



Understanding Micromobility Safety Behavior and Standardizing Safety Metrics for Transportation System Integration

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16. Abstract This project focused on exploring micromobility safety data and methods to improve injury surveillance. The project was broken into four core tasks that included exploration of new big data sources, injury surveillance methods, survey research assessment, and safety data. This report is brief, providing an introduction of the work conducted in each task. The core deliverables are included as appendices. They include journal articles, infographics, websites, and electronic media. The reader of this report is encouraged to access the deliverables offered in the appendices.			
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Project Summary

The purpose of this study is to accelerate shared learning around micromobility safety impacts and to fast-track improvements to injury surveillance of emerging modes such as e-scooters and related micromobility vehicles (e-bikes, electric skateboards, hoverboards, etc.) used on and around city streets. The primary aim was vehicles in shared mobility systems, but findings could be transferable to owned micromobility vehicles. The research focused on four specific tasks as follows:

1. Establish available data sources to support safety evaluations across multiple geographies
2. Engage stakeholders, examine current practices, and identify approaches to enhance injury surveillance systems
3. Development of a behavior-oriented survey instrument to understand micromobility users and riding behaviors for consistent application by municipalities and researchers
4. Formulate data structure for continuous tracking and analysis of micromobility sharing safety

This final report covers four disparate areas and includes deliverables that are best presented in different formats. For this report, we present a summary of the deliverables from the four tasks, then present the deliverable as an appendix. For Task 1 and 4, the deliverables are journal articles. For Task 2, the deliverables are a set of materials related to injury surveillance. For Task 3, the deliverable is a website.

Task 1: Data Sources to Support Safety Evaluations

In the micromobility domain, the introduction of high-resolution big data can be highly valuable. This is a particular advantage of e-scooters and other newer generation micromobility modes. For any shared e-scooter trip, the state-of-art database includes vehicle availability, trip origin coordinates, trip destination coordinates, trip start time, trip end time, trip duration, and sometimes the GPS trajectory of a trip, which earlier modes, such as bikesharing, fail to provide. The Mobility Data Specification (MDS), which evolved from the General Bikeshare Feed Specification (GBFS), is one example of high-resolution micromobility big data. The Mobility Data Specification (MDS) evolved from the General Bikeshare Feed Specification (GBFS). Both MDS and GBFS have been used for bikeshare and e-scooter sharing programs. The MDS is meant to be more generalizable across modes and data scientists and policy makers are supporting that specification for micromobility systems.

As a rapidly growing form of micromobility, shared e-scooters have been popular since their launch despite recent decline due to COVID-19. The USDOT Bureau of Transportation Statistics estimated that there were 82 U.S. cities served by shared e-scooter systems in 2018, the first year of e-scooter launch. This number soon reached a peak of 115 cities in 2019 and then dropped to 85 in 2020 due to the pandemic. In 2021, the number is rising back to 92 as cities and their transportation networks are gradually returning to normal. There are some reports that ridership has returned to pre-pandemic levels. In 2018, shared e-scooters registered 38.5 million trips in the U.S. A year later, the number more than doubled to 86 million. In 2020, National Association of City Transportation Officials (NACTO) reports that ridership on most transportation modes, including shared e-scooters, dropped about 70%.

The safety of e-scooter use has become a major concern given its increasing popularity. In August 2020, the U.S. Consumer Product Safety Commission (CPSC) issued a report on micromobility product safety and estimated that there were 50,000 Emergency Department (ED) visits related to e-scooters from 2017 to 2019. They also noted that e-scooter related ED visits grew yearly during this period. In 2017, the number of estimated ED visits was 7,700. A year later, this number was more than doubled to 14,500. In 2019, the number almost doubled again, with an estimate of 27,700. During this period, fatalities associated with e-scooters were also increasing. A total of 27 fatalities were reported, among which 9 were related to shared e-scooters. The reported numbers of fatalities related to e-scooters from 2017 to 2019 were 1, 5, and 21, respectively. Among them, there were 2 and 7 shared e-scooter fatalities in 2018 and 2019. Our work presented here documents shared e-scooter fatalities.

E-scooter rides alone contributed more than 80 million trips a year in the United States, many of them able to capture and report MDS data. These high-resolution trip data are promising in providing rich information that can enlighten policymaking in transportation. In Nashville, Tennessee, our research team has obtained access to data from more than one million high-resolution shared e-scooter trips in the city over the span of September 1, 2018, to August 31, 2019. This dataset followed Nashville's unique Shared Use Mobility Device (SUMD) data specification that parallels MDS. Importantly, this dataset includes probe vehicle data, the data that is generated over the time and space of an individual vehicle trip to allow tracking of routes and road segments used by riders. The importance of probe data is that it allows the researcher to assess location- and route-specific safety and exposure data. We cleaned the data and performed geospatial analyses to understand the use and impacts of these shared e-scooters in the city.

One main effort is to classify the trip types based on the trip characteristics such as time of day, trip distance, route, and trip duration. The classification of e-scooter trips can help identify trip purposes and understand their impacts. For example, to understand if the use of shared e-scooters is utilitarian (e.g., work-related) or recreational. Through machine learning algorithms such as Principal Component Analysis and K-means clustering, we identified five main types of e-scooter trips in Nashville: 1) daytime short errand trips, 2) utilitarian trips, 3) evening social trips, 4) night-time entertainment district trips, and 5) recreational (or joyride) trips. While we did not find any patterns that suggest shared e-scooters are used for commuting (following the traditional peak patterns) we did find that more than half of trips are for errands, utilitarian trips, and social trips. About 45% of trips are at night in the entertainment district or are recreational. Findings such as

these can inform better e-scooter policies. For example, safety surveillance can be enhanced at night-time in the downtown area for e-scooter users. In addition, cities and shared e-scooter operators can design incentives for commuter use of e-scooters. Some of these applications have included integration with transit systems and potentially linking payment or information methods through app-based integration. Scooter operators can offer dynamic pricing or other schemes to encourage different types of use.

The major findings and policy suggestions of this effort have been summarized and submitted to the Transportation Research Part A: Policy and Practice and is under review. In this study, we can assess, based solely on SUMD data patterns, what types of trips are taken, when they are taken, and how they could correlate with safety outcomes. In the near future, our research team intends to conduct a user survey in the Nashville area to further collect data and validate our research findings. However, it should be noted that these findings are based on the trip data in Nashville and may not be applicable to other cities.

Appendix A Transportation Research Part A Working Paper

Task 2: Injury Surveillance Systems

The improvements of e-scooter and transportation safety start with timely and correctly detecting and classifying the injuries and fatalities associated with e-scooters and other novel micromobility modes. This requires regular and necessary updates in the injury surveillance systems to reflect changes in the transportation domain. To date, there have been thousands of e-scooter related injuries and dozens of fatalities in the United States but not every city where e-scooters are currently operating is equipped with a system to report crashes that involve an e-scooter or a shared e-scooter. Because of this missing gap, many e-scooter crashes are not reported in the system, resulting in a limited resource pool to study these crashes and to propose safety counter measurements for e-scooter and micromobility safety. For example, one heated debate for shared e-scooters is if the use of helmets should be mandated. With a micromobility surveillance system, injuries related to shared e-scooters can be captured from which stakeholders can rely on to identify the need to mandate helmet use. Better injury surveillance can help researchers understand the effectiveness of helmets for different types of crashes and injuries. Similarly, there is ambiguity on the definitions of scooters and safety analysis is confounded by that ambiguity resulting in imprecise policy outcomes (e.g., nighttime bans, prohibited infrastructure). Improving injury surveillance systems can provide better tools for policy development.

The International Classification of Diseases, Tenth Revision, Clinical Modification (ICD-10-CM) is the global medical standard when it comes to classification and monitoring of causes of injury and death, including those that occur in transportation. In the United States, the ICD-10-CM is the official standard that is adopted by the hospitals for healthcare and other purposes. As far as transportation is concerned, the establishment of ICD-10-CM can help transportation practitioners identify injuries experienced by victims of crashes and improve injury reduction strategies. However, the current standard requires an update given that new modes of transportation such as e-scooters are emerging at an unprecedented rate. For example, it did not include the necessary codes that distinctly categorize micromobility-related injuries. This is of concern, because the increase in the use of e-scooters and other micromobility devices is anticipated to result in increasing numbers of injuries and fatalities related to the operation of these devices.

To address this, our research team formed a collaboration with stakeholders across the nation, called the “E-scooter Injury Surveillance Workgroup.” This Workgroup contained more than 50 members from academia, city hospitals, city and state public health departments, state trauma registries, the American College of Surgeons, the National Highway Traffic Safety Administration, Federal Highway Administration, and the Centers for Disease Control and Prevention. The primary objective of this collaboration was to help researchers, clinicians, and public health practitioners identify injuries associated with the use of micromobility devices, such as an injury due to a crash between an e-scooter rider and a car or pedestrian.

To achieve this objective, the E-scooter Injury Surveillance Workgroup shared best practices and developed preliminary guidance for identifying and classifying injuries related to e-scooters and other micromobility devices using the current version of *ICD-10-CM* (FY 2020). Many of these recommendations were informed by work initiated by [Vision Zero San Francisco Injury Prevention Research Collaborative](#). Our research team developed a poster titled, “New Modes, New Codes” to assist clinicians and medical coders in categorizing and assigning existing *ICD-10-CM* codes for the purposes of injury surveillance activities. The second objective of the E-scooter Injury Surveillance Workgroup was to develop and implement new micromobility injury-specific codes into *ICD-10-CM*. We directly contributed to the submission of a proposal for incorporating new e-scooter and micromobility codes into the FY2021 version of *ICD-10-CM*. The [proposal](#) was presented to the ICD-10 Coordination and Maintenance Committee Meeting on September 10, 2019. The proposal was accepted.

Our work contributed to the addition of the following codes in the FY 2021 version of *ICD-10-CM*. V00.03 (.031, .038) describes incidents in which pedestrians are injured after being struck by a micromobility device, V00.84 (.841, .842, .848) describes incidents in which a rider on a micromobility device is injured after falling on or striking a stationary object or the ground, V01 and V06 (.03, .13, .93) describe incidents in which a rider on a micromobility device is injured after being struck by a non-motorized vehicle, V02, V03, V04 (.03, .13, .93) describe incidents in which a rider on a micromobility device is injured after being struck by a motorized vehicle, and V05 (.03, .13, 93) describes incidents in which a rider on a micromobility device is injured after being struck by a railway train. The new codes were adopted in October 2020. Our research team developed a second poster titled, “Micromobility Modes, New Codes” to introduce these new codes.

The designs of both posters integrated feedback from governmental organizations across North Carolina, including the Injury and Violence Prevention Branch at the North Carolina Division of Public Health and the North Carolina Trauma Registry. One future step for this effort is to include e-bikes explicitly into the ICD-10-CM codes in future revisions. The ICD-10-CM codes for micromobility vehicles are included in this link: <https://www.icd10data.com/ICD10CM/Codes/V00-Y99/V00-V09/V00->. To date, the posters have been distributed to >1,500 clinicians and medical coders in North Carolina. The posters have also been distributed to the University of Maryland School of Medicine, the Agència de Salut Pública de Barcelona, the California Department of Public Health, DC Health, the Governors Highway Safety Association, Carilion Roanoke Memorial Hospital, and the Detroit Greenways Coalition. The posters are also available on the CSCRS website: https://www.roadsafety.unc.edu/wp-content/uploads/2020/09/MicromobilityCoding_Poster_v2_FINAL.pdf.

In Fall 2021, our team underwent a similar effort to explicitly identify electric bikes in the injury surveillance codes. Until now, e-bikes were ambiguously included as either bicycles or motorcycles. As a powered two-wheeler, they are technically coded as motorcycles and members of the same team proposed to explicitly include e-bikes in the ICD-10-CM codes for FY2022. That proposal is still under review.

E-scooter mortality surveillance is also challenging. The system for classifying fatalities on death certificates and autopsy reports, the *International Statistical Classification of Diseases and Related Health Problems, Tenth Revision (ICD-10)*, does not include specific codes for deaths related to the operation of e-scooters. Unfortunately, *ICD-10* is managed by the World Health Organization and the process for updating *ICD-10* is laborious and unlikely to be successful. Therefore, rather than working towards updating *ICD-10*, our research team took a different approach by creating a database containing data on all e-scooter fatalities reported in the media. The database contains information regarding victim demographics, location of fatal event, motor vehicle involvement, suspected alcohol- and drug-involvement, and links to media reports. This database is updated quarterly and is available on the CSCRS website: https://www.roadsafety.unc.edu/wp-content/uploads/2021/03/escooter_fatalities_Mar_2021.pdf.

Appendix B1 “New Modes, New Codes” poster developed to identify and classify injuries related to micromobility devices **prior** to the implementation of the new ICD-10-CM codes.

Appendix B2 “Micromobility Modes, New Codes” poster developed identify and classify injuries related to micromobility devices **after** the implementation of the new ICD-10-CM codes.

Task 3. Behavior-oriented Survey Instrument

Surveys are one of the most important tools to understand the impacts of a new transportation mode. Transportation agencies across the nation have relied on perception, behavior, and preference surveys to understand the impacts of micromobility such as bikesharing and e-scooter sharing on the transportation system. Compared to data analytics that is often technical and require specialized skillsets, surveys have low barriers to design and to implement. In practice, these surveys are typically designed by transportation staff and are distributed either on the street as an intercept survey or online through various platforms and smartphone applications. These surveys are typically shorter in length and target the impacts of a micromobility option or a program, unlike the National Household Travel Survey (NHTS) that is more broad-based. In addition, the questions on a micromobility survey can vary significantly given that agencies share different interests and motivations. Some common themes in these surveys include personal and household demographic information, use patterns and preferences, and attitude and evaluation of the program. Despite the richness in trip-level data in micromobility, important information can only be drawn out by surveys. However, errors or inexperience in survey design can result in outcomes that are not transferable or that result in findings that are difficult to interpret. This has been the case for micromobility when shared e-scooters deploy of major metropolitan areas following by cities developing their own independent surveys to assess the impacts of these new mobility options. However, the inconsistencies in the survey design have created problems both for researchers and policymakers.

