee, J., . . . Doucet, J. (2019). The e-merging e-pidemic of e-scooters. *Trauma Surgery & Acute Care Open, 4*(1), e000337. doi:10.1136/tsaco-2019-000337

Kovacevich, A. (2019, Dec 23, 2019). The Scooter/City Hype Cycle. Retrieved from https://adamkovac.medium.com/the-scooter-city-hype-cycle-5108e6f5d9bd

Langford, B. C., Cherry, C., Yoon, T., Worley, S., & Smith, D. (2013). North America's first E-Bikeshare: a year of experience. *Transportation research record, 2387*(1), 120-128.

Lazo, L. (2018). Dockless bike, scooter firms clash with U.S. cities over regulations. Retrieved from https://www.washingtonpost.com/local/trafficandcommuting/dockless-bike-scooter-firms-clash-with-us-cities-over-regulations/2018/08/04/0db29bd0-9419-11e8-a679-b09212fb69c2_story.html

Libby Thomas, Mike Vann, & UNC Highway Safety Research Center. (2020). *Development of PBCAT Version 3*. Federal Highway Administration.

Lime. (2018). *San Francisco Scooter Use Survey Results*. Retrieved from https://www.li.me/hubfs/Lime%20San%20Francisco%20Scooter%20Survey%20Findings.pdf

Lin, P., Weng, J., Liang, Q., Alivanistos, D., & Ma, S. (2020). Impact of Weather Conditions and Built Environment on Public Bikesharing Trips in Beijing. *Networks and Spatial Economics, 20*(1), 1-17. doi:10.1007/s11067-019-09465-6

Litman, T., & Laube, F. (2002). Automobile dependency and economic development. *Victoria Transport Policy Institute, Canada*.

Liu, M., Seeder, S., & Li, H. (2019). Analysis of E-Scooter Trips and Their Temporal Usage Patterns. *Institute of Transportation Engineers. ITE Journal, 89*(6), 44-49.

Liu, Y., Huang, D., Wang, M., & Wang, Y. (2020). How do service quality, value, pleasure, and satisfaction create loyalty to smart dockless bike-sharing systems? *Revista Brasileira de Gestão de Negócios, 22*, 705-728.

Lo, D., Mintrom, C., Robinson, K., & Thomas, R. (2020). Shared micromobility: The influence of regulation on travel mode choice. *New Zealand Geographer, 76*(2), 135-146.

Los Angeles County. (2022). Staying Safe While Riding in Los Angeles County. Retrieved from https://dcba.lacounty.gov/eridesafety/

Lusk, A. C., Asgarzadeh, M., & Farvid, M. S. (2015). Database improvements for motor vehicle/bicycle crash analysis. *Injury Prevention, 21*(4), 221. doi:10.1136/injuryprev-2014-041317

Lyft. (2021, April 15, 2021). Riding Together: Introducing the Lyft Multimodal Report. Retrieved from https://www.lyft.com/blog/posts/2021-lyft-multimodal-report

Ma, Q., Yang, H., Ma, Y., Yang, D., Hu, X., & Xie, K. (2021). Examining municipal guidelines for users of shared E-Scooters in the United States. *Transportation Research Part D: Transport and Environment, 92*, 102710.

Maas, S., Attard, M., & Caruana, M. A. (2020). Assessing spatial and social dimensions of shared bicycle use in a Southern European island context: The case of Las Palmas de Gran Canaria. *Transportation Research Part A: Policy and Practice, 140*, 81-97. doi:https://doi.org/10.1016/j.tra.2020.08.003

MacAlister, A., & Zuby, D. S. (2015). Cyclist crash scenarios and factors relevant to the design of cyclist detection systems. *Insurance Institute for Highway Safety, Arlington, VA*.

MacQueen, J. (1967). *Some methods for classification and analysis of multivariate observations.* Paper presented at the Proceedings of the fifth Berkeley symposium on mathematical statistics and probability.

Markolf, S. A., Hoehne, C., Fraser, A., Chester, M. V., & Underwood, B. S. (2019). Transportation resilience to climate change and extreme weather events–Beyond risk and robustness. *Transport policy, 74*, 174-186.

Masoud, M., Elhenawy, M., Almannaa, M. H., Liu, S. Q., Glaser, S., & Rakotonirainy, A. (2019). Heuristic approaches to solve e-scooter assignment problem. *IEEE Access, 7*, 175093-175105.

Mathew, J. K., Liu, M., & Bullock, D. M. (2019). *Impact of weather on shared electric scooter utilization.* Paper presented at the 2019 IEEE Intelligent Transportation Systems Conference (ITSC).

Matute, J., Cohen-D'Agostino, M., & Brown, A. (2020). Sharing Mobility Data for Planning and Policy Research.

McKenzie, G. (2019). Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, DC. *Journal of Transport Geography, 78*, 19-28.

Merlin, L. A., Guerra, E., & Dumbaugh, E. (2020). Crash risk, crash exposure, and the built environment: A conceptual review. *Accident Analysis & Prevention, 134*, 105244.

Metropolitan Government of Nashville and Davidson County, T., ,. (2021). *Park and Recreation Finder*. Retrieved from: https://maps.nashville.gov/NashvilleParksFinder/

Ministry for the Environment, N. Z., ,. (2003). *Sustainable Transportation in New Zealand* Retrieved from https://viastrada.nz/sites/default/files/Sustainable-Transportation.pdf

Miranda-Moreno, L. F., Nosal, T., Schneider, R. J., & Proulx, F. (2013). Classification of bicycle traffic patterns in five North American Cities. *Transportation research record, 2339*(1), 68-79.

Moran, M. E., Laa, B., & Emberger, G. (2020). Six scooter operators, six maps: Spatial coverage and regulation of micromobility in Vienna, Austria. *Case Studies on Transport Policy, 8*(2), 658-671.

Moreau, H., de Jamblinne de Meux, L., Zeller, V., D'Ans, P., Ruwet, C., & Achten, W. M. J. (2020). Dockless E-Scooter: A Green Solution for Mobility? Comparative Case Study between Dockless E-Scooters, Displaced Transport, and Personal E-Scooters. *Sustainability (Basel, Switzerland), 12*(5), 1803. doi:10.3390/su12051803

Morgan, A. (2019). E-Scooters Aren't for Kids: AAP Urges Safety Rules. Retrieved from https://www.healthychildren.org/English/safety-prevention/on-the-go/Pages/E-Scooters.aspx

Music City, I., ,. Statistics & Facts. Retrieved from https://www.visitmusiccity.com/explore-nashville/about/statistics

Music City, I., ,. (2021). Statistics & Facts. Retrieved from https://www.visitmusiccity.com/explore-nashville/about/statistics

NABSA. (2021). *Data Good Practices for Municipalities*. Retrieved from https://nabsa.net/wp-content/uploads/2021/01/FINAL-Data-Good-Practices-for-Municipalities_-Understanding-the-General-Bikeshare-Feed-Specification-GBFS-1.pdf

NABSA. (2022). Shared Micromobility State of the Industry Report. Retrieved from https://betterbikeshare.org/wp-content/uploads/2022/08/2021-State-of-the-Industry-Report.pdf

NACTO. (2019). *Guidelines for Regulating Shared Micromobility*. Retrieved from https://nacto.org/wp-content/uploads/2019/09/NACTO_Shared_Micromobility_Guidelines_Web.pdf

NACTO. (2020). *Shared Micromobility in the US: 2019*. Retrieved from https://nacto.org/wp-content/uploads/2020/08/2020bikesharesnapshot.pdf

Naghizadeh, A., & Metaxas, D. N. (2020). Condensed silhouette: An optimized filtering process for cluster selection in k-means. *Procedia Computer Science, 176*, 205-214.

National Association of City Transportation Officials. (2020). *Shared Micromobility in the U.S.: 2019*. Retrieved from https://nacto.org/shared-micromobility-2019/

National Transportation Safety Board. (2019). *Bicyclist Safety on US Roadways: Crash Risks and Countermeasures*. Retrieved from

Newberry, L. (2018, Aug. 10, 2018). Fed-up locals are setting electric scooters on fire and burying them at sea. *Los Angeles Times*. Retrieved from https://www.latimes.com/local/lanow/la-me-ln-bird-scooter-vandalism-20180809-story.html#:~:text=California-,Must%20Reads%3A%20Fed%2Dup%20locals%20are%20setting%20electric%20scooters%20on,on%20the%20Venice%20Beach%20boardwalk.&text=They've%20been%20crammed%20into,balconies%20and%20set%20on%20fire.

Newman, P., & Kenworthy, J. (1999). *Sustainability and cities: overcoming automobile dependence*: Island press.

NHTS. (2017). Popular Vehicle Trips Statistics. Retrieved from https://nhts.ornl.gov/vehicle-trips

NHTSA. (2008). *National Motor Vehicle Crash Causation Survey- CrashStats* (DOT HS 811 059). Retrieved from

Noland, R. B. (2019). Trip patterns and revenue of shared e-scooters in Louisville, Kentucky. *Transport Findings, 29*(4).

Noland, R. B. (2021). Scootin' in the rain: Does weather affect micromobility? *Transportation Research Part A: Policy and Practice, 149*, 114-123. doi:https://doi.org/10.1016/j.tra.2021.05.003

NUMO, NABSA, & OMF. (2020). Privacy Principles for Mobility Data. In.

Ojha, A. (2021). Only cycle lanes are not enough, stakeholders say. *The Kathmandu Post*. Retrieved from https://kathmandupost.com/valley/2021/03/16/only-cycle-lanes-are-not-enough-stakeholders-say

OMF. (2022). Mobility Data Specification (MDS). Retrieved from https://www.openmobilityfoundation.org/about-mds/

Öztaş Karlı, R. G., Karlı, H., & Çelikyay, H. S. (2022). Investigating the acceptance of shared e-scooters: Empirical evidence from Turkey. *Case Studies on Transport Policy, 10*(2), 1058-1068. doi:https://doi.org/10.1016/j.cstp.2022.03.018

Patel, S. J., & Patel, C. R. (2020). A stakeholders perspective on improving barriers in implementation of public bicycle sharing system (PBSS). *Transportation Research Part A: Policy and Practice, 138*, 353-366.

Pierpaolo Cazzola, P. C. (2020). *Good to Go? Assessing the Environmental Performance of New Mobility*. Retrieved from https://www.itf-oecd.org/good-go-assessing-environmental-performance-new-mobility

Portland Bureau of Transportation. (2018). *2018 E-scooter Pilot User Survey Results*. Retrieved from https://www.portlandoregon.gov/transportation/article/700916?utm_medium=email&utm_source=govdelivery

Portland Bureau of Transportation. (2019). 2018 E-Scooter Pilot Program.

Prajapati, R., Talchabhadel, R., Silwal, P., Upadhyay, S., Ertis, B., Thapa, B. R., & Davids, J. C. (2021). Less rain and rainy days—lessons from 45 years of rainfall data (1971–2015) in the Kathmandu Valley, Nepal. *Theoretical and Applied Climatology, 145*(3), 1369-1383.