Comparability is important to benchmark behavioral outcomes of a pilot and transfer those finding to other cities. For example, not every survey covers the key questions to assess the impacts of micromobility. In addition, the ways the questions are posed and answer options of similar questions can vary across surveys, diminishing the ability to compare across surveys. As a result, it has become difficult to evaluate the impacts of shared e-scooters comprehensively. More importantly, this can lead to misinformed and biased policymaking. To address this, the goal of this task is to create a survey library for e-scooters and related micromobility devices. This survey review's primary goal is to develop a comprehensive question library that covers all questions that are typically asked in surveys and formulating those questions in a consistent way that can be transferred to other surveys. This will substantially simplify survey generation for practitioners and allow the surveys to be consistently worded that will result in comparable outcomes.

To date, there has been several shared deliberate e-scooter surveys conducted across the nation. Among them, ten representative surveys were selected, including model-surveys such as the Portland survey. The first step of this work is to classify these survey questions into distinct categories. In total, seven main categories have been created, including 1) user demographics, 2) motivation and attitude, 3) travel behaviour and mode choice, 4) safety, 5) accessibility, 6) program evaluation, and 7) user experience questions. These categories cover 115 different questions on various aspects on micromobility. For each question, a recommended best practice question is highlighted. Future survey designers can select from these best practice questions so that surveys can be consistently developed. The question library is comprehensive and addresses most significant questions on micromobility.

In addition, knowing that each survey has its own emphasis, we have included several context-specific questions that allow more flexible customization of any future survey. For example, the survey in San Francisco includes the greatest number of demographics questions and these questions are available in our library. This work is now presented and hosted at the New Urban Mobility Alliance (NUMO) website: <https://www.numo.global/resources/electric-scooter-survey-question-library>. Along with the survey library, supplementary materials such as a blog and instructional videos will be made available on the website in the coming months. The website is expected to update regularly to include latest surveys and findings in micromobility.

Appendix C Survey library webpage

Appendix D Full survey question library

Appendix E Spreadsheet of survey question variations

Task 4: Safety Data Structure Formulation

Safety data is a key to safety improvement of micromobility. To date, there have been several e-scooter injuries and fatalities across the nation as reported above under Task 2. Yet, most of these incidents are reported in the media, where information is often limited and not appropriate for research needs. Other studies have analyzed hospital data, which provide detailed information about the outcomes of the incident, but little regarding the circumstances that precipitated the incident. Last, perception-based studies on safety aspects of micromobility rely on survey data, which is subject to the limitations and biases of stated-preference survey. In addition, in the event that a micromobility-related incident is captured by the local police report, the format of the crash report varies across jurisdictions, which can lead to the absence of some key information. For example, a shared e-scooter, may be described differently on different police reports, such as by the company name, or incorrectly (“moped”, “e-bike”, or other misleading term). Therefore, the lack of a uniform reporting system can potentially hinder the investigation of causes of micromobility crashes, which can be improved by the introduction of a sound management system. Understanding the value of consistent crash coding is important and that importance can be illustrated by detailed crash analysis.

We adopted the latest crash typology, The Pedestrian and Bicycle Crash Analysis Tool (PBCAT) developed by the UNC Highway Safety Research Center, to assess how crashes with cars occur between scooter riders and drivers. We also compared those crash types with geographically similar bicycle crashes. This is an important type of analysis because it does not focus as much on the injury epidemiology (i.e., who was injured), but on crash factors (i.e., how did the crash occur). Understanding crash factors is an important step in developing tools to reduce crashes overall, particularly crashes with cars that tend to be the most serious.

Briefly, this crash typology classifies a crash based on the location of the crash (such as at an intersection) and the type of maneuver by the road users (such as making a left turn). We then applied this tool to examine a comprehensive set of police crash reports concerning micromobility modes including e-scooters and bicycles over the past two years in Nashville, Tennessee. In total, 52 unique e-scooter and 79 bicycle crashes from April 2018 to 2020 were identified and analyzed from the Tennessee’s Integrated Traffic Analysis Network (TITAN). We further compared the e-scooter crashes with the bicycle crashes and noted many similarities, but also statistically significant differences in spatial and temporal distribution, demographics of the people involved, the lighting conditions, and distance to home from crash site between the two modes. Our findings are valuable as they can inform design improvements for the riding conditions for both e-scooters and bicycles, both of which are considered vulnerable in a crash scenario. The paper summarizing the findings of this work has been submitted and accepted by the Journal of Safety Research.

Appendix F Pre-print of the Journal of Safety Research article.

Conclusion

Micromobility options such as e-scooters are emerging rapidly and need immediate research attention. Safety is among the many aspects of micromobility that need to be addressed. Over the study period, our research team has dedicated time and resources to understand the safety behaviors and develop safety metrics for micromobility. First, with the richness in micromobility data, we analyzed a full year of shared e-scooter data in Nashville to understand the spatial and temporal patterns of e-scooter trips, but more importantly, to gain insights on the safety implications of e-scooter operation. With machine learning algorithms, we classified these trips based on their characteristics and found that scooter trips are distributed across a variety of trip patterns (including utility, recreation, and entertainment purposes) and that each of these patterns suggests different policy responses from a safety perspective.

Injury surveillance is incredibly important when developing safety policy. Our team worked to modify the existing surveillance system to capture the injury and fatality data for micromobility. A portion of the injuries and deaths associated with micromobility use is captured by hospital data in the United States. However, the existing data coding method (ICD-10-CM) that is used by American hospitals is not updated to identify micromobility injuries and deaths since some micromobility options such as e-scooters are still relatively new to hospital data though having an unprecedented ridership growth. Therefore, our second effort is to enhance micromobility safety surveillance by modifying the existing injury codes. With a collaboration with various stakeholders nationwide, our team has achieved to contribute to the addition of a set of new codes to the next update of ICD-10-CM for both most main micromobility modes, including scooters and e-bikes. In a parallel effort our team tracked of all the micromobility fatalities that were reported by the media in an online database as an interim database.

Surveys can be an important and necessary means to understand safety experiences and perceptions of micromobility users. There are many other aspects such as user demographic and alternative transportation mode that can be a part of the safety story that is drawn from surveys. This information is often captured and revealed by surveys that are conducted by the city transportation agencies. However, since these surveys are typically designed independently by the cities, the questions that are included and the way they are asked can vary significantly or may contain errors, resulting in non-comparable data and findings for research. To address this, our team conducted a review of these surveys across the nation. A total of ten surveys were summarized into a survey library as the first phase product of this work. This survey library presents all the survey questions that are asked and categorize them into seven groups (including one for the safety aspects). This survey library is currently hosted at World Resources Institute New Urban Mobility Alliance (NUMO) website, and it is intended as a tool kit for future transportation practitioners and researchers as a starting point for a standardized or customized survey.

Finally, conducted a case study to compare the crashes between bicycles and e-scooters in the Nashville area to demonstrate the use of safety data and crash typology. In addition to the hospital data, police reports can serve as another informative source of micromobility safety data. However, similar to hospital data, police report data also suffer potential underreporting of micromobility safety data due to differences in definitions and terminology. For example, some reports may refer to an e-scooter as an e-bike or a moped. We then applied the Pedestrian and Bicycle Crash Analysis Tool (PBCAT) as a crash typology method to classify the crashes of scooter riders and bicyclists based on crash location and rider maneuver. The advantage of this method is that it focuses on the contributing factors of a crash, which is helpful to formulate safety measures to prevent future crashes. Investigating crash factors is an important complement to injury surveillance methods addressed above. For example, we found that intersections and driveways are hotspots for crashes and the area between sidewalk and roadway is prone to e-scooter crashes. To address this, cities may consider increase signage and paint use in the short run and invest in multimodal streets with better separation between vehicles and micromobility riders such as a protected bike lanes, particularly on high-crash corridors.

Appendix A

Working Paper: Submitted to Transportation Research Part C

Why do people take e-scooter trips? Big Data and Unsupervised Machine Learning insights on temporal and spatial usage patterns.

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Highlights

- High-resolution micromobility data can evaluate spatiotemporal usage pattern
- Unsupervised machine learning identified five distinct e-scooter usage patterns
- Most popular use of e-scooter was travel within entertainment district at night
- E-scooter ridership increases during weekends and summer months in general
- Usage pattern can be helpful to make data driven decisions regarding micromobility

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, we scrutinized more than one million 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 daytime short errand, utilitarian, evening social, night-time entertainment district, and recreational trips.

Among other findings, the most popular use of e-scooters in Nashville was to travel within the entertainment district at night, which contributed to 26% of all e-scooter trips. We did not find e-scooter use patterns that resemble commuting. The average daily number of trips on a typical weekend was 84% higher than a typical weekday. We also found variation in e-scooter usage patterns over a year, with the number of trips for all usage patterns increasing in summer months. 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.

Keywords: e-scooters, micromobility, spatiotemporal analysis, big data, unsupervised machine learning

1. Introduction

Several options have evolved as mobility solutions in the past few decades. The advancement in cashless payment mechanisms, vehicle tracking systems, and business models (for example, dockless systems) has led to a new paradigm in human-scale urban mobility called micromobility. Furthermore, micromobility is considered “disruptive” as it requires transportation planners to fundamentally reconsider their approach to urban mobility by including additional modes other than automobiles, fixed-route transit, and pedestrians.

Electric scooter (e-scooter or simply “scooter”) sharing systems are one of the rapidly emerging and most popular micromobility services in the United States, with an estimated 86 million trips in 2019, which is over a 120% increase in trips as compared to 2018 (NACTO, 2020). These vehicles have an electric motor with a battery pack that can reach up to 20 miles per hour (SAE International, 2019). Most of these devices are shared devices that are rented through e-scooter service providers like Bird, Lime, or Spin (among others).

However, 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 (Shaheen & Cohen, 2019), there are several ongoing debates regarding their safety, operation, and actual impact on infrastructure and transportation systems.

This paper offers a framework to analyze the 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 paper 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.

1.1. *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, Smart, and Noland (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, Kluger, & Li, 2021). 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 is lacking 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 systems 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 paper is an exploratory study using existing spatiotemporal analysis techniques on the unique dataset of emerging micromobility. This study takes a much more detailed approach 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.

1.2. *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, Liu, & Bullock, 2019; 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; Faghieh-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; 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 et al., 2021). E-scooters usage was observed mainly in high population density areas (downtown), university, and commercial areas. Hosseinzadeh et al. (2021) 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.

1.3. *Research hypothesis*

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 hypotheses of the study to examine the spatiotemporal usage characteristics are as follows:

- 1) Electric scooters have distinct patterns based on temporal and spatial features, as well as weather characteristics
- 2) Geospatial visualization can supplement the temporal and spatial information to understand the scooter usage patterns

2. **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.

2.1. *Research design*

The integration of GPS-enabled smartphones with micromobility operations has allowed the collection of trip-level data. *Fig. 1* 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.

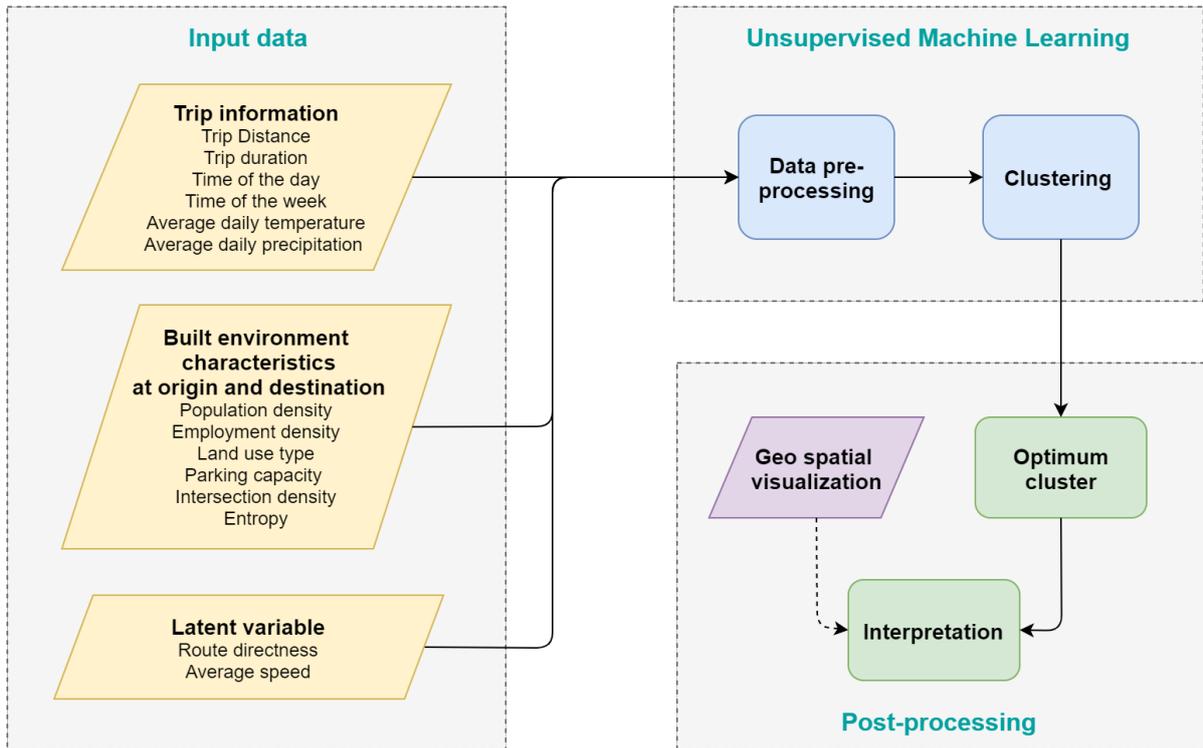


Fig. 1. Research design framework

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

2.1.1. *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.

2.1.2. *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, we 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:

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

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 ($t = 1, \dots, l$ and $\sum_{t=1}^l x_t = 0$), where each input is of m dimension.

$$x_t = (x_t(1), x_t(2), \dots, x_t(m))^T \text{ for } (m < l)$$

PCA transforms each vector x_t linearly into a new set of s_t by $s_t = U^T x_t$, where U is $m \times m$ 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, Hierarchical clustering, and Gaussian Mixture Model (GMM). Using a subset of the data used in the paper, 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:

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

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 $b(i)$ is the measure of how dissimilar i is to its neighboring cluster.

2.1.3. 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.

2.2. Case study

Using the aforementioned methodology, we 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.

2.2.1. 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.

2.2.2. *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 than 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. We obtained the shapefile of data from the Nashville Area MPO. We 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. We extracted the subset of weather data from Nashville International Airport for the study period.

2.2.3. *Data cleaning*

Before preparing the data for analysis, we first cleaned the data for erroneous trips. Out of the 1,546,920 scooter trips extracted from September 1, 2018 to August 31, 2019, we first removed 25,711 trip records that had missing values. We also removed 17,857 trip records that had zero trip distance based on the GPS trace records. Next, we 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. We therefore removed 127,463 trips that were less than 60 seconds and greater than 180 minutes. We also deleted 182,529 trips that were less than 200 feet and greater than 10 miles.

Further, we 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 Euclidean distance, we 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).

2.2.4. *Data preparation*

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

Next, we created dummy variables to indicate the trip start time throughout the day, as well as weekend trips. The dummy variable “AM Peak” indicates a 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 scooter trips are completed between 4 pm on Friday and the end of the day on Sunday (see (a) in *Fig. 2*), we also added a dummy variable to indicate weekend trips.

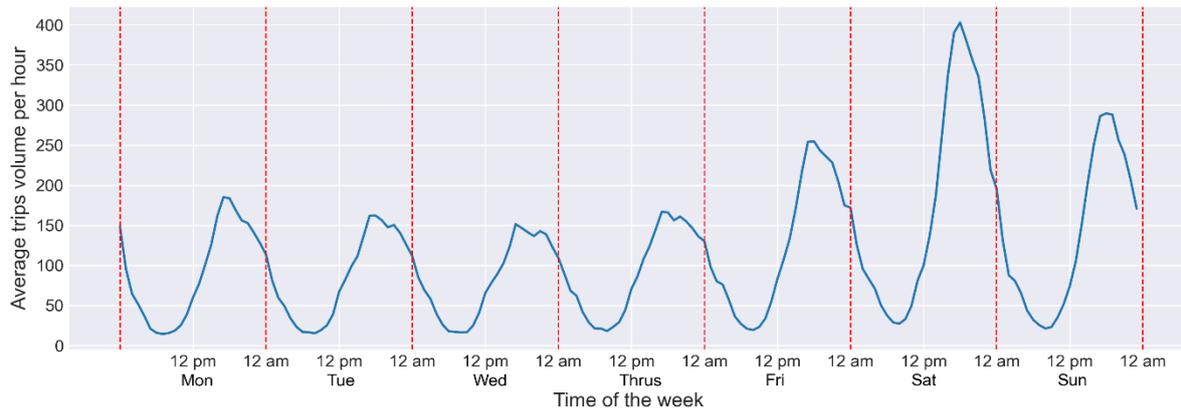
As seen in *Fig. 2* (b), the number of scooter trips increased in March, peaked in May, and gradually decreased in June. There are some high spikes in daily scooter trips between April and June 2019. For example, April 27, 2019, which coincides with the National Football League (NFL) draft, has the highest daily trip count in Nashville. As the 15 days with the highest daily trips account for 13.8% of all trips, we created a dummy variable indicating the trips during special events in Nashville.

After adding the latent variables, we 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, we 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, we 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, we 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.

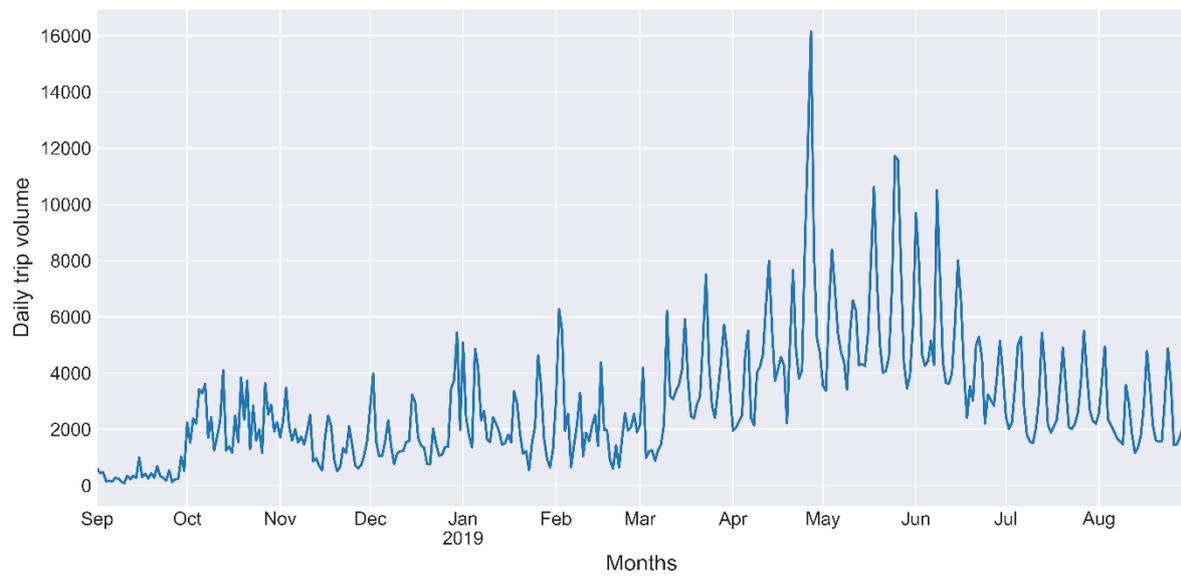
Next, we calculated the average proportion of land-use type for each grid square, including central business district (CBD), urban, and suburban. These land-use variables were obtained from the MPO travel demand model aggregated at TAZ. We complemented the land use data by manually scraping POI data from Google Maps that we reclassified into eight categories: basic amenities, entertainment, government institutions and organizations, hotels, restaurants, bars, retails and services, and transportation. Then, we 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



(a)



(b)

Fig. 2. (a) Scooter trips start time by time of day and day of the week and (b) Daily scooter trips over a year.

Boeing, 2017).

Table 1 presents the descriptive statistics of all the variables used in the study.

3. 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. In the final section, we grouped similar clusters of K-means to simplify the segmentation of e-scooter usage.

Table 1
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 sub-urban 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 sub-urban 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	144053 (13.7%)			
Weekend trips	Dummy	340935 (32.5%)			
AM Peak trips (7 am to 10 am)	Dummy	23941 (2.3%)			
Day-time trips (10 am to 4 pm)	Dummy	209901 (20%)			
Evening Peak trips (4 pm to 8 pm)	Dummy	342033 (32.6%)			
Night trips (8 pm to 7 am)	Dummy	474166 (45.2%)			

3.1. PCA decomposition

This section presents the results of a principal component analysis, which indicates the significance of variables on the scooter trip data variance. *Fig. 3* illustrates the loading factor of 30 variables on the first eleven principal components (PC). While there is no specific

consensus on what should be the correct number of PCs, we decided to use eleven PCs as they explain 91.5% of the variance in the data.

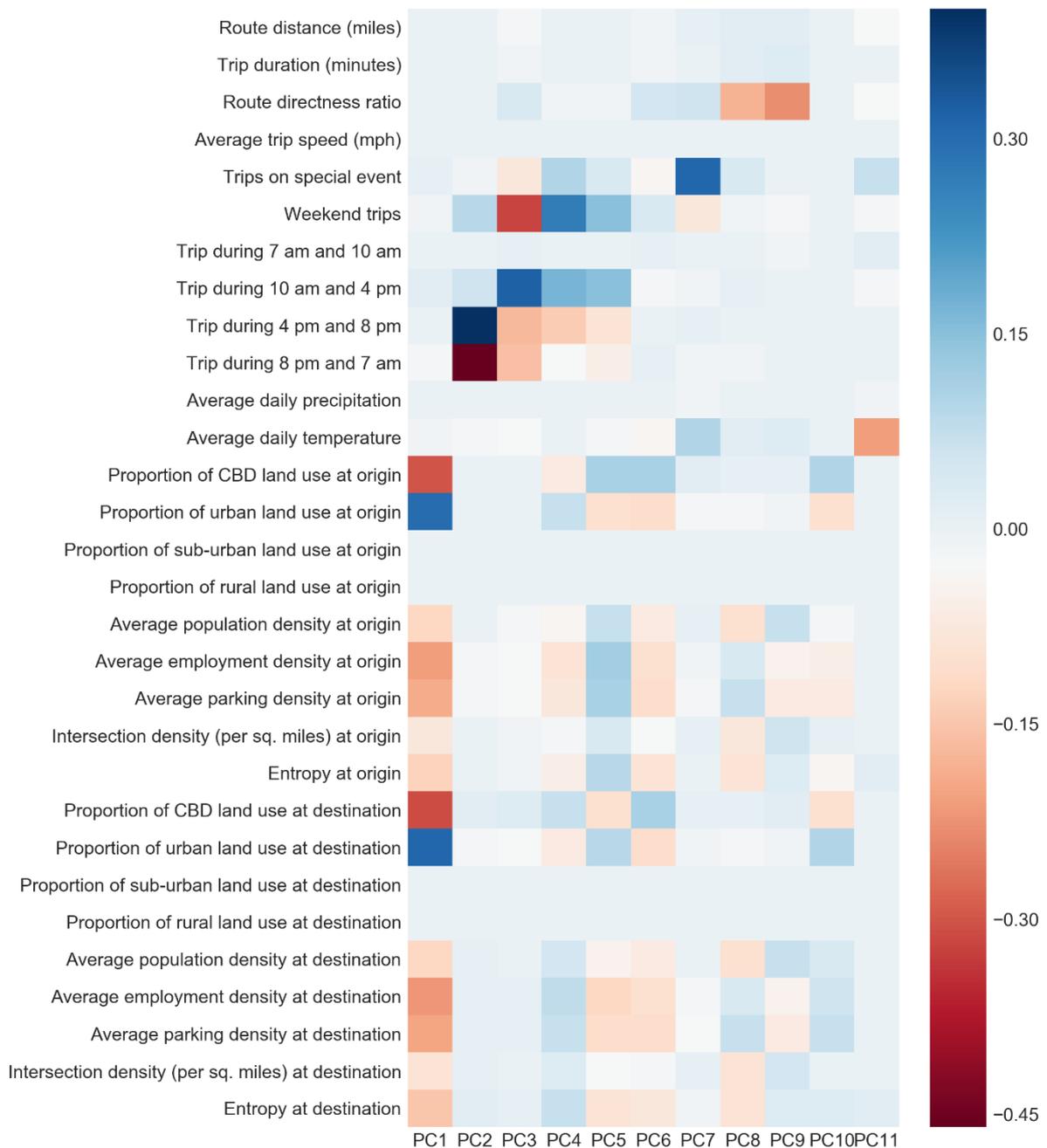


Fig. 3. Loadings on the first eleven principal components of the scooter trip

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 very strong correlation of scooter start time (hours of the day and day of the week) and the proportion of land use (CBD and urban) with scooter use.

The route directness and average daily temperature also explain the pattern of trips. Furthermore, the loadings of PCA indicate contributions of population, employment, and parking density, and land use mixture of origin and destination in scooter usage. We removed intersection density variable since it did not add meaningful interpretation in the clusters.

3.2. 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 and the interpretation of the optimum model.

3.2.1. Evaluation of K-means models

We evaluated 23 K-means models that ranged in number of clusters between 2 to 24 and an increment of one. Although the silhouette score was highest for the model with eight clusters, we decided to interpret models with higher than eight number of clusters and later regroup clusters based on their similarity. This approach allowed us more flexibility to merge some clusters based on trip start time, and others based on origin and destination characteristics. The difference between the silhouette score of the next two best models (12 and 16 clusters) was negligible. Therefore, we decided to select the model with 16 clusters for interpretation.

3.2.2. Interpreting clusters

Fig. 4 summarizes the results of the optimum model selected for interpretation. The trip start time during the day is plotted in Fig. 4 (a), which explains the start time characteristics of the scooter trips. The built environment and remaining trip variables are illustrated in Fig. 4 (b) as a radar plot, which is normalized between 0 and 1 to make comparisons among clusters.

Based on the attributes, we can describe the general trip characteristics of each of the clusters. Trips in Cluster C2, for instance, were made during the night time on weekdays. The origin of trips was concentrated in downtown Nashville and a few commercial zones to the north of Vanderbilt University. Destinations, on the other hand, were distributed throughout other urban areas and were more scattered than the origins. Therefore, we can deduce that cluster C2 was weekday night return trips from downtown Nashville to other urban areas.