Raptopoulou, A., Basbas, S., Stamatiadis, N., & Nikiforiadis, A. (2020). *A first look at e-scooter users.* Paper presented at the Conference on Sustainable Urban Mobility.

Rayle, L., Dai, D., Chan, N., Cervero, R., & Shaheen, S. (2016). Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. *Transport policy, 45*, 168-178.

Reck, D. J., & Axhausen, K. W. (2021). Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. *Transportation Research Part D: Transport and Environment, 94*, 102803.

Reck, D. J., Haitao, H., Guidon, S., & Axhausen, K. W. (2021). Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies, 124*, 102947.

Reed, T. (2019). Micromobility Potential in the US, UK and Germany.

Reinhardt, K., & Deakin, E. (2020). Best Practices for the Public Management of Electric Scooters.

Remix. (2018). *Micromobility's opportunity to serve the underserved edges*. Retrieved from https://www.remix.com/resources-library/micromobilitys-opportunity-to-serve-the-underserved-edges

Rose, J. M., & Bliemer, M. C. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews, 29*(5), 587-617.

RSG. (2016). *Nashville ABM User Guide*. Retrieved from

SAE International. (2019). Taxonomy and Classification of Powered Micromobility Vehicles. In.

Salingaros, N. A. (2006). Compact city replaces sprawl. *Chapter in: Crossover: Architecture, Urbanism, Technology, Edited by Arie Graafland & Leslie Kavanaugh (010 Publishers, Rotterdam, Holland)*, 100-115.

San Francisco Municipal Transportation Agency. (2019). *Powered Scooter Share Mid-Pilot Evaluation*. Retrieved from https://www.sfmta.com/sites/default/files/reports-and-documents/2019/08/powered_scooter_share_mid-pilot_evaluation_final.pdf

Sanders, R. L., Branion-Calles, M., & Nelson, T. A. (2020). To scoot or not to scoot: Findings from a recent survey about the benefits and barriers of using E-scooters for riders and non-riders. *Transportation Research Part A: Policy and Practice, 139*, 217-227. doi:10.1016/j.tra.2020.07.009

Santacreu, A., Yannis, G., de Saint Leon, O., & CRIST, P. (2020a). *Safe micromobility*. Retrieved from https://www.itf-oecd.org/safe-micromobility

Santacreu, A., Yannis, G., de Saint Leon, O., & Crist, P. (2020b). Safe micromobility.

Schneider, R. J., & Stefanich, J. (2016). Application of the Location–Movement Classification Method for Pedestrian and Bicycle Crash Typing. *Transportation research record, 2601*(1), 72-83.

Severengiz, S., Finke, S., Schelte, N., & Wendt, N. (2020). *Life cycle assessment on the mobility service E-scooter sharing.* Paper presented at the 2020 IEEE European Technology and Engineering Management Summit (E-TEMS).

Shah, N. (2020). Big Data and Unsupervised Machine Learning Approach to Understand Why People Ride E-Scooter in Nashville, Tennessee.

Shah, N. R. (2020). *Big Data and Unsupervised Machine Learning Approach to Understand Why People Ride E-Scooter in Nashville, Tennessee.* (MS Thesis). University of Tennessee,

Shah, N. R., Aryal, S., Wen, Y., & Cherry, C. R. (2021). Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology. *Journal of Safety Research*(77), 217-228. doi:https://doi.org/10.1016/j.jsr.2021.03.005

Shah, N. R., & Cherry, C. R. (2021). Different safety awareness and route choice between frequent and infrequent bicyclists: findings from revealed preference study using bikeshare data. *Transportation research record, 2675*(11), 269-279.

Shah, N. R., & Cherry, C. R. (2022). The Chance of Getting Struck by a Car on an e-Scooter is Twice as High at Night. *Findings*, 36195. Retrieved from https://trace.tennessee.edu/cgi/viewcontent.cgi?article=7088&context=utk_gradthes

Shah, N. R., Guo, J., Lee, H. D., & Cherry, C. (In review). *Why Do People Take E-Scooter Trips? Insights on Temporal and Spatial Usage Patterns of Detailed Trip Data*. Insights on Temporal and Spatial Usage Patterns of Detailed Trip Data. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3988137

Shah, N. R., Parajuli, S., & Cherry, C. R. (In review). Ride-hailing users are likely early adopters of shared micromobility in mid-sized cities of developing countries: A case study of Kathmandu, Nepal. *Transportation Research Board Annual Meeting*

Shah, N. R., Ziedan, A., Brakewood, C., & Cherry, C. (In review). Shared E-Scooter Service Providers with Large Fleet Size Have a Competitive Advantage: Findings from E-Scooter Demand and

Supply Analysis of Nashville, Tennessee. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4167543

Shaheen, S., & Cohen, A. (2019). Shared micromoblity policy toolkit: Docked and dockless bike and scooter sharing.

Shaheen, S., Guzman, S., & Zhang, H. (2012). Bikesharing across the globe. *City cycling, 183*.

Shaheen, S. A., Zhang, H., Martin, E., & Guzman, S. (2011). China's Hangzhou public bicycle: understanding early adoption and behavioral response to bikesharing. *Transportation research record, 2247*(1), 33-41.

Sharmeen, F., Ghosh, B., & Mateo-Babiano, I. (2021). Policy, users and discourses: Examples from bikeshare programs in (Kolkata) India and (Manila) Philippines. *Journal of Transport Geography, 90*, 102898. doi:https://doi.org/10.1016/j.jtrangeo.2020.102898

Sikka, N., Vila, C., Stratton, M., Ghassemi, M., & Pourmand, A. (2019). Sharing the sidewalk: A case of E-scooter related pedestrian injury. *The American journal of emergency medicine, 37*(9), 1807. e1805-1807. e1807.

Sisson, P. (2018, Feb 14, 2018). Bird electric scooters are now all over the Westside. *Curbed Los Angeles*. Retrieved from https://la.curbed.com/2018/2/14/17010034/bird-electric-scooters-transit-venice-santa-monica

Snyder, M. B., & Knoblauch, R. L. (1971). *Pedestrian Safety: The Identification of Precipitating Factors and Possible Countermeasures: Volume I and Volume II* (FH-11-7312). Retrieved from Washington, D.C.:

Sombatphanit, K., Panyasakulchai, K., Chenyawanich, P., Adunyarittigun, D., & Chuenmanuse, P. (2020). Identifying Factors Affecting the Decision Not to Use Bike Sharing Service in Bangkok, Thailand.

StataCorp. (2021). *Stata 17 Base Reference Manual*. Retrieved from College Station, TX: Stata Press.:

Steinbach, R., Edwards, P., & Grundy, C. (2013). The road most travelled: the geographic distribution of road traffic injuries in England. *International journal of health geographics, 12*(1), 1-7.

Streicher, B. (2019, August 28, 2019). Sabotaged scooters found on Rainey Street in downtown Austin. *KVUE*. Retrieved from https://www.kvue.com/article/news/sabotaged-scooters-found-in-downtown-austin/269-05fb842e-1356-48bd-9e25-1a8b8c08260f

Sun, Y., Mobasheri, A., Hu, X., & Wang, W. (2017). Investigating Impacts of Environmental Factors on the Cycling Behavior of Bicycle-Sharing Users. *Sustainability, 9*, 1060.

Tamburin, A. (2019). Mayor David Briley directs city lawyers to draft plan to 'terminate' existing scooter program, start new plan. *The Tennessean*. Retrieved from https://www.tennessean.com/story/news/2019/06/21/nashville-scooters-mayor-david-briley-directs-city-lawyers-draft-plan-terminate-program/1524881001/

Tennessee Highway Safety Office. (2020a). *Tennessee Integrated Traffic Analysis Network (TITAN)* Retrieved from: https://tntrafficsafety.org/

Tennessee Highway Safety Office. (2020b). TITAN. In.

Tin, S. T., Woodward, A., & Ameratunga, S. (2013). Completeness and accuracy of crash outcome data in a cohort of cyclists: a validation study. *BMC Public Health, 13*(1), 420.

Todd Litman, D. B. (2006). Issues in sustainable transportation. *International Journal of Global Environmental Issues, 6*(4), 331–347.

Train, K. E. (2009). *Discrete choice methods with simulation*: Cambridge university press.

Trivedi, T. K., Liu, C., Antonio, A. L. M., Wheaton, N., Kreger, V., Yap, A., . . . Elmore, J. G. (2019). Injuries associated with standing electric scooter use. *JAMA network open, 2*(1), e187381-e187381.

Tu, W., Cao, R., Yue, Y., Zhou, B., Li, Q., & Li, Q. (2018). Spatial variations in urban public ridership derived from GPS trajectories and smart card data. *Journal of Transport Geography, 69*, 45-57.

Tuli, F. M., Mitra, S., & Crews, M. B. (2021). Factors influencing the usage of shared E-scooters in Chicago. *Transportation Research Part A: Policy and Practice, 154*, 164-185.

U.S. Census Bureau. Resident Population in Nashville-Davidson--Murfreesboro--Franklin, TN (MSA) Retrieved from https://fred.stlouisfed.org/series/NVLPOP

U.S. Census Bureau. (2021). *Resident Population in Nashville-Davidson--Murfreesboro--Franklin, TN (MSA)* Retrieved from https://fred.stlouisfed.org/series/NVLPOP

Unagi, I. (2020). The Comprehensive Guide to Electric Scooter Laws. Retrieved from https://unagiscooters.com/articles/the-comprehensive-guide-to-electric-scooter-laws/

Vergel-Tovar, C. E., & Rodriguez, D. A. (2018). The ridership performance of the built environment for BRT systems: Evidence from Latin America. *Journal of Transport Geography, 73*, 172-184.

Vio. (2020). Ride Like Voila. Retrieved from https://ridelikevoila.com/enter

Wang, X., Lindsey, G., Schoner, J. E., & Harrison, A. (2016). Modeling bike share station activity: Effects of nearby businesses and jobs on trips to and from stations. *Journal of Urban Planning and Development, 142*(1), 04015001.

Washington, S., Karlaftis, M., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis*: Chapman and Hall/CRC.

Watkins, K., Berrebi, S., Erhardt, G., Hoque, J., Goyal, V., Brakewood, C., . . . Kressner, J. (2021). Recent Decline in Public Transportation Ridership: Analysis, Causes, and Responses. *TCRP Research Report*(231).

Weyn, J. A., Durran, D. R., & Caruana, R. (2020). Improving data-driven global weather prediction using deep convolutional neural networks on a cubed sphere. *Journal of Advances in Modeling Earth Systems, 12*(9), e2020MS002109.

World Bank. (2013). *Managing Nepal's Urban Transition*. Retrieved from https://www.worldbank.org/en/news/feature/2013/04/01/managing-nepals-urban-transition.

Wortmann, C., Syré, A. M., Grahle, A., & Göhlich, D. (2021). Analysis of Electric Moped Scooter Sharing in Berlin: A Technical, Economic and Environmental Perspective. *World Electric Vehicle Journal, 12*(3), 96.

Xu, Y., Chen, D., Zhang, X., Tu, W., Chen, Y., Shen, Y., & Ratti, C. (2019). Unravel the landscape and pulses of cycling activities from a dockless bike-sharing system. *Computers, Environment and Urban Systems, 75*, 184-203. doi:https://doi.org/10.1016/j.compenvurbsys.2019.02.002

Yang, H., Ma, Q., Wang, Z., Cai, Q., Xie, K., & Yang, D. (2020). Safety of micro-mobility: analysis of E-Scooter crashes by mining news reports. *Accident Analysis & Prevention, 143*, 105608.

Ye, F., & Lord, D. (2014). Comparing three commonly used crash severity models on sample size requirements: Multinomial logit, ordered probit and mixed logit models. *Analytic methods in accident research, 1*, 72-85.

Younes, H., Zou, Z., Wu, J., & Baiocchi, G. (2020). Comparing the Temporal Determinants of Dockless Scooter-share and Station-based Bike-share in Washington, DC. *Transportation Research Part A: Policy and Practice, 134*, 308-320.

Zhang, W., Buehler, R., Broaddus, A., & Sweeney, T. (2021). What type of infrastructures do e-scooter riders prefer? A route choice model. *Transportation Research Part D: Transport and Environment, 94*, 102761. doi:https://doi.org/10.1016/j.trd.2021.102761

Zhang, Y., Thomas, T., Brussel, M., & Van Maarseveen, M. (2017). Exploring the impact of built environment factors on the use of public bikes at bike stations: case study in Zhongshan, China. *Journal of Transport Geography, 58*, 59-70.

Zhao, Y., Cao, J., Ma, Y., Mubarik, S., Bai, J., Yang, D., . . . Yu, C. (2022). Demographics of road injuries and micromobility injuries among China, India, Japan, and the United States population: evidence from an age-period-cohort analysis. *BMC Public Health, 22*(1), 1-12.

Zhou, M., Wang, D., Li, Q., Yue, Y., Tu, W., & Cao, R. (2017). Impacts of weather on public transport ridership: Results from mining data from different sources. *Transportation Research Part C: Emerging Technologies, 75*, 17-29.

Ziedan, A., Darling, W., Brakewood, C., Erhardt, G., & Watkins, K. (2021). The impacts of shared e-scooters on bus ridership. *Transportation Research Part A: Policy and Practice, 153*, 20-34.

Ziedan, A., Shah, N. R., Wen, Y., Brakewood, C., Cherry, C. R., & Cole, J. (2021). Complement or compete? The effects of shared electric scooters on bus ridership. *Transportation Research Part D: Transport and Environment*, *101*, 103098.

Zivin, J. S. G., Kotchen, M. J., & Mansur, E. T. (2014). Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies. *Journal of Economic Behavior & Organization*, *107*, 248-268.

Appendices

A1. SUMD data

I used the Trip Summary and Device Availability dataset of Shared Urban Mobility Device (SUMD) data acquired through a data request made to the City of Nashville. The Trip Summary dataset includes trip-related information, such as trip distance, trip duration, timestamp and geolocation of trip origin and destination, as illustrated in Figure A1.1.

Table A1.1 summarizes the data description of the trip dataset.

The Device Availability is another dataset of SUMD, which includes timestamped geolocations of each deployed e-scooters with information about battery charge level, as illustrated Figure A1.2. This dataset updates every five minutes.

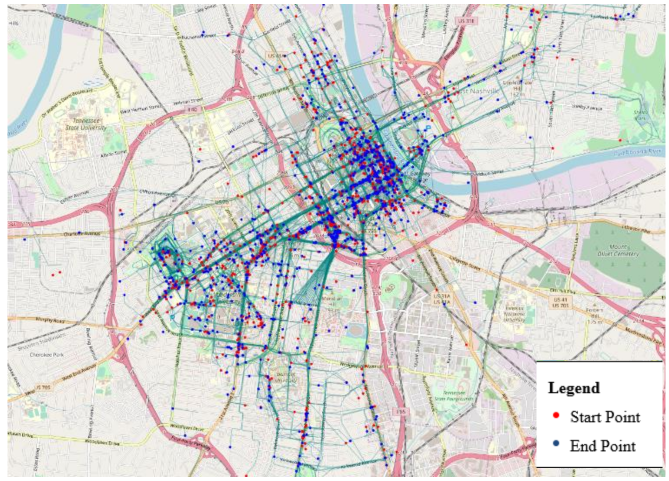
Table A1.2 summarizes the data description of the device availability dataset.

A2. The spatial plot of demand elasticity

Figure A2.1, Figure A2.2, and Figure A2.3 illustrate the spatial distribution of e-scooter trips and deployment (measured in hours per square miles) for large, medium, and small service provider groups. The color bands for e-scooter trips and deployment for these three figures represent different values, as indicated in the respective legends.

```
[
"SUMD": {
        "pubTimestamp"        :    "2018-09-01T18:25:43.511Z",
        "companyName"         :    "Example Co.",
        "sumdType"            :    "Powered",
        "sumdGroup"           :    "Scooter",
        "tripRecordNum"       :    "EXC01",
        "sumdID"              :    "PoweredEXC00001",
        "tripDuration"        :    "2.352",
        "tripDistance"        :    "1024.8934",
        "startDate"           :    "2018-09-01",
        "startTime"           :    "08:12:43",
        "endDate"             :    "2018-09-01",
        "endTime"             :    "08:15:01",
        "startLatitude"       :    "36.153816671",
        "startLongitude"      :    "-86.76871038",
        "endLatitude"         :    "36.159953125",
        "endLongitude"        :    "-86.77837077",
        "tripRoute"           :    [
                                       ["36.153816671", "-86.76871038"],
                                       ["36.157768018", "-86.77652629"],
                                       ["36.156312719", "-86.77563580"],
                                       ["36.154770766", "-86.77289994"],
                                       ["36.154562860", "-86.77009972"],
                                       ["36.159953125", "-86.77837077"]
                                   ]
        }
```


a) Data specification



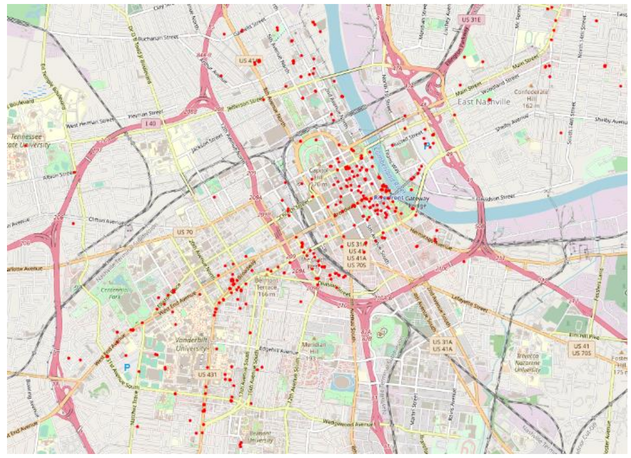
b) Sample plot

Figure A1.1 SUMD’s Trip Summary example data

Table A1.1 Data description of SUMD trip dataset

Field Name	**Description**	**Example**
pubTimestamp	Timestamp of SUMD pulled	"2018-09-01T18:25:43.511Z",
Company Name	Company Name	"Example Co.",
Type of SUMD	"Standard or "Powered"	"Powered",
SUMD Group	Name of the SUMD group	"Scooter",
Trip record number	3 letter company acronym + consecutive trip #, Xxx#, xxx#+1, xxx#+2, ...	"EXC01",
SUMD ID number	SUMD Type + Unique identifier for every SUMD, determined by company	"PoweredEXC00001",
Trip duration	Minutes	"2.352",
Trip distance	Feet	"1024.8934",
Start date	n/a	"2018-09-01",
Start time	n/a	"08:12:43",
End date	n/a	"2018-09-01",
End time	n/a	"08:15:01",
Start latitude	Point location X	"36.153816671",
Start longitude	Point location Y	"-86.76871038",
End latitude	Point location X	"36.159953125",
End longitude	Point location Y	"-86.77837077",
Trip Route	Sequential GPS coordinates for entire trip duration at a minimum collection frequency of one per 30 seconds.	[["36.153816671", "-86.76871038”], ["36.157768018", "-86.77652629”], ["36.156312719", "-86.77563580”], ["36.154770766", "-86.77289994"], ["36.154562860", "-86.77009972"], ["36.159953125", "-86.77837077"]]

```
[
"SUMD": {
        "pubTimestamp"      :       "2018-09-01T18:25:43.511Z",
        "latitude"          :       "36.153816671",
        "longitude"         :       "-86.76871038",
        "sumdID"            :       "PoweredEXC00001",
        "sumdType"          :       "Powered",
        "chargeLevel"       :       "78.4862",
        "sumdGroup"         :       "Scooter",
        "costPerMin"        :       "0.48"
        }
]
```

a) Data specification

b) Sample data

Figure A1.2 SUMD's Device Availability example data

Table A1.2 Data description of SUMD device availability dataset

Field Name	Description	Example
pubTimestamp	Timestamp of SUMD pulled	2018-09-01T18:25:43.511Z
Latitude	Point location X	36.153816671
Longitude	Point location Y	-86.76871038
SUMD ID number	SUMD Type + Unique identifier for every SUMD, determined by company	PoweredEXC00001
Type of SUMD	“Standard” or “Powered”	Powered
Fuel/charge level	Ratio of charge level to full charge (50.1234%)	78.4862
SUMD Group	Name of the SUMD group (“bicycle”, “tricycle”, “scooter”, “hover board”, “skateboard”, “pedal car” or "other”)	Scooter
Current rental rate per minute	In dollar	0.48