Following a similar interpretation, a short description of all 16 clusters is as follows:

Cluster C0: Weekday night recreational scooter trip around the urban area

Cluster C1: Weekday night trips around Nashville downtown and Vanderbilt University

Cluster C2: Trips from Nashville downtown to urban locations at night

Cluster C3: Weekday evening trips mostly around Vanderbilt University

Cluster C4: Weekday night trips at entertainment district at downtown

Cluster C5: Daytime weekend errands mostly at downtown

Cluster C6: Weekend evening social trips in downtown

Cluster C7: Weekend night trips at the entertainment district

Cluster C8: Day-time errands in Vanderbilt University and urban Nashville

Cluster C9: Weekday evening social trips in downtown

Cluster C10: Weekday night entertainment district at both Vanderbilt area and downtown

Cluster C11: Weekday evening social and recreational at urban area

Cluster C12: Early night weekend social and recreational at urban locations
 Cluster C13: Weekend evening social event nearby downtown
 Cluster C14: Weekday day errand around Nashville downtown
 Cluster C15: Weekend evening recreational at urban Nashville

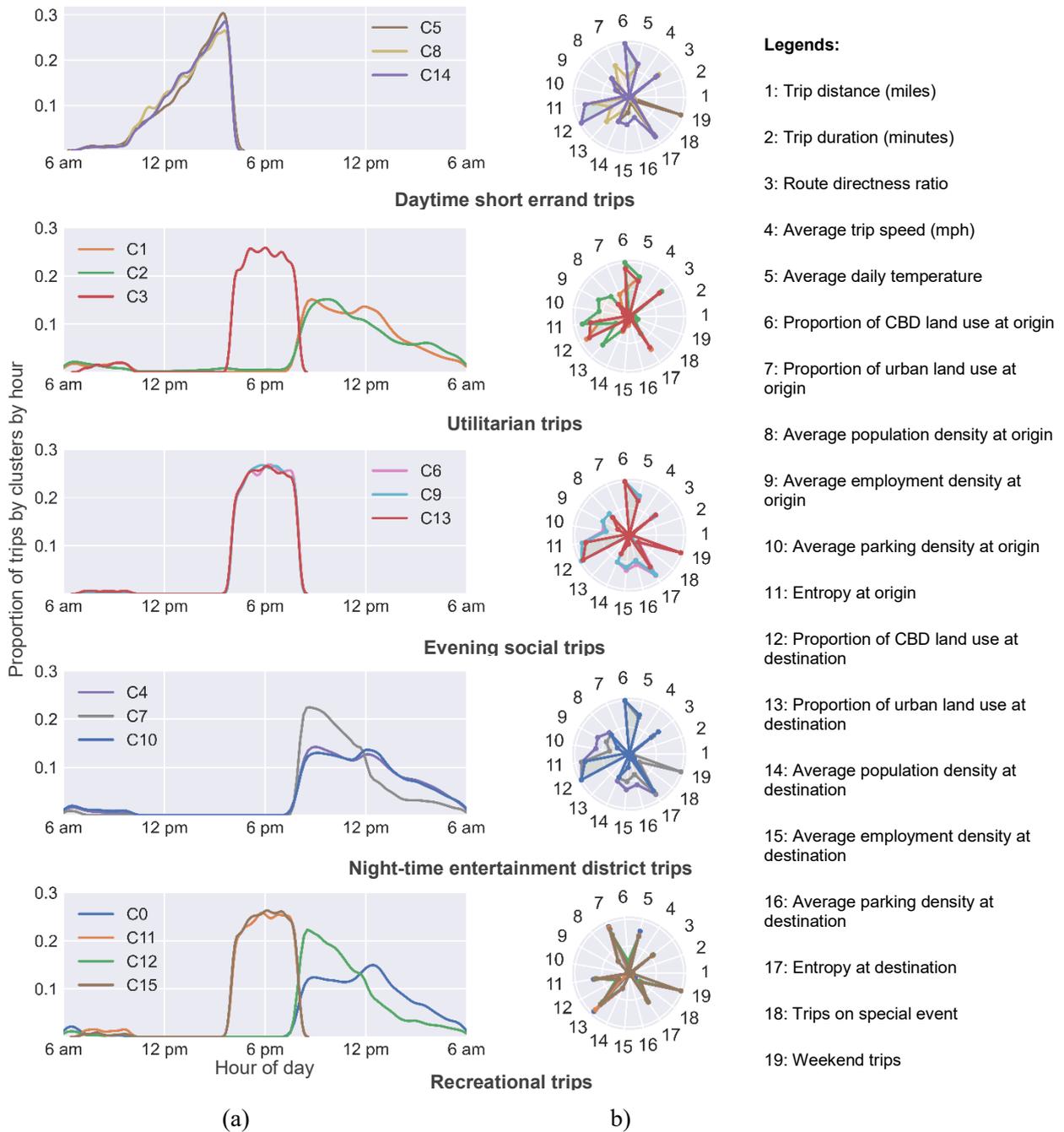


Fig. 4. Clustering results grouped by usage. (a) Trip start of e-scooter trips and (b) built environment characteristics of e-scooter trips

3.3. E-scooter Usage-grouped clusters

Some clusters of the optimum model have similar origins and destinations, as well as trip start times. Therefore, we combined clusters from the K-means analysis into five usage-

grouped clusters to simplify the interpretation of e-scooter travel behavior in Nashville (Fig. 4).

Table 2 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.

Table 2

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

Variables	Usage-grouped cluster name				
	Daytime short Errand	Utilitarian	Evening social	Night-time Entertainment District	Recreational
Route distance (miles)	0.47	0.88	0.80	0.71	0.81
Trip duration (minutes)	15.2	16.5	17.8	15.9	17.0
Route directness ratio	0.58	0.64	0.53	0.54	0.48
Average trip speed (mph)	2.28	3.54	2.95	3.06	3.10
Average daily temperature	61.26	64.52	65.52	66.26	65.97
Proportion of CBD land use at origin	0.65	0.66	0.85	0.87	0.18
Proportion of urban land use at origin	0.25	0.22	0.04	0.02	0.71
Average population density at origin	7707.69	6204.37	10075.70	10108.88	5508.78
Average employment density at origin	62585.68	59247.41	106301.74	111923.47	14411.83
Average parking density at origin	9866.51	9799.12	19185.28	20171.78	440.64
Entropy at origin	0.64	0.58	0.75	0.76	0.50
Proportion of CBD land use at destination	0.67	0.59	0.84	0.88	0.21
Proportion of urban land use at destination	0.22	0.29	0.05	0.02	0.69
Average population density at destination	7975.28	5445.85	9990.78	9880.06	5793.85
Average employment density at destination	74526.68	40907.61	112108.87	112132.53	17317.11
Average parking density at destination	12649.46	5783.25	20691.33	20066.81	1154.57
Entropy at destination	0.65	0.52	0.75	0.75	0.47
Trips on special event	0.11	0.09	0.15	0.15	0.18
Weekend trips	0.17	0.04	0.56	0.35	0.48
Summary of trips					
Percentage of trips by count	20.4	16.8	18.9	26.1	17.8
Percentage of trips by Vehicle-Miles Travelled (VMT)	13.3	20.5	20.9	25.4	20.0
Percentage of trips by travel duration	19.0	16.9	20.5	25.2	18.5

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

A brief description of each usage-grouped clusters are as follows:

Daytime short errand trips: These e-scooter trips were completed during day-time on weekdays in downtown Nashville and the Vanderbilt University area and had the lowest route distance 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 lowest among all usage-grouped clusters, which suggests that these trips were made on days with cooler temperatures.

Utilitarian trips: These trips, on the other hand, were longer in route distance and had the highest average travel speed as compared to other usage-grouped clusters. The higher value of route directness indicates that these trips are shorter path between origin and destination among other groups. These trips were completed during evening and night during weekdays in downtown Nashville and Vanderbilt University.

Evening social trips: These trips exhibited characteristics that might be affiliated with social activities. The trips tended to be longer on average and occur on evenings and weekends. They generally started and ended in the commercial areas of downtown and nearby Vanderbilt University. There is likely some overlap between what we describe as evening social trips and night-time entertainment district trips.

Night-time entertainment district trips: These trips were completed at night time, and the majority of them were on weekends. The start and end location of the trips were nearby entertainment services, like bars. This category accounts for the largest proportion of all e-scooter trips in Nashville.

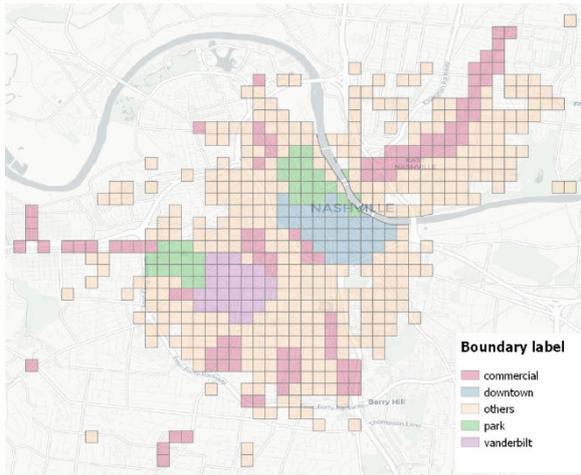
Recreational trips: The trips in this category had the lower value of route directness, which indicate that the trips were much longer than the shortest possible distance between origin and destination. Most of the trips were made during weekends nearby urban parks.

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

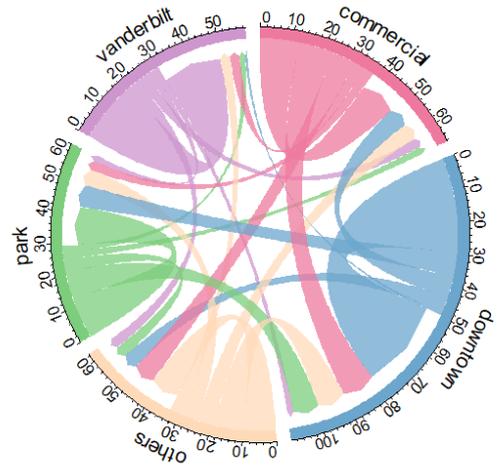
3.3.1. *Spatial distribution*

A big part of the e-scooter usage story is related to the spatial distribution of those trips. We can identify origin and destination of trips, which reveals a large component of the trip patterns. *Fig. 5* illustrates the spatial distribution of usage-grouped clusters in Nashville through chord diagrams. *Fig. 5 (a)* represents the area within Nashville that we 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. *Fig. 5 (b) - (f)* summarize the origin and destination of each usage-grouped cluster among the areas represented in *Fig. 5 (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.

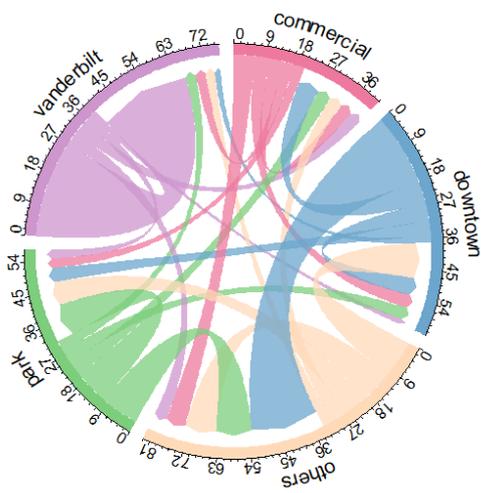
The starting and ending locations of daytime short errand and utilitarian trips are relatively evenly distributed among the area categories, whereas a large portion of evening social and nighttime entertainment district trips start and end in downtown Nashville. Furthermore, the origin and destination of the e-scooter trips can be associated with specific usage-groups. For instance, trips starting and ending at Vanderbilt University are predominantly utilitarian, daytime short errands, and recreational.



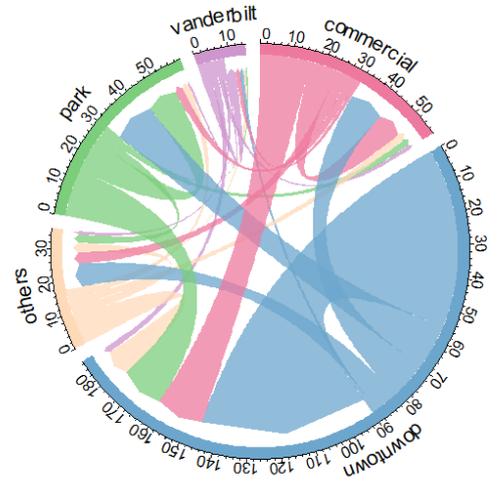
(a)



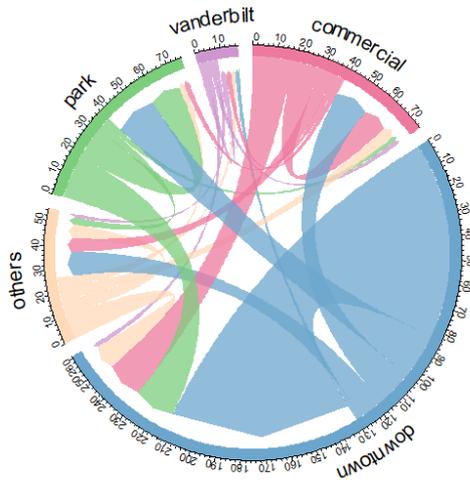
(b)



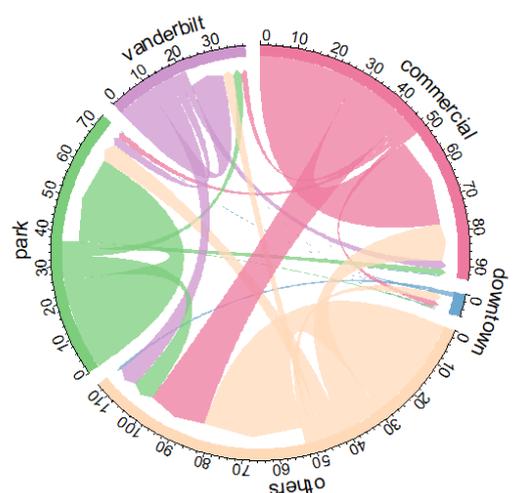
(c)



(d)



(e)



(f)

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

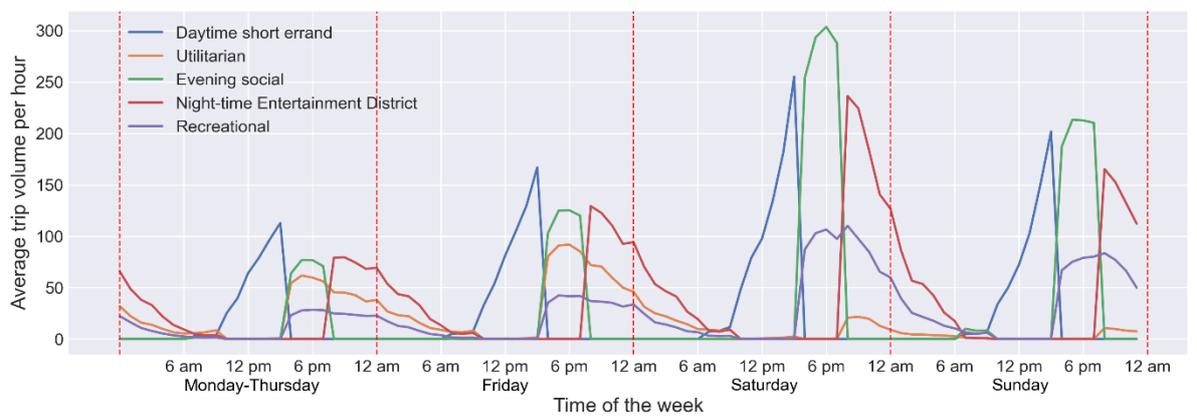
Fig. 5. Spatial distribution of usage-grouped clusters. (a) Boundary for chord diagram (b) Daytime short errands trips (c) Utilitarian trips (d) Evening social trips (e) Night-time Entertainment District trips and (f) Recreational trips