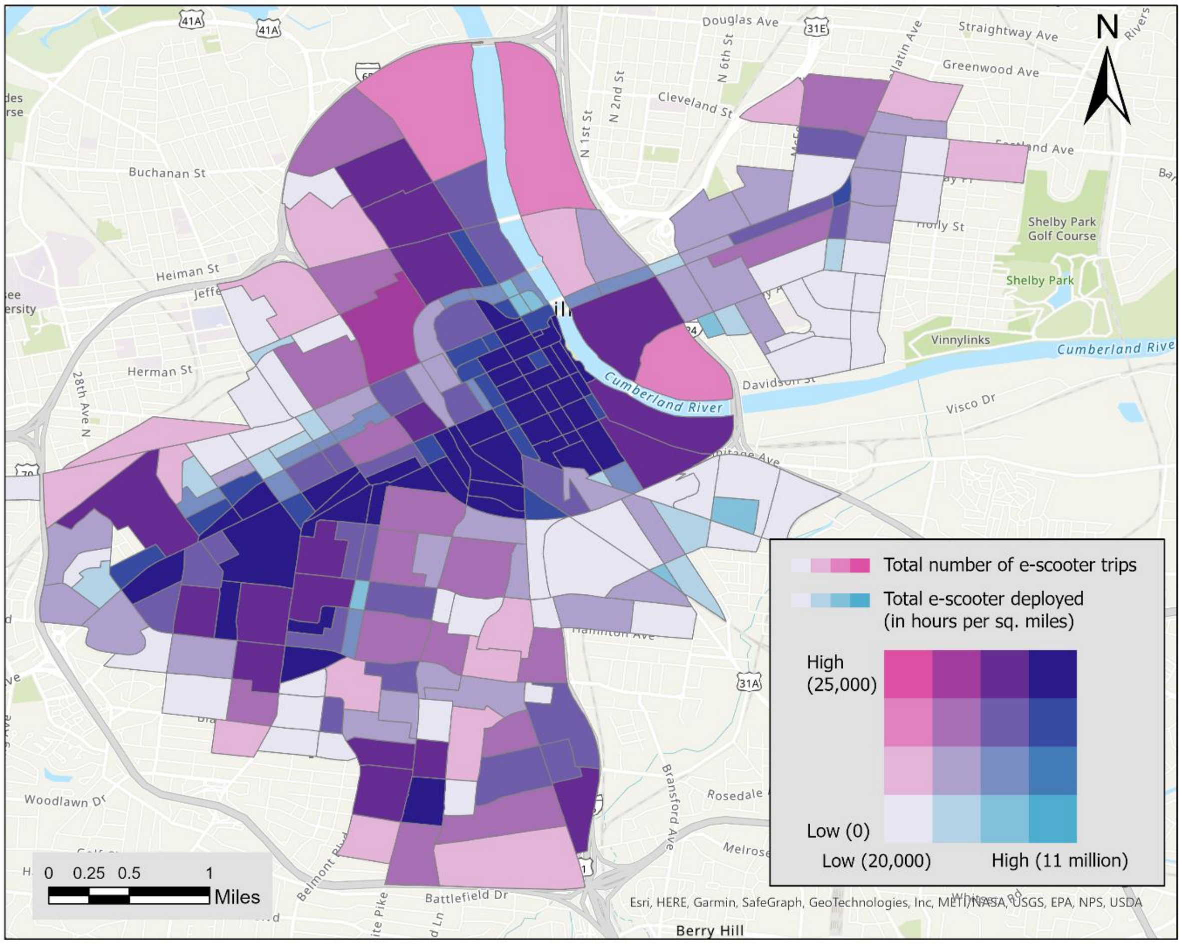


Figure A2.1 Bivariate map of the total e-scooter trips and vehicles deployed at each TAZ throughout the study period for large service providers' group

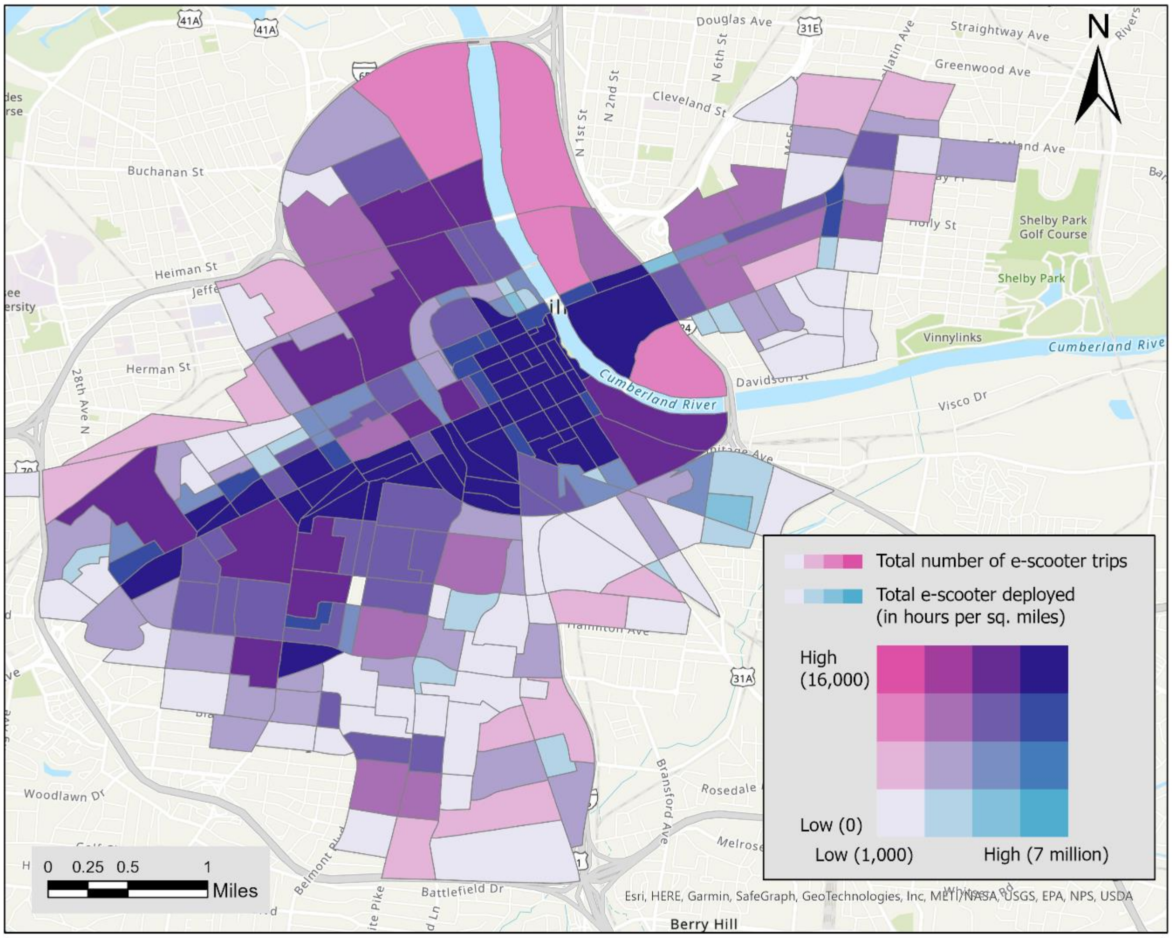


Figure A2.2 Bivariate map of the total e-scooter trips and vehicles deployed at each TAZ throughout the study period for medium service providers' group

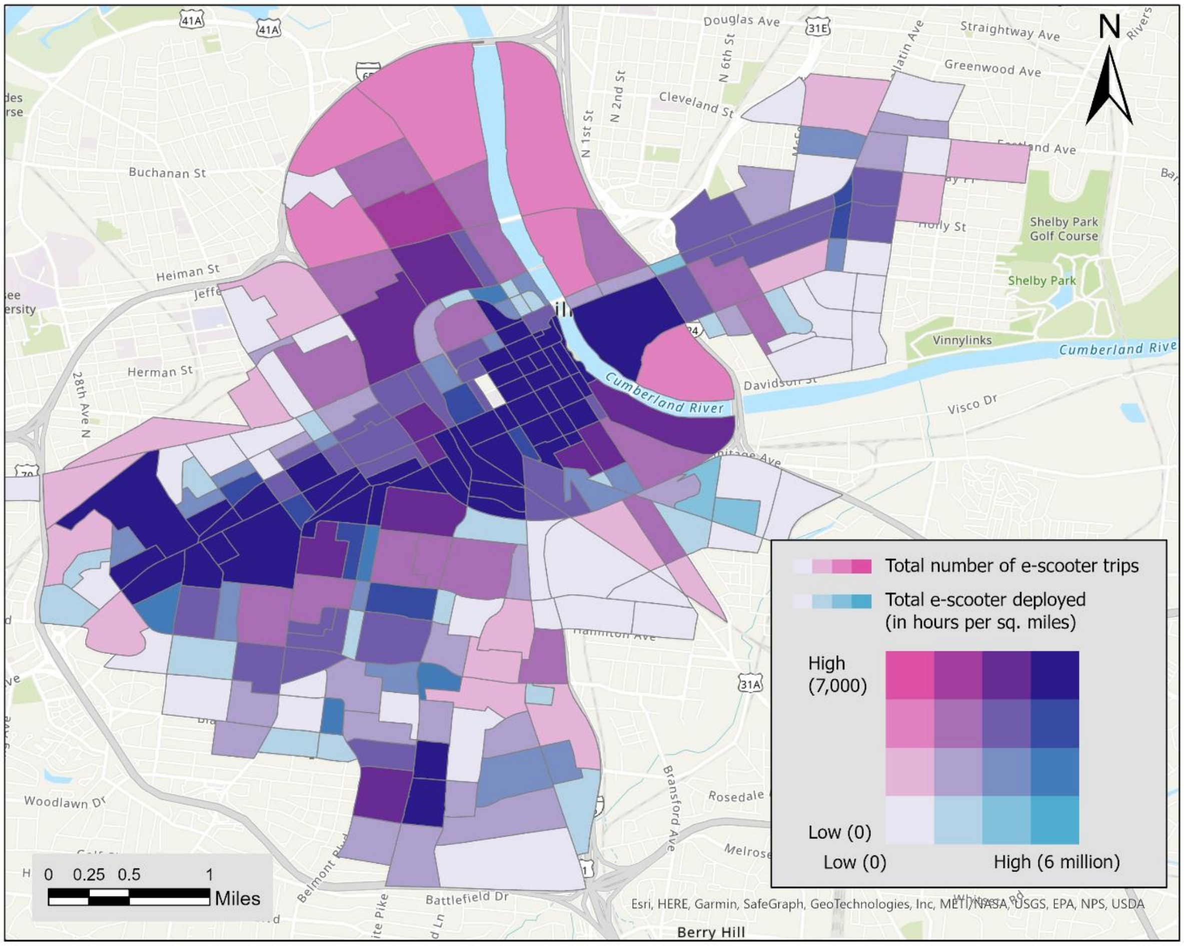


Figure A2.3 Bivariate map of the total e-scooter trips and vehicles deployed at each TAZ throughout the study period for small service providers' group

A3. Micromobility survey

A3.1 Consent

Research Study Title:

Micromobility acceptance in mid-sized cities of developing countries: A case study of Kathmandu, Nepal

Researcher(s):

- Nitesh Shah, University of Tennessee, Knoxville
- Chris Cherry, University of Tennessee, Knoxville

We are asking you to be in this research study because you live in the study area and might be eligible for the study. You must be age 18 or older to participate in the study. The information in this consent form is to help you decide if you want to be in this research study. Please take your time reading this form and contact the researchers to ask questions if there is anything you do not understand.

Why is the research being done?

The purpose of the research study is to understand the choice of shared micromobility vehicles (e.g. bikeshare, shared e-bike, and shared e-scooters) in Kathmandu, Nepal.

The research team is receiving funding from W.K. McClure Scholarship for the Study of World Affairs from the University of Tennessee.

What will I do in this study?

If you agree to be in this study, you will complete an online survey. The survey includes questions about your recent travel in the city, choice of travel mode for given scenarios, and sociodemographic information and should take you about 15 minutes to complete. You can skip questions that you do not want to answer.

There are four parts of the survey questions as follows:

Part 1: Screening questions to verify your eligibility for the survey

Part 2: Travel diary for your recent travel within the city

Part 3: Questions to understand your choice of new micromobility modes

Part 4: Sociodemographic questions to understand your background

Can I say "No"?