3.3.2. Temporal distribution

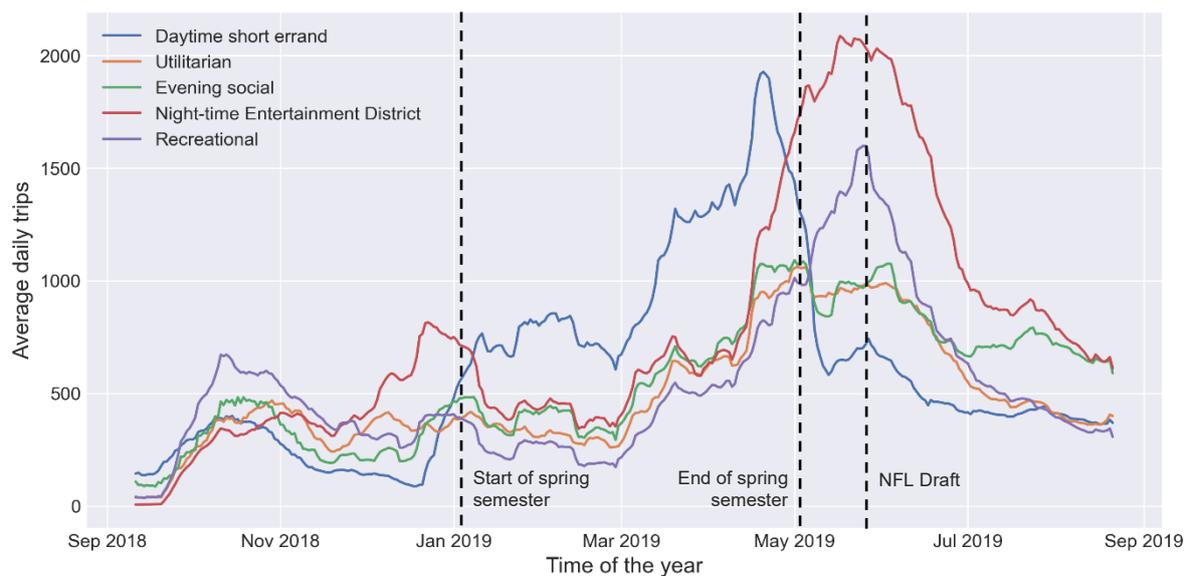
The analysis of a full year scooter trip data enables us to understand the scooter pattern on time of the day, time of the week, and time of the year. *Fig. 6 (a)* illustrates start time of the usage-grouped clusters over day and week, while *Fig. 6 (b)* presents the daily usage pattern over the year. We used 21 days rolling average to get a smoother trend over a year pattern as the daily scooter trips have high variation during weekends and special events in Nashville.

Except for the utilitarian trips, all the other e-scooter usage-grouped clusters increased during the weekends. The peak of evening social as well as recreational trips on the weekends is almost twice the peak on the weekdays. Furthermore, all usage-group clusters' daily average trips increased during the summer months, indicating high scooter usage during warm weather. The number of scooter trips for all usage-grouped clusters is higher at the end of September 2019 compared to the beginning of September 2018 with increasing average daily trips, which suggests increasing popularity of scooters in Nashville.

There was a prominent surge in night-time entertainment district trips during the Christmas and New Year holidays. Similarly, the number of daytime short errand trips increased in the first week of January and decreased significantly in the first week of May, aligning with the spring semester at Vanderbilt University.



(a)



(b)

Fig. 6. 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

4. Discussion

The following chapter 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.

4.1. *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 policy makers have adopted a combination of recall surveys from the 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.

Nashville's data is of higher resolution than most other cities, operators reported route-level data that allows us to understand how direct riders traveled from origin to destination. We propose the use of the route directness ratio, in addition to essential trip information like trip start time, to classify various e-scooter use patterns. For instance, recreational trips have a lower route directness ratio, which indicates people take a longer path than the shortest distance possible. Utilitarian trips, on the other hand, have a higher route directness ratio that indicates paths closer to the shortest distance. This analysis is only possible with route-level trace data. We 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 high-resolution analysis of micromobility data.

4.2. *Nashville application*

Several temporal and spatial variables can explain the scooter use pattern in Nashville. The trip start time in terms of 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 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 use is similar to previous studies of e-scooters (Bai & Jiao, 2020; Caspi et al., 2020) and bikeshare

(Bachand-Marleau, Lee, & El-Geneidy, 2012; Faghieh-Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014).

These temporal and spatial attributes can be used to identify distinct usage patterns of e-scooters. The night-time trips in the entertainment district in downtown Nashville and nearby Vanderbilt University was the most popular e-scooter use in Nashville, contributing to 26% of all e-scooter trips. Other studies also found high scooter use in downtown and university areas of other cities (Bai & Jiao, 2020; Liu, Seeder, & Li, 2019). There may also be some overlap between the night-time entertainment district trips and the evening social trips that accounted for 20% of all e-scooter trips. An additional 20% of e-scooter trips were completed during day time around downtown Nashville and Vanderbilt University, which were likely to be for short errands. Utilitarian trips to travel between two locations contributed to 17% of all trips, while 18% were recreational trips at locations like urban parks. Similar to e-scooter use in Austin (Caspi et al., 2020), we did not find any pieces of evidence of e-scooter use for commuting purposes in Nashville, such as a morning peak in the daily trip count. The temporal use pattern of e-scooters in Nashville somewhat resembles casual bikeshare use in Washington, D.C. (McKenzie, 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 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 trips peaked in the afternoon on both weekends and weekdays. Additionally, the average daily number of trips on a typical weekend is 84% higher than a typical weekday, with the highest peak on Saturday evenings. These findings are consistent with previous research of scooter use peaking in the evening (Bai & Jiao, 2020; Caspi et al., 2020; McKenzie, 2019).

The scooter usage also changed over a year, with all usage-grouped clusters peaking during the summer and increasing over the analysis period in general. Several large-scale events in the city and outdoor activities attract more scooter users in the summer, while increasing usage indicates the popularity of scooters over time. The number of night-time entertainment district trips increased during special events like the Christmas holidays and NFL draft. The peak suggests e-scooters could be popular among tourists visiting Nashville for these events. The number of daytime short errand trips plummeted during the first week of May, which coincides with the end of the spring semester at Vanderbilt University. This indicates that a lot of daytime short errands trips were possibly made by Vanderbilt students.

The daytime short errand trips were made on the days with relatively lower average temperatures than other groups. Although not conclusive, the results suggest that people ride scooters during the day-time on days with cooler temperatures. Mathew et al. (2019) also found daily temperature as one of the critical predictors of hourly scooter trip volume in Indianapolis.

4.3. *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 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 for nuanced travel behavior, like the average traffic volume of road segments on the trip. 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. While the findings in this analysis are based on the e-scooter activity in Nashville, Tennessee that might not necessarily be the same in other cities; the methods developed here can be readily transferred to other geographies. Future studies can compare e-scooter usage findings from different cities to develop a comprehensive summary of e-scooter use characteristics.

5. Conclusion

This study proposes a novel approach to analyze high-resolution micromobility data based on unsupervised machine learning. The framework is further applied to the Nashville SUMD dataset as a case study. The findings of this study can be useful to city administrations, planners, and micromobility operators. The heavy use of scooters at nighttime in the Nashville entertainment district could indicate riders that have different needs than day-time users.

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

Supplement material

The code for the analysis can be found in the following GitHub repository:
<https://github.com/niteshshah12/E-scooter-trip-pattern-analysis-of-Nasvhille>

Acknowledgments

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Author contributions

The authors confirm contribution to the paper as follows: study conception and design: Shah and Cherry.; data collection: Shah, Cherry, and Guo; analysis and interpretation of results: Shah, Cherry, and Lee; draft manuscript preparation: Shah, Guo, Cherry, and Lee. All authors reviewed the results and approved the final version of the manuscript.

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New Modes, New Codes!

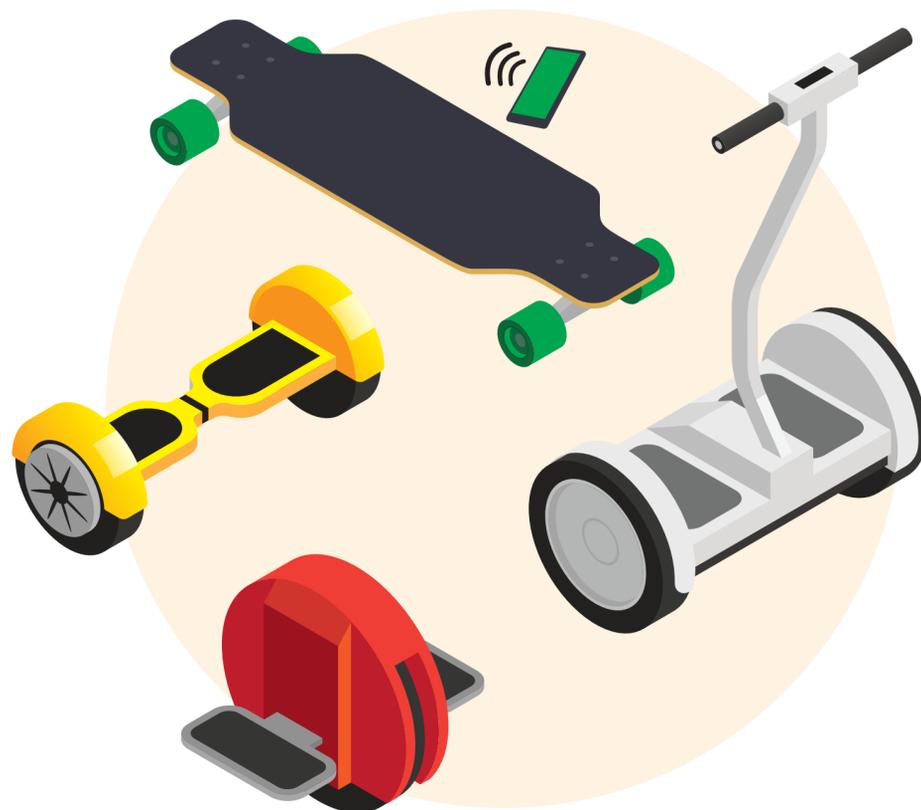
Categorizing injuries related to emerging micromobility transportation.



e-Scooters

Keyword for Chief Complaint:
e-scooter + Brand

(Bird, Gotcha, Jump, Lime, Spin, Razor, etc.)



Other Devices

Keywords for Chief Complaint:
e-skateboard, e-hoverboard,
Segway®, e-unicycle

ICD-10-CM Codes

V00.09 Pedestrian on foot injured in collision with other pedestrian conveyance

V00.181, V00.182, V00.188 Accident on other rolling type pedestrian conveyance

V01-V06 (.09, .19, .99) Pedestrian with other conveyance injured in transportation collision

NOT considered e-scooters

These devices are not considered e-scooters and have their own set of ICD-10-CM codes.



mobility
scooters



mopeds



motor
scooters



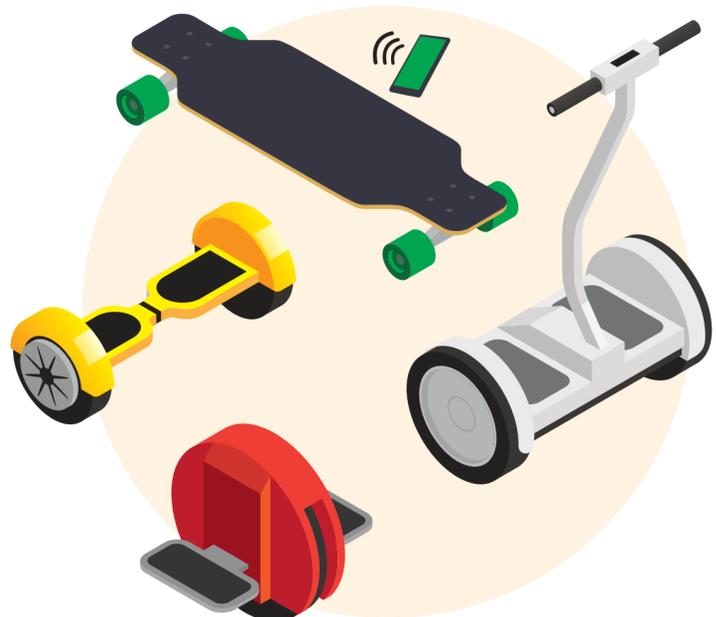
Micromobility Modes, New Codes!

Categorizing injuries related to emerging transportation.



e-Scooters

Keyword for Chief Complaint:
e-scooter + Brand
(Bird, Gotcha, Jump, Lime, Spin, Razor, etc.)



Other Devices

Keywords for Chief Complaint:
e-skateboard, e-hoverboard,
Segway®, e-unicycle

A rider on a micromobility device falls on or strikes

a pedestrian

Pedestrian on foot injured in collision with
standing micromobility conveyance

V00.03 (.031, .038)

a stationary object or the ground

Accident with standing micromobility
pedestrian conveyance

V00.84 (.841, .842, .848)

A rider on a micromobility device is struck by

a non-motorized vehicle (e.g. bicycle)	V01 and V06 (.03, .13, .93)
a motorized vehicle (e.g. car, bus)	V02, V03, V04 (.03, .13, .93)
a railway train	V05 (.03, .13, 93)

For a full list of codes, visit <https://go.unc.edu/ICD10CM>



Appendix C

Shared Micromobility Survey Library



Project Background

Shared micromobility options such as shared electric scooters (e-scooters) are becoming popular at an unprecedented rate. These services are changing the landscape of transportation in their own ways. These changes can both be trip specific and long-termed. Surveys have been widely used in the transportation domain to understand these unknowns as in the study of electric vehicles and bike sharing. The aim of this project is to conduct a survey of surveys to understand what questions are in place to assess the unknowns with shared micromobility, and to provide a starting point for researchers to employ new micromobility surveys.



The Power of Surveys

User surveys are an important tool to examine the impacts brought by shared micromobility, together with observational studies and trip level data analysis from big-data datasets. To date, there are a number of evaluation reports of shared micromobility systems in the United States that are often led by local government agencies. In general, these cities are largely the major population centers in the country. Geographically, the majority are located in the Pacific West, the Midwest, and the Northeast areas (Figure 1). Most of these reports rely on surveys as the main assessment tool and provide information on demographics, behaviors, preferences and perception of shared micromobility users. Table 1 summarizes a list of these reports and the types of shared micromobility services that are studied.

Table 1 Shared Micromobility Studies in the United States (by report release date).

Location	Lead Agency	Report Date	Shared Micromobility Types
San Francisco, CA	Lime [1]	2018.6	E-scooters
Portland, OR	Portland Bureau of Transportation [2]	2019.1	E-scooters
Denver, CO	Denver Department of Public Works [3]	2019.2	Bicycles E-bikes E-scooters
San Francisco, CA	San Francisco Municipal Transportation Agency [4]	2019.4	E-scooters
Bloomington, IN	City of Bloomington [5]	2019.4	E-scooters
Arlington, VA	Mobility Lab [6]	2019.9	E-scooters E-bikes
Santa Monica, CA	City of Santa Monica [7]	2019.11	E-scooters
Chicago, IL	City of Chicago [8]	2020.1	E-scooters
Baltimore, MD	Baltimore City Department of Transportation [9]	2020.5	Bicycles E-scooters
Tempe, AZ	Sanders et al [10]	2020.9	E-scooters

Note:

(a) the above shared micromobility types are dockless, unless otherwise noted

Project Objectives

Drawing upon the existing surveys of shared micromobility in the United States, this effort aims at providing a summary of the survey questions that are included in these studies, and a classification of these questions. In addition, this work will review and document the methods that are applied to conduct these studies. This toolkit platform is prepared for practitioners and researchers with various needs to easily navigate through the archived survey questions and locate the information they desire. A survey developer should be able to identify topics they're interested in and find validated questions that have been used in other studies to consistently apply in their own study.

The selected ten surveys explore an array of questions related to the use of shared micromobility vehicles. These themes include but are not limited to 1) user demographics, 2) motivation and attitude, 3) travel behavior and mode choice, 4) safety, 5) accessibility, 6) program evaluation, 7) user experience. The choice of questions in the survey often reflects the motivations of an organization to introduce a shared micromobility scheme. For example, ten out of the 16 questions in the San Francisco Municipal Transportation Agency (SFMTA) [4] survey concern demographics since one major goal of the shared micromobility program is to address rider diversity. While survey data was collected both in-person and online, the majority of the surveys were conducted online (or in-app) only. A variety of survey platforms were used which were often advertised through websites, emails and social media. Survey logic is commonly used to distribute the right set of questions to the corresponding users. For example, the Portland survey [2] asks slightly different questions to residents and visitors with the use of survey logic. Multiple choice (MC), select all that apply (SA), open-ended (OE), multiple choice with open-ended option(s) (MCOE), and select all that apply with open-ended option(s) (SAOE) are the five question types that constitute all the surveys.

Sample Key Survey Questions

1) User Demographic Questions

User demographic questions can reveal key attributes of the user group. Such information is important in assessing whom the shared micromobility is serving and if shared micromobility user group is more diverse. A total of 19 questions and their variants are found in this category. The most included questions are residence ZIP code, race/ethnicity, gender, age, income, and disability. The majority of the questions under this category are multiple choice questions. For demographic questions such as race, gender and age, we recommend using the same set of options from the American Community Survey (ACS) to provide identifiable and accurate responses. This also ensures consistency when comparing across multiple survey results.

For example, when it comes to the race question, we recommend to ask in the following way

Please identify your race (choose one or more)

White

Black or African American

American Indian or Alaska Native

Asians

Native Hawaiian

Click to download all the recommended questions under this category

2) Motivation and Attitude Questions

Motivation and attitude questions assess a rider's reasons and barriers to adopt micromobility. Under this category, there are three main questions: impression about the shared micromobility services, adoption motivations, and adoption barriers. Often, these questions offer attitudinal likert scale responses. Of note, different from the trip specific questions that are introduced in the next category, these questions are rather general. Since there are multiple possible responses, it is recommended to use a "Select all that apply" style question.

Choose the top 3 reasons that you ride micromobility devices.

It can be the fastest way to get where I need to go

It is easy

Avoid parking

It is fun

Save money on transportation

It is environmentally friendly

It is healthy

Other (please specify:)

Click to download all the recommended questions under this category

3) Travel Behavior and Mode Choice Questions

The mode choice question can help evaluate the impact of micromobility on other modes of transportation from which their impacts on the environment can be estimated. This question category intends to study how the use of shared micromobility affects other modes of transportation. This is a key category in the survey library as mode substitution data is fundamental when it comes to understanding the transportation, environmental, and health impacts of shared micromobility. In addition, it enables more informed multimodal transportation planning. Most questions are asked in the context of a recent shared micromobility trip, mirroring a travel diary approach. In this category, common questions include trip purposes and types, alternative and complementary modes, use frequency of shared micromobility, use frequency changes in other modes, changes in automobile ownership. A sound question should include all the possible alternative modes of transportation to micromobility in the area. In practice, it is recommended to ask the rider about a specific micromobility trip to generate more accurate response. This approach is known as the travel diary approach with which important information such as trip distance can also be obtained.

How would you complete your trip if a shared e-scooter had not been available in your last trip? (Choose one).

Driven a personal vehicle, carshare vehicle, or other motor

Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person

Taken a taxi, Uber or Lyft

Taken a bus/other local public transportation options

Walked

Ridden a personal e-scooter

Ridden the local bike share

Ridden a personal bike

Would not have made the trip

Other (please specify:)

4) Safety Questions

Safety is a prime concern in shared micromobility which has been reflected in survey questions. Themes of safety questions cover infrastructure use and preferences, crash and near-crash experience, safety perceptions towards different road users, parking and helmet use. However, It typically mainly concerns the infrastructure and the conflicts with other road users. Since riders may not be familiar with the infrastructure terminologies, it is recommendable to attach images of such infrastructure.

Regardless of where you currently ride e-scooters, where would you prefer to ride e-scooters in this area? Please indicate your preferences for the following infrastructure from 1 to 5 with 5 as most preferred and 1 as least preferred.

Protected bike lane (image attached):

Bike lane (image attached):

Trail (image attached):

Sidewalk (image attached):

Shared lane (image attached):

[Click to download all the recommended questions under this category](#)

5) Accessibility Questions

In this context, accessibility refers to both the access to the shared micromobility devices and access to other modes of transportation through shared micromobility. The use of micromobility devices to connect public transportation is a major concern in accessibility and equity issues in transportation. Understanding how riders use micromobility in connection with transit helps develop measures to improve the operation of micromobility services.

For your most recent trip, did you use the service to get to or from public transportation? (Choose one)

Yes

No

Other (please specify:)

[Click to download all the recommended questions under this category](#)

6) Program Evaluation Questions

Program-related questions serve two main purposes. First, they are to understand users' familiarity with the program specific rules regarding shared micromobility. The other purpose is to solicit feedback to improve the program. The question on familiarity with the program rules is the most popular question. Typically, the question states a list of rules and ask survey respondents to indicate which ones are correct or they prefer. Municipalities can also choose to include some other specific questions in the survey to identify room of improvement for the micromobility program as an evaluation measure. This question can be mostly open-ended but it is recommendable to put in some responses to inspire thoughts from the survey respondents.

What changes to the rules would encourage you to use the program more often? (Select all that apply)

Allow more e-scooters

Create dedicated spaces for e-scooter parking

Create dedicated spaces for e-scooter riding

Other (please describe:)

Click to download all the recommended questions under this category

7) User Experience Questions

The user experience questions serve very similar purposes as program evaluation questions but from the service provider and customer service perspectives. Topics range from device availability, choice of service providers, payment, fleet maintenance, to suggestions to encourage more use. User experience questions serve as the final chance for riders to input information that the survey may otherwise fail to capture. These aspects are of equal importance when it comes to improve the micromobility program.

If you had positive experience with the pilot, what contributed to your positive experience? (Open-ended)

Click to download all the recommended questions under this category

[Access all the questions in a single Word document \(last updates: Feb 2, 2021\)](#)

[Access the whole library here \(last updates: Feb 2, 2021\)](#)

The Emergence of In-app Surveys

A characteristic difference in shared micromobility is the use of smartphone applications (apps). Almost all shared micromobility service providers operate through these apps which offer a unique opportunity for researchers to conduct instant surveys in addition to bringing convenience to the users. For example, after every trip, a short survey concerning trip purpose, alternative mode of transportation can pop up on the screen. Alternatively, users can visit every previous trip to fill out the questions at a later time. One benefit of this novel travel diary style survey method is the trip specificity which provides better accuracy compared to the traditional pen and paper approach given that users do not have to recall back on recent trips on their own.

Route History

Thursday, Dec 05, 2019, 01:15 PM

For this trip, my purpose is:

Commute

Recreation

Social/Errands

For this trip, my primary mode substitution is:



Walk



Bike



Transit



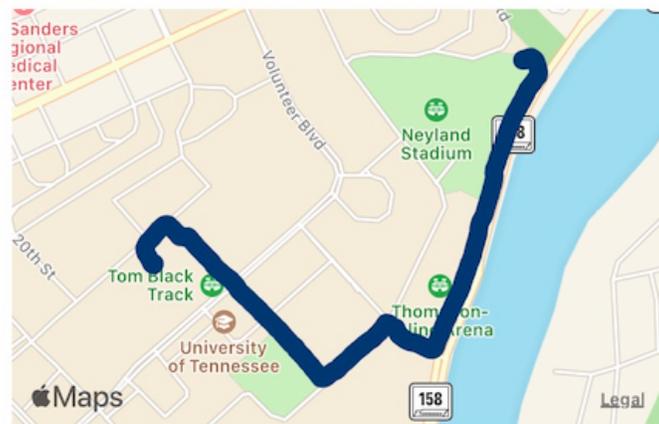
Personal Car



No Trip



Others



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Appendix D

Shared Micromobility Survey Library (Complete Version) User Demographic Questions

[1] Residence Location (Zip Code)

What is Zip code of your primary residence?

[2] Residence Location (Yes or No)

Do you live or work in this area? (Choose one)

- Yes
- No
- Neither

[3] Residence Duration

How long have you lived here? (Choose one)

- Less than 1 year
- 1-5 years
- 6-10 years
- 11-15 years
- 16 years or more

[4] Visiting Duration

How long was your most recent visit to the area? (Choose one)

- Less than 24 hours
- 1-2 days
- 3-4 days
- 5-7 days
- Over one week

[5] Race/Ethnicity

Please identify your race (Choose one or more)

- White
- Black or African American
- American Indian or Alaska Native
- Asians
- Native Hawaiian
- Pacific Islanders
- Others (please specify)

[6] Gender

Please identify your sex (Choose one)

- Male
- Female
- Others

[7] Hispanic Origin

Are you of Hispanic, Latinx, or Spanish origin? (Choose one)

- No, not of Hispanic, Latinx, or Spanish origin
- Yes (includes Mexican, Mexican American, Chicano, Puerto Rican, Cuban, Dominican, etc.)
- Prefer not to say

[8] Age

Please indicate your age (In years)

[9] Income

Please indicate your income (Choose one)

- Less than \$15,000
- \$15,000 - 29,999
- \$30,000 - 49,999
- \$50,000 - 74,999
- \$75,000 and beyond
- Decline to say

[10] Parenthood (Yes or No)

Do you have any children? (Choose one)

- Yes
- No
- Decline to say

[11] Age of Children

How many of your children are under age 16? (Choose one)

- 0
- 1 child
- 2 children
- 3 children
- 4 or more children

[12] Education

What is the highest degree or level of school have you completed? (Choose one)

- No school completed
- Nursery or preschool through Grade 12
- High school graduate
- College or some college
- After bachelor's degree
- Others (please specify:)

[13] Occupation Industry

What industry do you work in? (Choose one)

- Education
- Government
- Technology
- Construction
- Energy
- Non-profit
- Financial services
- Hotel/Tourism
- Professional & business services
- Retail/restaurant
- Real estate
- Healthcare
- Others (please specify:)

[14] University Affiliation

What is your affiliation with the university? (Choose one)

- Visiting student
- Undergraduate student
- Graduate student
- Faculty
- Staff
- No current affiliation
- Other (please describe)
- Decline to say

[15] Household Size

In total, how many people live in your household?

[16] Housing Type

What is your housing type? (Choose one)

- Apartment or condominium
- Single-family, detached home
- Townhome, attached to other houses
- NA/prefer not to answer
- Other (please specify)

[17] Language

What is the primary language spoken in your household? (Choose one)

- English
- Spanish
- Others (please specify)

[18] Disability and Health Conditions

Do you have a disability or health condition that affects the travel choices you make in City X? (Choose one)

- Yes
- No
- Prefer not to say

[19] Mobility Disability

Do you regularly use a wheelchair or other necessary mobility devices to get around? (Choose one)

- Yes
- No
- Decline to say

[20] Disability Type

If any, please indicate your disability (Choose one or more)

- Mobility or dexterity (e.g. walking, climbing stairs)
- Visual (e.g. blind, low vision)
- Deaf or hard-of-hearing
- Speech or communication
- Other (please specify)

[21] Access to Smartphones

Do you have a smartphone with a data plan? (Choose one)

- Yes
- No
- Others (please specify:)

[22] Access to Bank Cards

Do you have a debit or credit card? (Choose one)

- Yes
- No
- Others (please specify:)

[23] Driver's License

Do you have a current driver's license? (Choose one)

- Yes
- No
- Others (please specify:)

Motivation and Attitude Questions

[24] Overall Impression

What is your overall impression of the scooters (or the electric/pedal assist bicycles) in City X?
(Choose one)

- Love them
- Like them, need a few changes
- Do not have an opinion, neutral
- Do not like them, with some changes I may like them
- Hate them, nothing will make me like them.
- Other (please specify:)

[25] Overall Adoption Motivations

Choose the top 3 reasons that you ride micromobility devices.