Being in this study is up to you. You can stop up until you submit the survey. After you submit the survey, we cannot remove your responses because we will not know which responses came from you.

Are there any risks to me?

We don't know of any risks to you from being in the study that is greater than the risks you encounter in everyday life.

Are there any benefits to me?

We do not expect you to benefit from being in this study. Your participation may help us to learn more about the adoption of shared micromobility in Kathmandu, Nepal. We hope the knowledge gained from this study will benefit others in the future.

What will happen with the information collected for this study?

The survey is anonymous, and no one will be able to link your responses back to you. Your responses to the survey will not be linked to your computer, email address or other electronic identifiers. Please do not include your name or other information that could be used to identify you in your survey responses. Information provided in this survey can only be kept as secure as any other online communication.
Information collected for this study will be published and possibly presented at scientific meetings.

Will I be paid for being in this research study?

You will be paid Rs. 50 for being in this study. If you are eligible for the survey and once you have completed the survey, you will be asked to enter your email address and phone number where we will issue a gift card within 48 hours of submitting the response. Please note that your email address and phone number can not be linked to your response. Each participant will be paid only once through a gift card or balance transfer to the provided phone number or email address.

Who can answer my questions about this research study?

If you have questions or concerns about this study, or have experienced a research-related problem or injury, contact the researchers,

- Nitesh Shah, Email: nshah12@vols.utk.edu, Phone no: +977-9849500135, +1-865-244-8260
- Chris Cherry, Email: cherry@utk.edu, Phone no: +1-865-974-7710

For questions or concerns about your rights or to speak with someone other than the research team about the study, please contact:
Institutional Review Board
The University of Tennessee, Knoxville
1534 White Avenue
Blount Hall, Room 408
Knoxville, TN 37996-1529
Phone: +1-865-974-7697
Email: utkirb@utk.edu

Statement of Consent

I have read this form, been given the chance to ask questions and have my questions answered. If I have more questions, I have been told who to contact. By selecting “I Agree” below, I am providing my signature by electronic means and agree to be in this study. I can print or save a copy of this consent information for future reference. If I do not want to be in this study, I can select “I Do Not Agree” to exit out of the survey.

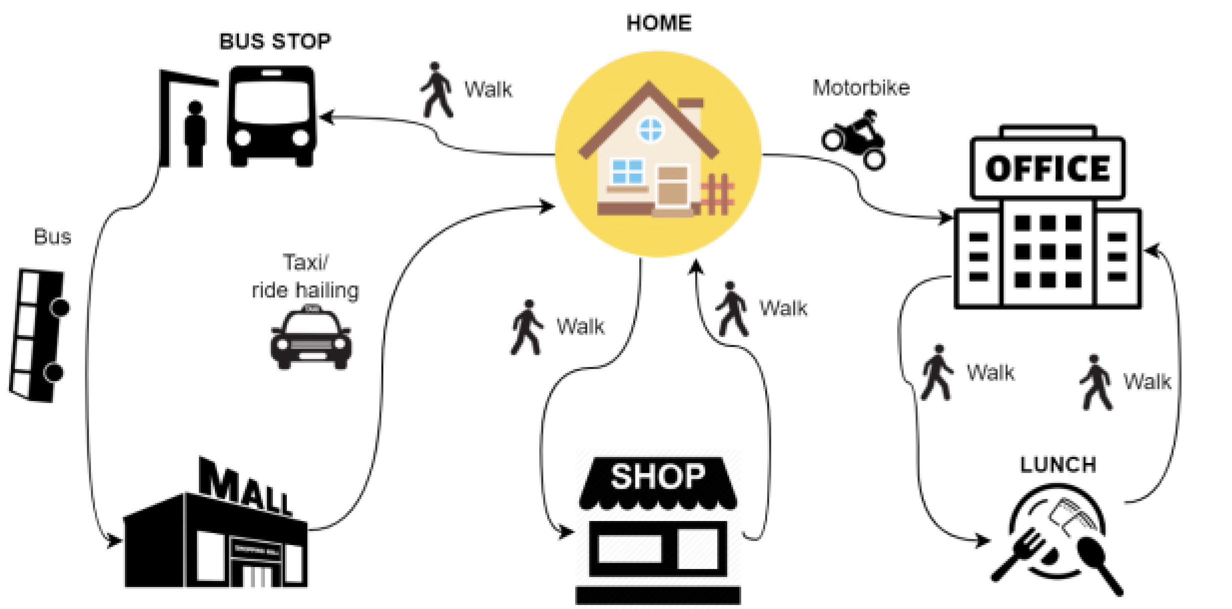
- ○ I agree to participate
- ○ I do not agree to participate

A3.2 Part 1: Screening questions to verify your eligibility for the survey

What is your age group?

- ○ Below 18
- ○ 19-30
- ◉ 31-40
- ○ 41-50
- ○ 51-60
- ○ 61+

Please think about a trip you made within last week that was between 0.5 km (about a 5-minute walk) to 10 km (about a 15-minute drive) in distance. As illustrated by the arrows in the below figure, a trip is traveling between two locations (e.g. home to office or home to bus stop) by any travel mode, such as walking, motorbike, and taxi/Pathao/Tootle.



Did you make a trip within last week that was more than 0.5 km (about a 5-minute walk) and less than 10 km (about a 15-minute drive)?

- Yes
- No

Please estimate the trip distance in km:

A3.3 Part 2: Travel diary for your recent travel within the city

Please answer the following questions about the trip you thought of.

Where did you start the trip?

- Home
- Work
- School/ University

- Bus stop
- Shop
- Restaurant/ Cafe
- Others

Where did you end the trip?

- Home
- Work
- School/ University
- Bus stop
- Shop
- Restaurant/ Cafe
- Others

What was the purpose of the trip?

- Work
- School
- Shopping
- Family (e.g. picking up kids from school)
- Social (e.g. visiting friend)
- Running errand
- Others

What was the mode of the trip?

- Bus/ micro-bus/ tempo

- Drive motor bike/ scooter
- Passenger in motor bike/ scooter
- Drive personal car
- Passenger in car
- Bicycle
- Taxi/ Four-wheeler Pathao/Tootle
- Two-wheeler Pathao/Tootle
- Walking
- Others

A3.4 Part 3: Questions to understand your choice of new micromobility modes

In this section, you will be given six scenarios. In each scenario, you will be given **a situation** for the trip information you provided in the previous section. First, you will have to **choose among the existing travel modes** in Kathmandu and **enter travel time and travel cost**.

A sample question is provided below for a hypothetical person who reported a 2 km trip from home to work:

Suppose it is ***hot,*** **raining lightly,** ***and the route has no bicycle lane*** (illustrated in the picture below). You have to complete the trip you mentioned in the previous section (2 km trip from home to work).

In this scenario, which travel mode would you prefer?

○ Bus/micro/tempo

● Motorbike/scooter

○ Car

○ Two-wheeler Pathao/Tootle

○ Four-wheeler Pathao/Tootle

○ Taxi

○ Walking

○ Bicycling

○ Others

What would the approximate travel time be (in minutes)?

10

What would the approximate trip cost be in Rupees? (including fare, parking, and approximate fuel)

23

The next page will display your travel mode choice, and three shared micromobility modes (bicycle share, shared pedelec e-bicycle, and shared electric scooter). **Similar to Pathao and Tootle, you don't need to own any of these vehicles**. You need to pay for using the service and drive it yourself. A user can rent these new transportation modes by first locating a vehicle either at a docking station or through a smartphone app. A fee is required to unlock the vehicle, which can be paid either by cash/coin or through digital payment methods. At the end of the travel, these vehicles can be returned to the nearby docking station or designated parking area. A brief description of each of these modes is summarized as follows:

Bicycle share: It is a *c*onventional bicycle (as illustrated in the figure on the right), which users can ride following road rules similar to private bicycles. A driving license is not required and riders can use the bicycle lane if available.	
Shared pedelec e-bicycle: It is an electric bicycle (as illustrated in the figure on the right), which has a pedal and electric motor to assist in riding. Similar to bicycle share, a driving license is not required and users can ride in the bicycle lane if available.	

Shared electric scooter: It is an electric scooter (as illustrated in the figure on the right), which is similar to a petrol-powered scooter but instead powered by a battery. Similar to the road rules of riding a petrol-powered scooter, a user needs to have a driving license and cannot use a bicycle lane.	

For the second question in each scenario, you will be asked to **choose a travel mode among four options**, where features of the micromobility vehicles along with travel time and travel cost will be summarized in a table.
For the same hypothetical person above, a sample question is provided below:

Now suppose you had an opportunity to use either the mode previously selected or among shared micromobility modes: bicycle share, shared pedelec e-bicycle, or shared electric scooter (illustrated in the table below with a description of key features and picture). **Similar to Pathao and Tootle, you don't need to own any of these shared micromobility vehicles**. You need to pay for using the service and drive it yourself. Also suppose it is ***hot, raining lightly, and the route has no bicycle lane*** (illustrated in the picture below) throughout the 2 km trip from home to work.

The travel time and cost for the trip above are as follows:

Mode	**Motorbike/scooter**	**Bicycle share**	**Shared pedelec e-bicycle**	**Shared electric scooter**
Picture	-			
Required physical effort	-	Entirely	Some, assisted by motor	None
License required?	-	No	No	Yes
Allowed in bicycle lane?	-	Yes	Yes	No
Travel time (in minutes)	10	20	15	10
Cost (in Rupees)	23	10	25	80

In this scenario, which new travel mode would you choose for the trip?

- Motorbike/scooter
- Bicycle Share
- Shared pedelec e-bicycle
- Shared e-scooter

Phew! That was a lot of information. Please click the next button to continue.

Scenario 1 of 6:

Suppose it is ***hot (>25 °C), raining lightly, and the route has unprotected bicycle lane*** (illustrated in the picture below). You have to complete the trip you mentioned in the previous section (4 km trip from Bus stop to Home).

In this scenario, which travel mode would you prefer?

- Bus/micro/tempo
- Motorbike/scooter
- Car
- Two-wheeler Pathao/Tootle
- Four-wheeler Pathao/Tootle
- Taxi
- Walking
- Bicycling

Others

What would the approximate travel time be (in minutes)?

What would the approximate trip cost be in Rupee? (including fare, parking, and approximate fuel)

Now suppose you had an opportunity to use a bicycle share, shared pedelec e-bicycle, or shared electric scooters (illustrated in the table below with a description of key features and picture). **Similar to Pathao and Tootle, you do not need to own the vehicle**. You would need to pay for using the service and would need to drive it yourself. Also suppose it is ***hot (>25 °C), raining lightly, and the route has unprotected bicycle lane*** (illustrated in the picture below) throughout the 4 km trip from Bus stop to Home.

The travel time and cost for the trip above are as follows:

Mode	**Two-wheeler Pathao/Tootle**	**Bicycle share**	**Shared pedelec e-bicycle**	**Shared electric scooter**
Picture	-			
Required physical effort	-	Entirely	Some, assisted by motor	None
License required?	-	No	No	Yes
Allowed in bicycle lane?	-	Yes	Yes	No
Travel time (in minutes)	10	25▲	20▲	10 =
Cost (in Rupees)	150	10▼	25▼	75▼

In this scenario, which travel mode would you choose for the trip?

- ○ Two-wheeler Pathao/Tootle
- ○ Bicycle share
- ○ Shared pedelec e-bicycle
- ○ Shared electric scooter

Five more sets of scenario questions were included in the survey.

A3.4 Part 4: Sociodemographic questions to understand your background

Below are some attributes that were not included in the choices above. How important are the following vehicle attributes when deciding to use any modes of travel?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Stylish/Fashionable	○	○	○	○	○
Comfortable	○	○	○	○	○
Luggage Compartments	○	○	○	○	○
Road Safety	○	○	○	○	○
COVID-19 Safety	○	○	○	○	○
Reliability	○	○	○	○	○
Fuel efficiency	○	○	○	○	○

Which gender do you identify yourself as?

○ Male

○ Female

○ Non-binary / third gender

○ Prefer not to say

How much schooling have you completed?

○ No education

○ Primary school

- Secondary school
- High school
- Bachelor
- Master
- Doctoral or similar

How many people are there in your household?

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- More than 10

How many of each type of vehicle do you or other members of your household have?

Bicycles 0

Motorbike and scooter 0

Cars 0

Others 0

Total

Do you have a location to park a vehicle at home?

- Yes
- No

How often do you use online payment (e-Sewa, Khalti)?

- Never
- Sometimes
- Always

What is your average monthly household income (combined income for all adults)?

- Less than Rs 5,000
- Rs 5,000 - 20,000
- Rs 20,000 - 35,000
- Rs 35,000 - 50,000
- Rs 50,000 - 65,000
- Rs 65,000 - 70,000
- Rs 70,000 - 85,000
- Rs 85,000 - 100,000
- More than 100,000

Where do you live?

Region

Locality

If you have anything more to say about these new transportation modes (bikeshare, shared e-bike, and shared e-scooters), please drop your comments below.

A4. Trip clustering

The code for the analysis can be found in the following GitHub repository:
https://github.com/niteshshah12/E-scooter-trip-pattern-analysis-of-Nasvhille

This section also includes two supplemental materials: a summary of clustering quality metrics and heat maps of the origin and destination of each K-means cluster of the optimal model.

A4.1 Clustering quality metrics

The graph illustrating the clustering quality metrics are as follows:

A4.2 Heat maps of origin and destination

The heat maps of the origin and destination of each K-means cluster are as follows:

A5. Distribution fitting for micromobility emissions and energy usage

Table A5.1 and Table A5.2 includes the results of model selection criteria for the distribution of usage and operational variables of Service Provider #1 and #2 used in the Chapter 6.

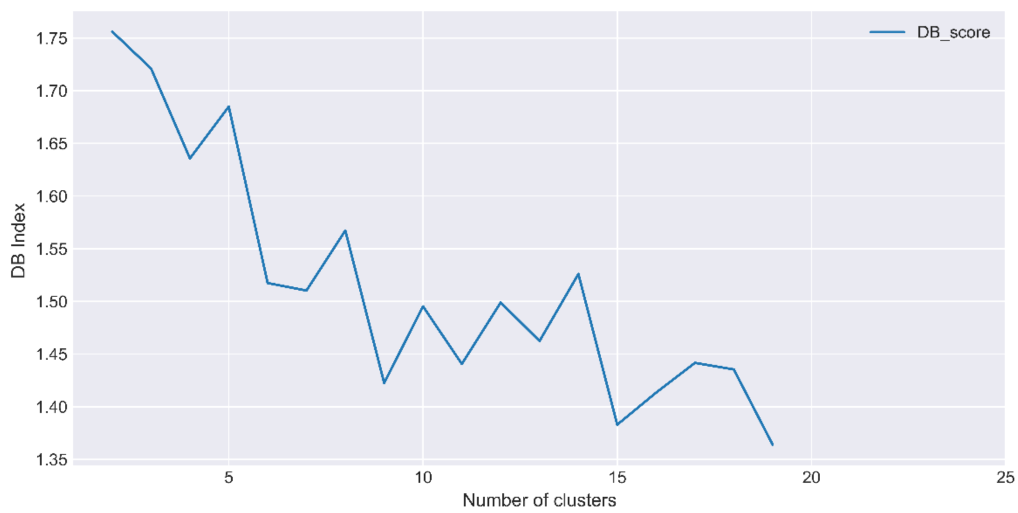


Figure A4.1 DB index of K-mean clusters

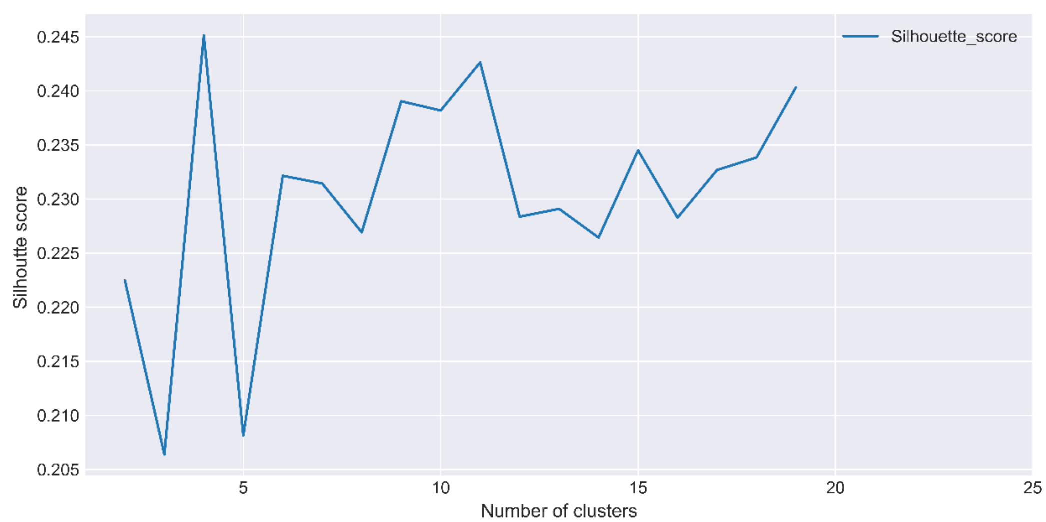
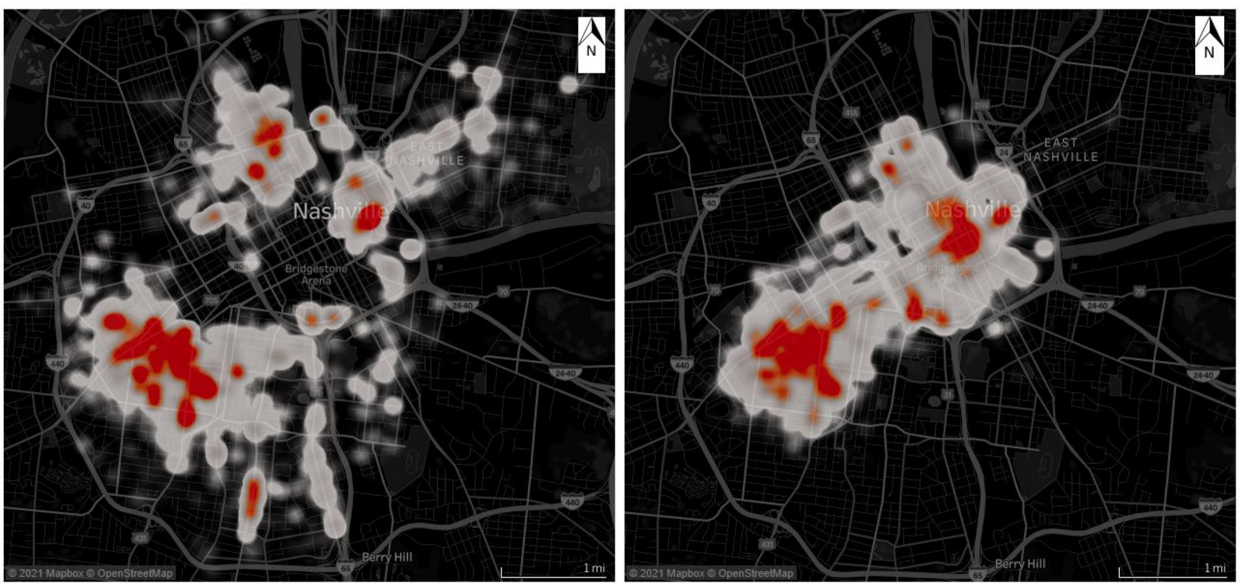