- It can be the fastest way to get where I need to go
- It is easy
- Avoid parking
- It is fun
- Save money on transportation
- It is environmentally friendly
- It is healthy
- Other (please specify:)

[26] Overall Adoption Barriers

Choose the top 3 issues that stop you from riding micromobility devices more frequently.

- The lack of availability of vehicles near me
- Weather
- Availability of safe places to ride
- Traffic safety concerns
- Cost
- The lack of availability of non-scooter vehicles

- Bike or scooter vehicle safety concerns
- Other (please specify)

Travel Behaviors and Mode Choice Questions

[27] Device type

What type of dockless vehicle do you utilize most often? (Choose one)

- Dockless scooter
- Electric/pedal-assist bicycle
- Other (please specify:)
- I do not ride either dockless scooters or electric-pedal-assist bicycles

[28] Use Status

Have you ever ridden an e-scooter? (Choose one)

- Yes
- No
- I don't know what an e-scooter is
- Other (please specify:)

[29] Future Use Status

How likely is it that you will use an e-scooter at some point in the next year? (Choose one)

- Very likely
- Somewhat likely
- Somewhat unlikely
- Very unlikely
- Don't know
- Other (please specify:)

[30] Use Purposes/Scenarios

What was the primary purpose of your most recent trip? (Choose one)

- Transportation to or from work
- Transportation to or from activities
- Transportation to or from school
- Leisure or fun
- Shopping or to run other errands
- Socializing - meeting up with family or friends
- Other (please specify)

[31] Trip Motivation

Thinking about your most recent e-scooter trip, why did you choose to take an e-scooter? (Choose one)

- It was the fastest and most reliable
- It was less expensive than other ways to get there
- Didn't want to get sweaty
- Parking is difficult at that time/destination
- No bus/train at that time/destination
- Don't have a car
- It was just for fun
- Other (please specify below)

[32] Trip Types

What are the top three trip types for which you use shared e-scooters? (Choose up to three)

- Go to or from work
- Go to or from a public transportation stop
- Go to or from school
- Social/entertainment
- Go to or from a restaurant
- Get exercise
- For fun/recreation
- Shopping or errands
- Go to or from a work-related meeting/appointment

- Other (please specify)

[33] Trip Destination

If you work or attend school, what is your work or school zip code?

[34] Use Frequency

How often do you ride e-scooters? (Choose one)

- I've never ridden e-scooters
- I've only ridden once
- Occasionally, but less than once per week
- 1-3x per week
- 3-6x per week
- Daily
- More than 1x per day

[35] Number of Rides

In total, how many rides have you taken on micromobility? (Choose one)

- 1 ride
- 2 rides
- 3 rides
- 4 rides
- 5 or more rides

[36] Frequent Mode

Overall, which mode of transportation do you use most often to get around? (Choose one)

- Driven a personal vehicle, carshare vehicle, or other motor vehicles
- Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person
- Taken a taxi, Uber or Lyft
- Walked
- Taken a bus/other local public transportation options
- Ridden a personal e-scooter
- Ridden the local bike share
- Ridden a personal bike
- Would not have made the trip
- Other (please specify:)

[37] Alternative Mode

How would you complete your trip if a shared e-scooter had not been available in your last trip? (Choose one)

- Driven a personal vehicle, carshare vehicle, or other motor vehicles
- Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person
- Taken a taxi, Uber or Lyft
- Walked
- Taken a bus/other local public transportation options
- Ridden a personal e-scooter
- Ridden the local bike share
- Ridden a personal bike
- Would not have made the trip
- Other (please specify:)

[38] Complementary Mode

For my most recent shared micromobility trip, I also used the following additional transportation (Choose one or more)

- Driven a personal vehicle, carshare vehicle, or other motor vehicles
- Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person
- Taken a taxi, Uber or Lyft
- Walked
- Taken a bus/other local public transportation options
- Ridden a personal e-scooter
- Ridden the local bike share
- Ridden a personal bike
- No other modes involved
- Other (please specify:)

[39] Use Frequency of Other Modes

Indicate your frequency of using the following modes before e-scooters with “X”

	Never	Less than 1x per week	1-3x per week	More than 3x per week	Daily
Driven a personal vehicle, carshare vehicle, or other motor vehicles					
Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person					
Taken a taxi, Uber or Lyft					
Walked					
Taken a bus/other local public transportation options					
Ridden a personal e-scooter					
Ridden the local bike share					
Ridden a personal bike					

Other (please specify:)					
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[40] Frequency in Walking

How often have you walked to get somewhere in the last month? (Choose one)

- Never
- Occasionally, but less than once a week
- 1 to 3 times a week
- 4 to 5 times a week
- More than 5 times a week

[41] Use Frequency Changes of Other Modes

Since first using shared e-scooters, how has your use of the following options changed? Please indicate with "X". (If your behavior hasn't changed or if you never used one of the below options, select "About the same".)

	Less often	About the same	More often
Driven a personal vehicle, carshare vehicle, or other motor vehicles			
Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person			
Taken a taxi, Uber or Lyft			
Walked			
Taken a bus/other local public transportation options			
Ridden a personal e-scooter			
Ridden the local bike share			
Ridden a personal bike			
Other (please specify:)			

[42] Types of Bicycles Ridden

What type(s) of bicycle(s) have you ridden? (Choose one or more)

- Regular, non-electric bicycle (not bike share)
- Electric bicycles/e-bikes (e.g., Jump, personal e-bike)
- Bike share (e.g., Grid, Lime)
- Other (please describe)

[43] Use Frequency Changes in Bike (Share) Use

How has riding an e-scooter changed how often you bike or use a bike share? (Choose one)

- Less often
- About the same
- More often

[44] Use Frequency Changes in Public Transportation Use

How has riding an e-scooter changed how often you use public transportation? (Choose one)

- Less often
- About the same
- More often

[45] Access to Motor Vehicles

Do you have access to a motor vehicle? (Choose your main option)

- Yes, own vehicle
- Yes, through car sharing services
- Yes, through family/friend/roommate
- No vehicle access
- Other (please specify:)

[46] Frequency of Driving

In the average week, how many days do you drive a car? (Choose one)

- I don't drive
- 1 day per week
- 2 or 3 days per week
- 4-6 days per week
- Daily

[47] Changes of Automobile and Other Vehicle Ownership

Have you reduced the number of automobiles you (or your family) own because of e-scooters?
(Choose one)

- Yes
- No
- No, but I've considered it
- N/A, I didn't own an automobile before using e-scooters and currently don't own one
- Other (please specify:)

Safety Questions

[48] Infrastructure Improvements

What infrastructure changes would make you feel safer on or around dockless e-bikes or e-scooters? (Choose one or more)

- Bike lanes separated from motor vehicle traffic with a physical barrier
- Smoother pavement
- Wider bike lanes
- Designated e-scooter parking
- None of the above
- Other (please specify:)

[49] Infrastructure Use Status

When you ride an e-scooter/e-bike where do you tend to ride? (Choose one or more)

- On-street without bike lanes
- On-street but only if there are bicycle facilities (bike lanes, protected bike lanes, greenways, etc.)
- Off-street greenways and trails
- On sidewalks
- Other (please specify)

[50] Infrastructure Use Preferences

Regardless of where you currently ride e-scooters, where would you prefer to ride e-scooters in City X? Please circle your preferences for the following infrastructure from 1 to 5 with 5 as most preferred and 1 as least preferred.

Protected bike lane (image attached):	1	2	3	4	5
Bike lane (image attached):	1	2	3	4	5
Trail (image attached):	1	2	3	4	5
Sidewalk (image attached):	1	2	3	4	5
Shared lane (image attached):	1	2	3	4	5

[51] Infrastructure Use Motivations

If you primarily ride on the sidewalk, please select up to 2 contributing factors.

- I don't know where else to ride
- I don't think about whether I ride on the street or sidewalk
- The sidewalk is more convenient
- The sidewalk offers a smoother ride
- The sidewalk feels safer.
- Other reason (please specify)

[52] Overall Safety Perception

How safe do you generally feel when... (please indicate with "X")

	Very safe	Somewhat safe	Somewhat unsafe	Very unsafe	N/A
Riding an e-scooter					
Walking					
Riding a bike					
Driving					
Skateboarding					
Other (please specify:)					

[53] Occurrence of Crashes, Near Crashes and Injuries (Yes or No)

In regard to scooters (or electric/pedal-assist bicycles) in particular, check all that apply:

- I have been hit or almost hit by a scooter while walking
- I have been hit or almost hit by a scooter while riding a bicycle
- I have been hit or almost hit by a scooter while riding a scooter
- I have been hit or almost hit by a scooter while driving a car
- While riding a scooter, I have hit or almost hit someone walking
- While riding a scooter, I have hit or almost hit someone riding a bicycle
- While riding a scooter, I have hit or almost hit someone riding a scooter
- While riding a scooter, I have hit or almost hit someone driving a car
- I have ridden a scooter while under the influence of drugs and/or alcohol
- None of the above
- Other (please specify:)
- Comments about above choices:

[54] Crash Experience, Occurrence, and Frequency

How many times did you crash or nearly crash while riding an e-scooter? (Choose one)

- Never
- Once
- Twice
- Three or more times

[55] Crash or Near Crash Causes

What happened to cause your first crash or near crash? (Choose one or more)

- I fell off or almost fell off the scooter (without hitting something else)
- I hit or almost hit something above ground (e.g., a pole or curb)
- I hit or almost hit another person
- Another person hit or almost hit me
- The scooter malfunctioned or broke while I was riding
- I was on a wet/slippery surface (e.g., sand, gravel, wet train tracks)
- I hit or almost hit something on the ground (e.g., pothole, cracked pavement)
- Other (please describe)

[56] Additional Crash Causes

Did any of the following contribute to your first crash or near crash? (Choose one or more)

- I was going too fast and lost control
- I was distracted/not paying attention
- I was intoxicated
- Other (please describe)
- None of the above

[57] Incident to Crash

Did the incident result in a crash? (Choose one)

- Yes
- No
- Other (please specify:)

[58] Crash Reporting

Was a crash or injury report filed with any of the following? (Choose one or more)

- Yes, with the city policy
- Yes, with the university police
- Yes, with the e-scooter company
- Yes, with the hospital or clinic I visited
- Yes, with some other entity (please list)
- No
- Other situations (please specify:)

[59] Crash Personnel Involved

In your most recent crash, who else was involved? (Choose one or more)

- No one
- Person in a car
- Person scooting
- Person walking
- Person biking
- Person in a wheelchair or similar device
- Other (please describe)

[60] Crash Party Traveling Mode (Person being Hit or Almost Hit)

How was the person you hit or almost hit traveling? (Choose one)

- Walking/running
- Bicycling
- Riding an e-scooter
- Driving
- Other (please describe)

[61] Crash Party Traveling Mode (Person who Hit you or Almost hit you)

How was the person who hit or almost hit you traveling? (Choose one)

- Walking/running
- Bicycling
- Riding an e-scooter
- Driving
- Other (please describe)

[62] Scooter Malfunction during the Crash/Near Crash

How did the scooter malfunction? (Choose one or more)

- The brakes locked or failed to engage
- The accelerator got stuck
- Part of the scooter physically broke
- The wheels were not steady
- Other (please describe)

[63] Crash-related Injuries (Yes or No)

Were you injured? (Choose one)

- Yes
- No
- Other (please specify:)

[64] Crash-related Injuries (Severity Level)

How serious was the injury? (Choose one)

- Minor - road rash or scrapes
- Major - broken bones or concussion
- Severe - organ damage or other life-altering bodily damage
- Other (please specify:)

[65] Crash-related Injuries (Body Parts)

Which parts of your body were injured? (Choose one or more)

- Head/neck
- Torso/chest
- Hands/wrists/arms
- Feet/ankles/legs
- Hips/back
- Other (please describe)

[66] Hospital or Clinic Visit

Did you go to a hospital or clinic? (Choose one)

- Yes
- No
- Other (please specify:)

[67] Serious Injury Perception

How likely do you think it is that you would ever be seriously injured (e.g., broken bones, head injury) while...(please indicate with "X")

	Very likely	Somewhat likely	Somewhat unlikely	Very unlikely	Don't know
Riding an e-scooter					
Walking					
Riding a bike					
Driving					
Skateboarding					
Other (please specify:)					

[68] Near Crash Experience, Occurrence and Frequency

How often do you have a close call where you almost crash? (Choose one)

- Every trip
- On more than half of my trips
- On less than half of my trips
- On less than 10% of my trips
- Never
- Other (please specify:)

[69] Concerns of being hit when riding an E-scooter

How worried are you about being hit by the following) while riding an e-scooter? Please circle the following scale: very worried (4), somewhat worried (3), not very worries (2), not very at all (1).

Vehicle	4	3	2	1
Other e-scooter rider	4	3	2	1
Bicyclist	4	3	2	1
Skateboarder	4	3	2	1
Person walking/running	4	3	2	1
Other (please specify:)	4	3	2	1

[70] Concerns of hitting others when riding an E-scooter

How worried are you about hitting the following) while riding an e-scooter? Please circle the following scale: very worried (4), somewhat worried (3), not very worries (2), not very at all (1).

Vehicle	4	3	2	1
Other e-scooter rider	4	3	2	1
Bicyclist	4	3	2	1
Skateboarder	4	3	2	1
Person walking/running	4	3	2	1
Other (please specify:)	4	3	2	1

[71] Pedestrian Safety Perceptions towards Shared Micromobility and Other Modes

As a pedestrian in City X, how safe do you feel around riders on the following modes? Please indicate with “X”.