Figure A4.2 Silhouette score of K-mean clusters

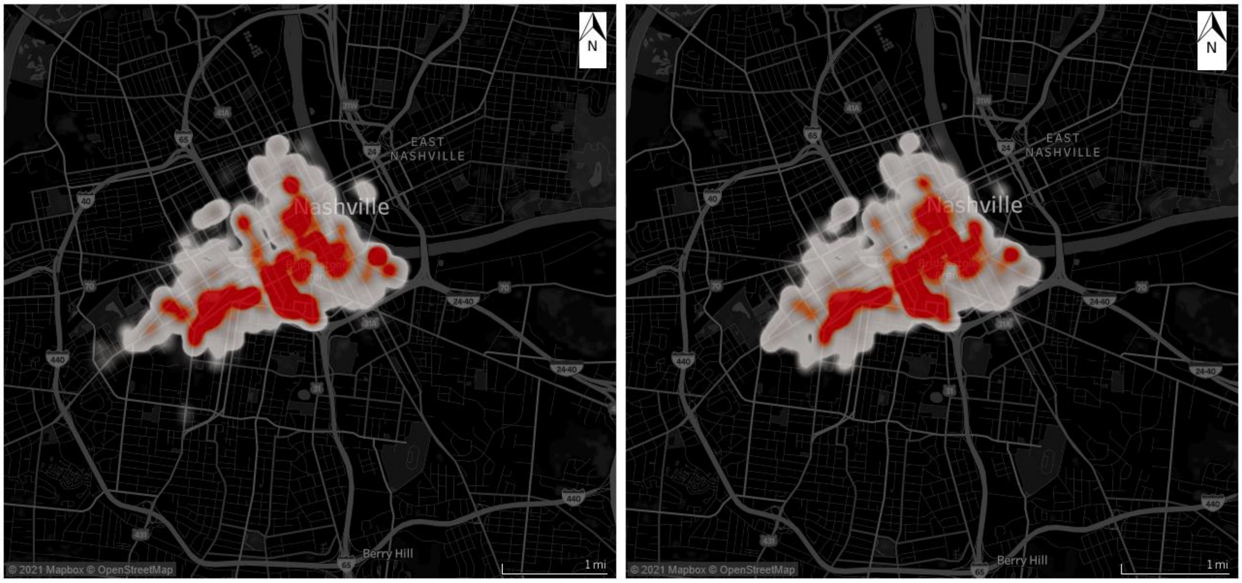
Origin Heatmap **Destination Heatmap**

Figure A4.3: Origin and destination heat map of Cluster C0



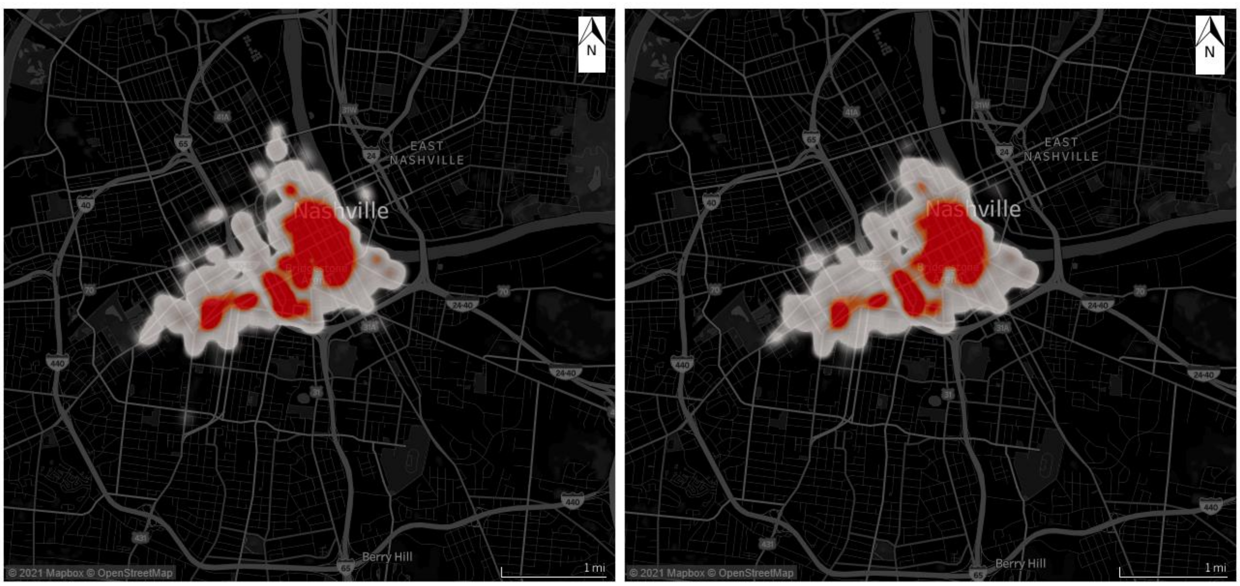
Origin Heatmap **Destination Heatmap**

Figure A4.4: Origin and destination heat map of Cluster C1C1



Origin Heatmap **Destination Heatmap**

Figure A4.4: Origin and destination heat map of Cluster C2



Origin Heatmap **Destination Heatmap**

Figure A4.5: Origin and destination heat map of Cluster C3

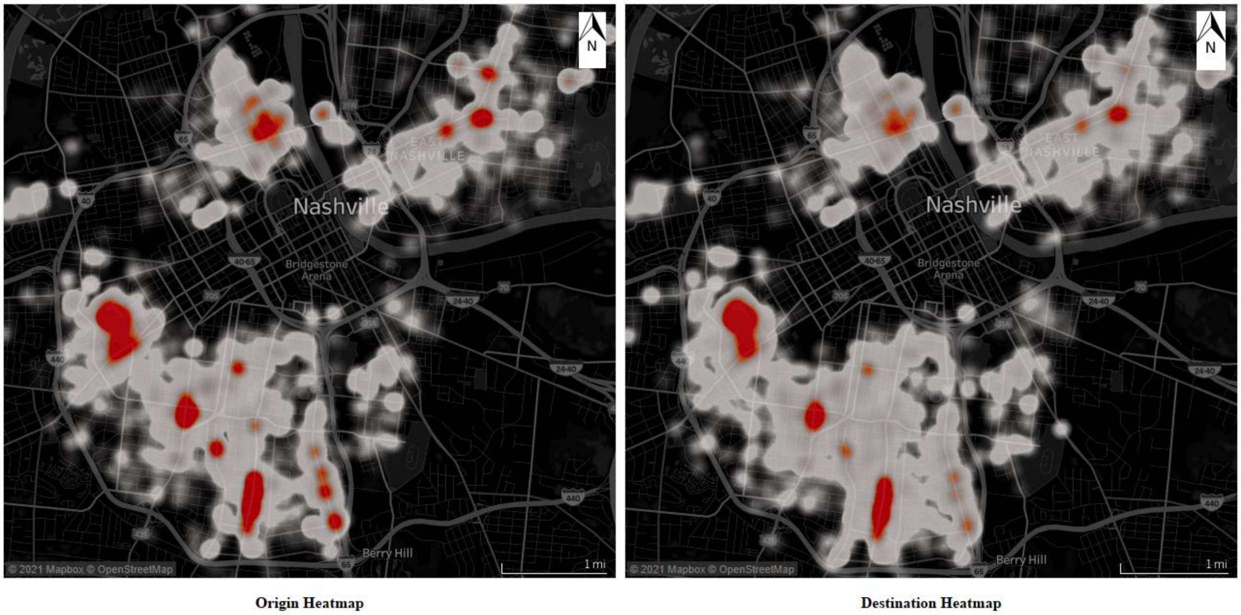
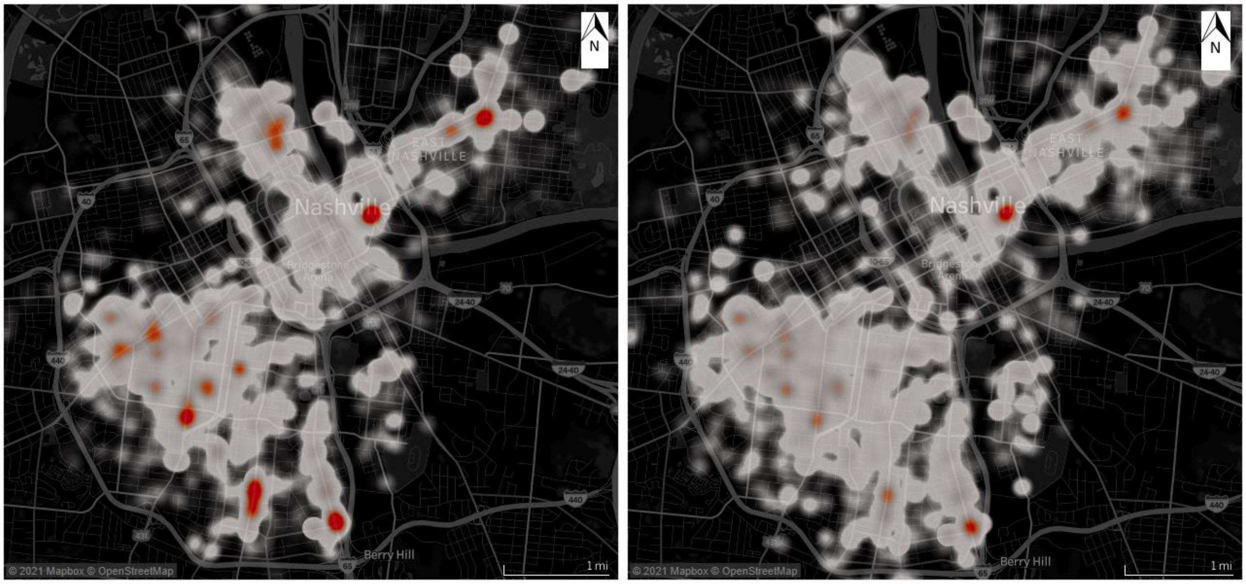


Figure A4.6: Origin and destination heat map of Cluster C4

Figure A4.7: Origin and destination heat map of Cluster C5



Origin Heatmap

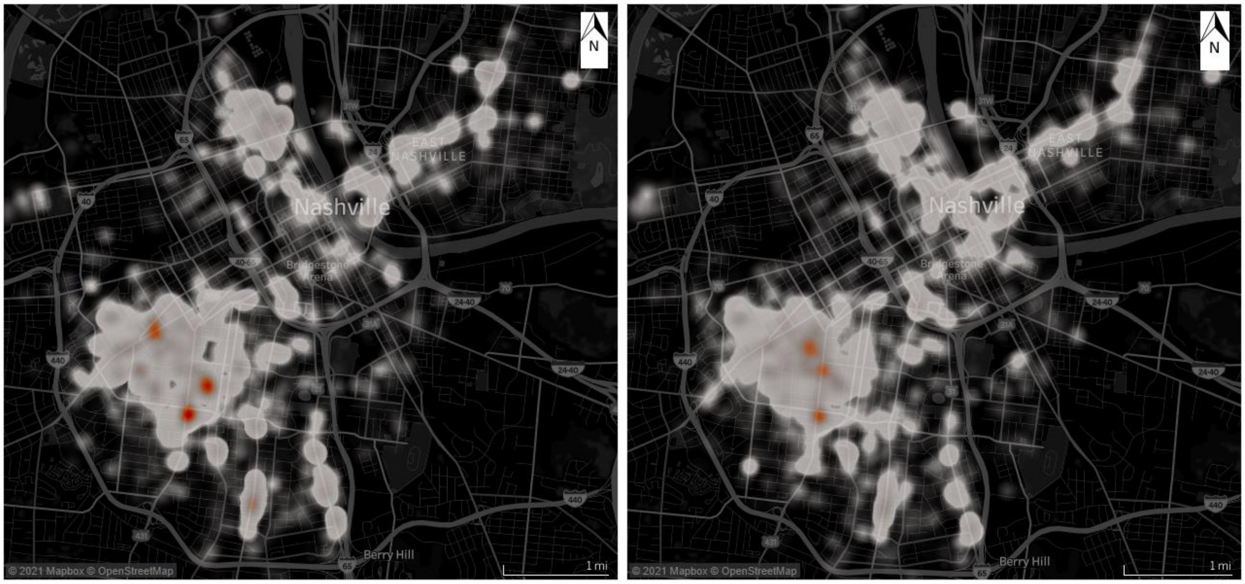
Destination Heatmap

Figure A4.8: Origin and destination heat map of Cluster C6

Origin Heatmap

Destination Heatmap

Figure A4.9: Origin and destination heat map of Cluster C7

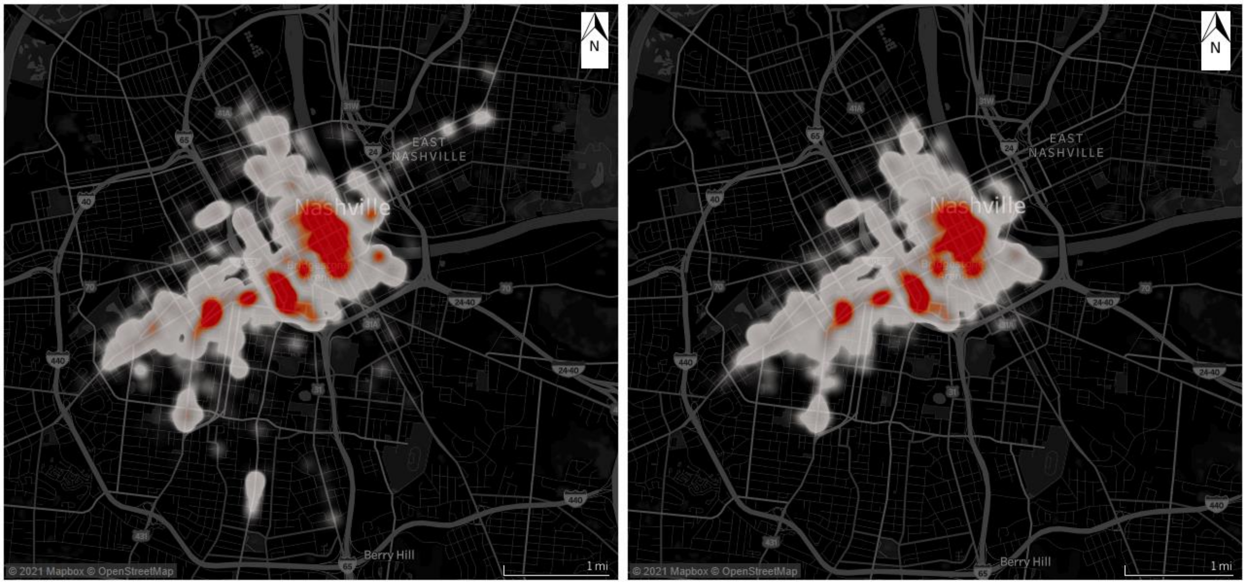


Origin Heatmap **Destination Heatmap**

Figure A4.10: Origin and destination heat map of Cluster C8

Origin Heatmap **Destination Heatmap**

Figure A4.11: Origin and destination heat map of Cluster C9

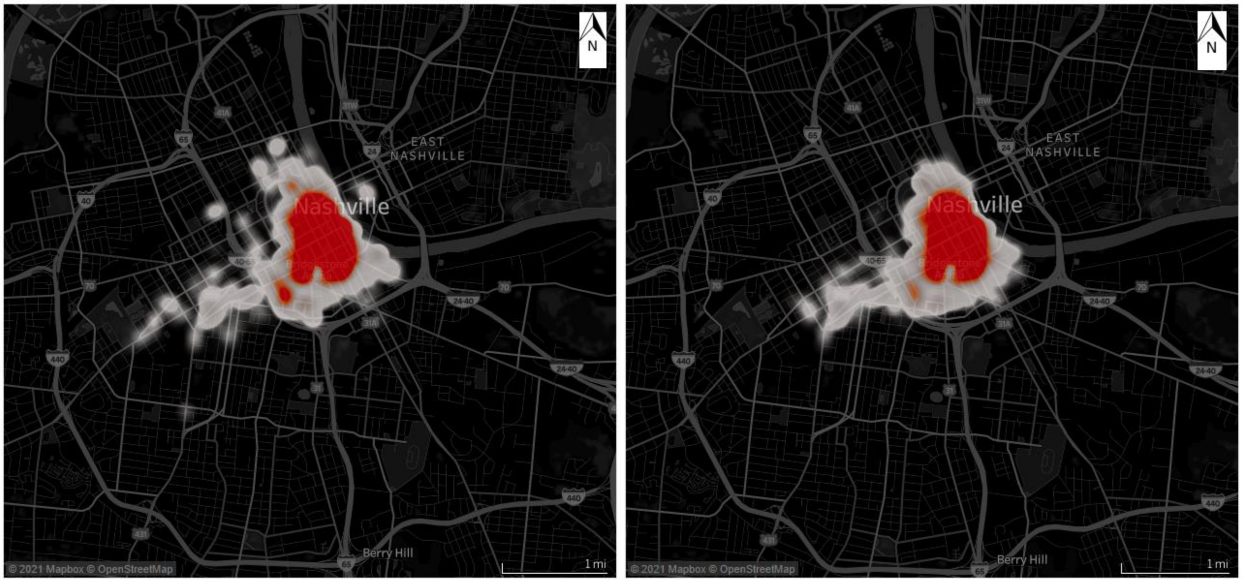


Origin Heatmap **Destination Heatmap**

Figure A4.12: Origin and destination heat map of Cluster C10

Origin Heatmap **Destination Heatmap**

Figure A4.13: Origin and destination heat map of Cluster C11

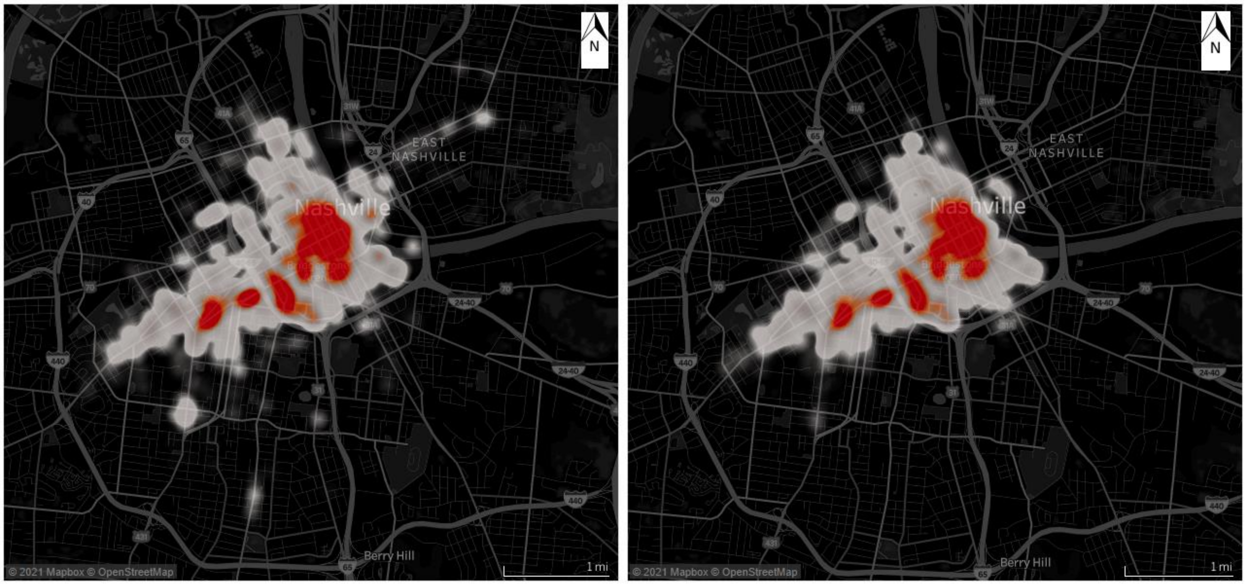


Origin Heatmap **Destination Heatmap**

Figure A4.14: Origin and destination heat map of Cluster C12

Origin Heatmap **Destination Heatmap**

Figure A4.15: Origin and destination heat map of Cluster C13



Origin Heatmap **Destination Heatmap**

Figure A4.16: Origin and destination heat map of Cluster C14

Table A5.1 Model selection criteria of usage and operational variables of Service Provider #1

Variable	**Distribution**	**AIC**	**CAIC**	**BIC**	**ICOMP**
Usage phase					
Lifespan (months)	Lognormal	1,923	1,933	1,931	1,921
	Exponential	1,940	1,945	1,944	1,941
	Gamma	1,671	1,681	1,679	1,669
	Weibull	*1,313*	*1,323*	*1,321*	*1,310*
	Inverse Gamma	1,989	1,999	1,997	1,987
Daily mileage (km)	Lognormal	-1,180	-1,170	-1,172	-1,183
	Exponential	-996	-991	-992	-997
	Gamma	-1,027	-1,017	-1,019	-1,031
	Weibull	*-905*	*-895*	*-897*	*-909*
	Inverse Gamma	-1,037	-1,027	-1,029	-1,040
Operational phase					
Frequency of pick-up for charging (days)	Lognormal	171,433	171,453	171,451	171,434
	Exponential	*81,178*	*81,189*	*81,188*	*81,179*
	Gamma	124,939	124,959	124,957	124,936
	Weibull	136,413	136,434	136,432	136,410
	Inverse Gamma	120,848	120,869	120,867	120,849
Average daily redistribution distance per e-scooter vehicle (km)	Lognormal	252,276	252,297	252,295	252,276
	Exponential	39,078	39,089	39,088	39,078
	Gamma	11,359	11,380	11,378	11,357
	Weibull	*-11,411*	*-11,390*	*-11,392*	*-11,413*
	Inverse Gamma	202,108	202,130	202,128	202,107

Table A5.2 Model selection criteria of usage and operational variables of Service Provider #2

Variable	**Distribution**	**AIC**	**CAIC**	**BIC**	**ICOMP**
Usage phase					
Lifespan (months)	Lognormal	1,165	1,176	1,174	1,162
	Exponential	1,753	1,759	1,758	1,754
	Gamma	1,105	1,116	1,114	1,102
	Weibull	1,269	1,280	1,278	1,265
	Inverse Gamma	1,153	1,164	1,162	1,150
Daily mileage (km)	Lognormal	18	28	26	14
	Exponential	-506	-500	-501	-507
	Gamma	-1,029	-1,018	-1,020	-1,032
	Weibull	*-1,769*	*-1,758*	*-1,760*	*-1,771*
	Inverse Gamma	70	81	79	67
Operational phase					
Frequency of pick-up for charging (days)	Lognormal	154,132	154,152	154,150	154,132
	Exponential	150,490	150,500	150,499	150,489
	Gamma	196,091	196,112	196,110	196,088
	Weibull	194,030	194,051	194,049	194,027
	Inverse Gamma	*128,203*	*128,223*	*128,221*	*128,201*
Average daily redistribution distance per e-scooter vehicle (km)	Lognormal	238,001	238,022	238,020	238,000
	Exponential	56,968	56,979	56,978	56,968
	Gamma	15,161	15,182	15,180	15,158
	Weibull	*-22,270*	*-22,248*	*-22,250*	*-22,272*
	Inverse Gamma	196,279	196,300	196,298	196,277

Vita

Born and raised in Kathmandu, Nepal, Nitesh Shah received his undergraduate degree in Civil Engineering from Pulchowk Campus, Nepal and worked as a Civil Engineer for three years on high-speed railway design projects in Nepal. He joined the University of Tennessee in 2018 and received an MS degree in Transportation Engineering in 2020. As a Graduate Research Assistant, he worked on an innovative statewide bicycle and pedestrian count program for the Tennessee Department of Transportation (TDOT) during his MS program. He also completed a three-month summer internship in 2019 at New Urban Mobility Alliance (NUMO), hosted by the World Resources Institute (WRI) in Washington, DC. He continued his graduate program at the University of Tennessee to receive a Ph.D. in Civil Engineering with a minor in Statistics in 2022. His Ph.D. was funded by Graduate Advancement Training and Education (GATE) fellowship from Oak Ridge National Laboratory (ORNL).