	Very safe	Safe	Neutral	Unsafe	Very unsafe	NA
E-scooters						
Dockless e-bikes						
Bikeshare						
Regular bike						
Other (please specify:)						

[72] Pedestrian Safety Perception towards E-scooters and the Riders

As a pedestrian, how safe do you feel around riders on e-scooters (Choose one)

- Very safe
- Safe
- Neutral
- Unsafe
- Very unsafe
- N/A

[73] Pedestrian Perception towards improper Parking Issues of Shared Micromobility

As a pedestrian, how often do you encounter blocked sidewalks due to shared micromobility being improperly parked? (Choose one)

- Never
- Rarely
- Sometimes
- Often
- Always
- N/A

[74] Pedestrian Perception towards Improper Parking Issues of E-scooters

As a pedestrian in the area, how often do you encounter blocked sidewalks due to e-scooters being improperly parked? (Choose one)

- Never
- Rarely
- Sometimes
- Often
- Always
- NA

[75] Driver Perception towards Improper Parking Issues of Shared Micromobility and Other Modes

As a driver in the area, how comfortable do you feel around riders of the following modes? Please indicate with "X".

	Very comfortable	Comfortable	Neutral	Uncomfortable	Very uncomfortable	NA
Dockless e-bikes						
E-scooters						
Bikeshare						
Regular bike						
Other (please specify:)						

[76] Driver Safety Perception towards E-scooter Riders

As a driver, how safe do you feel around riders on e-scooters? (Choose one)

- Very comfortable
- Comfortable
- Neutral
- Uncomfortable
- Very uncomfortable

- N/A

[77] Improper Parking Impacts

How do improperly parked SMDs impact you? (Choose one or more)

- SMDs block my path
- Safety hazard
- Clutter
- A concern for people with mobility issues
- I just walk around them
- Impacted negatively (general feeling)
- Difficult when SMDs tip over
- Left on private property
- Other (please specify:)
- No impact

[78] Helmet Use

How often do you wear a helmet when riding an e-scooter? (Choose one)

- Never
- Rarely
- Sometimes
- Usually
- Always
- Other (please specify:)

Accessibility Questions

[79] Access to and from Public Transportation

For your most recent trip, did you use the service to get to or from public transportation?
(Choose one)

- Yes
- No
- Other (please specify:)

[80] Frequency of Access to and from Public Transportation

How often do you use e-scooters to access public transportation? (Choose one)

- Never
- Occasionally, but less than once per week
- 1-3x per week
- 3-6x per week
- Daily
- More than 1x day

[81] Access to Shared Micromobility

Thinking of your most recent e-scooter trip, how did you get to the e-scooter that you rode?
(Choose one)

- Driven a personal vehicle, carshare vehicle, or other motor vehicles
- Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person
- Taken a taxi, Uber or Lyft
- Walked
- Taken a bus/other local public transportation options
- Ridden a personal e-scooter
- Ridden the local bike share
- Ridden a personal bike
- Other (please specify:)

Program Evaluation Questions

[82] Impact Evaluation

Thinking about e-scooters in City X: in your opinion, what impact have e-scooters had on.... (please indicate with "X").

	Very positive	Somewhat positive	Neutral	Somewhat negative	Very negative
The image of City X					
Road/sidewalk within City X					
Personal safety (from crime) within City X					
The ease of traveling within City X					
The promotion of active transportation within City X					
The health of the population within City X					
The ease of connecting to public transportation in City X					
The ease of connecting to daily necessities within City X					
Other (please specify:)					

[83] Familiarity with the Program

How familiar are you with shared mobility program? (Choose one)

- Very familiar
- Familiar
- Somewhat familiar
- Not at all familiar
- Other (please specify:)

[84] Familiarity with Particular City Rules

Have you ever noticed "Dismount Zone" signage or markings? (Choose one)

- Yes
- No
- Other (please specify:)

[85] Program Improvement Evaluation

Has the Dockless Vehicle Program improved over the last year? (Choose one)

- Yes
- No
- Other (please specify:)

[86] Program Continuation Feedback

Do you think shared e-scooter companies should continue operating in the area? (Choose one)

- Yes
- No
- Other (please specify:)

[87] Program Suggestions

How could the city improve the program? (Choose one or more)

- Build more connected, safe, and comfortable bike lanes
- Improve maintenance and enforcement of existing bike lanes
- Allow companies to provide more dockless scooters
- Make existing bike lanes safer/more comfortable
- Change street design and/or increase enforcement to slow down cars
- Build designated parking for dockless bikes and scooters
- Require companies to provide more dockless bikes
- Create more PSAs and messaging directed to drivers about safety
- Require companies to provide more adaptive vehicles (vehicles for people with disabilities)

- Create more safety tips for riders
- Other (please specify)

[88] Complaints

Please provide any complaints about the program

[89] Familiarity with the Rules

Which of the following are local laws related to e-scooters? (Select all that apply)

- A valid driver's license is required
- All users must wear a helmet when riding an e-scooter
- E-scooters are not allowed to ride on the sidewalk
- E-scooters are not allowed to ride in the street
- E-scooters are not allowed to ride on the waterfront trails
- E-scooters are not allowed to ride or park in parks
- I don't know what the e-scooter laws are
- None of the above

[90] Sources to learn about the Rules

How did you learn about e-scooter laws? (Choose one or more)

- Through the companies' e-scooter apps
- Community event
- DOT flyer on e-scooter
- On e-scooter vehicle
- Social media
- Google it (or used another search engine)
- Newspaper, blog, magazine, radio/TV news
- From a friend, family member, co-worker
- From an e-scooter representative
- DOT website
- I don't know what the e-scooter laws are
- Other (please specify)

[91] Familiarity with the Device Parking Rules

Do you know where scooters are and are not allowed to be parked? (Choose one)

- Yes
- No
- Other (please specify:)

[92] Parking Improvements

What would encourage proper scooter (or electric/pedal-assist bicycle) parking for you? (Choose one or more)

- More education about how to park properly
- Incentives from operators (i.e. free ride times, etc.)
- Clearly signed or striped and designated parking areas for scooter and bicycles
- Disincentives for parking violations (fees/fines)
- Other (please specify)

[93] Parking Rule Suggestion

Would you like free, designated parking for scooters? (Choose one)

- Yes
- No
- Don't care
- Other (please specify:)

[94] Device Availability Improvements

The city has imposed a cap of scooters for the permit program. Do you think the city should allow... ? (Choose one)

- More scooters than that
- Less scooters than that
- About the same
- Other (please specify:)

[95] Ordinance Suggestions

If you could ask the city to make any improvements for traveling within the area, what would you request? (Choose up to three)

- Allow more e-scooters on campus
- Modify the bike share to include e-bikes
- Create separate spaces for pedestrians (no bikes or e-scooters allowed)
- Create separate spaces for e-scooters (no bikes or pedestrian allowed)
- Create separate spaces for bicyclists (no pedestrian or e-scooters allowed)
- Lower and enforce the speed limit for e-scooters and bikes
- Ban e-scooters from campus
- Ban bicyclists from campus
- Other (please describe:)

[96] Rule Changes to encourage Use

What changes to the rules would encourage you to use the program more often? (Select all that apply)

- Allow more e-scooters
- Create dedicated spaces for e-scooter parking
- Create dedicated spaces for e-scooter riding
- Lower and enforce e-scooter speed
- Ban e-scooters
- Other (please describe:)

[97] Bicycle versus Scooter Rules

Would you like to see the same rules that apply to bicycles apply to electric scooters? (Choose one)

- Yes
- No
- Other (please specify:)

[98] Helmet Requirements

Would you support a law mandating helmet use for riders? (Choose one)

- Yes, for everyone
- Yes, for kids (under age 18) only
- No
- Not sure
- Other (please specify:)

[99] Age Requirements

Would you support a law requiring a certain age for scooter riders? (Choose one)

- Yes (please list age)
- No
- Not sure
- Other (please specify:)

Travel Behaviors and Mode Choice Questions

[100] Overall Experience

Is there anything else you would like to tell us about your experience with dockless bikes or scooters?

[101] Positive Experience

If you had positive experience with the pilot, what contributed to your positive experience?

[102] Enjoyment Level

How much do you enjoy... (please indicate with "X").

	I really enjoy it	I enjoy it somewhat	I don't enjoy it much	I don't enjoy it at all	N/A
Riding an e-scooter					
Walking					
Riding a bike					
Driving					
Skateboarding					
Other (please specify:)					

[103] Negative Experience

Is there anything you don't like about riding e-scooters? (Choose one or more)

- I am happy with my current transportation options/not interested in e-scooters
- They feel unsteady/I worry I will fall off
- They are impractical for longer distances
- They are sometimes broken
- I can't always find one when I need one
- I can't always find one with a charged battery
- I worry the equipment will break or malfunction
- I worry about hitting or being hit by a vehicle, bicyclist, skateboarder, or other e-scooter rider
- I worry about my personal safety (from crime)
- I can't carry much or transport others while riding an e-scooter
- It can be too hot to ride an e-scooter
- It's too complex to rent an e-scooter
- I don't always feel in control when I'm riding
- There are not enough safe places to ride
- Other (please describe)

[104] Device Availability

How often could you find a scooter when you wanted one? (Choose one)

- Almost always
- Most of the time
- About half of the time
- Rarely
- Never
- Other (please specify:)

[105] Customer Service

How would you rate the following brands for customer service? (With 5 the best service and 1 the worst). Please circle your choice.

Provider A	1	2	3	4	5
Provider B	1	2	3	4	5
.....	1	2	3	4	5

[106] Use of Service Provider

Which brands of shared e-scooter/e-bike have you ridden? (Choose one or more)

- Provider A
- Provider B
-

[107] Service Provide Choice Reasons

How do you decide which brand to ride? (Choose one or more)

- Availability of dockless bikes and scooters near me
- Pricing
- Maintenance condition of the available dockless bikes and scooters at the time I am renting
- Quality of app
- I have a weekly subscription or alternative sign-up plan (such as a low-income plan)
- Other (please specify)

[108] Payment and Subscription Plans

Do you have any of the following plans? (Choose one or more)

- Low income
- Cash payment
- Weekly subscription
- Non-smartphone/text to unlock
- None of these

- Other (please specify:)

[109] Use Instructions from Service Providers

Have you received any instructions from the e-scooter operators regarding the following in City X? Please circle your choice.

Parking	Yes	No
User etiquette	Yes	No
Local regulation	Yes	No
Filing a complaint	Yes	No

[110] Service Provider Satisfaction (Riding Experience)

Rate your overall riding experience from the following companies (Please rate each e-scooter feature on a scale of 1 to 4, where 1 is Poor and 4 is Excellent, circle your choice).

Provider A	1	2	3	4
Provider B	1	2	3	4
.....	1	2	3	4

[111] Service Provider Improvement Suggestions

How could the Permit Holders improve the Dockless Vehicle Program? (Choose one or more)

- Provide more vehicles for rent
- Make vehicles available in more neighborhoods
- Better vehicle maintenance
- Reduce rental cost
- Improve vehicle design to make them safer
- Provide more dockless bikes, specifically
- Fix app issues
- Make rental easier without a credit card
- Provide new vehicles which fit my size or physical needs
- Make rental easier without a smartphone
- More responsible customer service
- Have more instructions in the app about learning to ride safely
- Have more safety events
- Other (please specify)

[112] Fleet Maintenance

How would you rate the follow brands for maintenance? (With 5 the best and 1 the worst)
Please circle your choice.

Provider A	1	2	3	4	5
Provider B	1	2	3	4	5
.....	1	2	3	4	5

[113] Changes to Encourage Use or More Use

What changes would encourage you to use e-scooters more often? (Choose one or more)

- More e-scooters available
- E-scooters in surrounding cities
- Lower cost
- E-scooters with seats
- Safer places to ride (e.g. bike lanes or paths separated from vehicles)
- Longer battery life
- Different e-scooter design (e.g. more stable)
- None of these changes would encourage me to use e-scooters more often
- Other (please specify)

[114] Recommendation to a Friend

How likely are you to recommend shared e-scooters to a friend? (Choose one)

- Extremely likely
- Very likely
- Somewhat likely
- Not so likely
- Not at all likely
- Other (please specify:)

[115] General Feedback

Do you have any additional feedback or recommendations regarding the e-scooter program?

Appendix E



Item	Description	Material		Labor		Equipment		Subcontractors		Permits		Safety		Quality		Risk		Sustainability		
		Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code	Quantity	Code
1	Excavation and foundation work	Excavation	1000	Foundation	2000	Excavator	100	Foundation Contractor	1000	Permit	100	Safety	100	Quality	100	Risk	100	Sustainability	100	100
2	Structural steel framing	Steel	5000	Structural Steel	1000	Steel Erection	50	Structural Steel Contractor	5000	Permit	50	Safety	50	Quality	50	Risk	50	Sustainability	50	50
3	Roofing and waterproofing	Roofing	3000	Waterproofing	1500	Roofing Crew	150	Roofing Contractor	3000	Permit	150	Safety	150	Quality	150	Risk	150	Sustainability	150	150
4	Interior wall and ceiling construction	Wall	8000	Ceiling	4000	Interior Crew	400	Interior Contractor	8000	Permit	400	Safety	400	Quality	400	Risk	400	Sustainability	400	400
5	Electrical and plumbing systems	Electrical	2000	Plumbing	1500	Electrical	100	Plumbing	2000	Permit	100	Safety	100	Quality	100	Risk	100	Sustainability	100	100
6	Final finishing and painting	Finishing	6000	Painting	3000	Finishing Crew	300	Finishing Contractor	6000	Permit	300	Safety	300	Quality	300	Risk	300	Sustainability	300	300
7	Site cleanup and final inspection	Cleanup	1000	Inspection	500	Site Crew	50	Inspection	1000	Permit	50	Safety	50	Quality	50	Risk	50	Sustainability	50	50

Activity	Description	Start	End	Duration	Predecessors	Successors	Resources	Cost	Notes
01	Project Initiation	2023-01-01	2023-01-01	1				0	
02	Project Planning	2023-01-02	2023-01-02	1				0	
03	Project Execution	2023-01-03	2023-01-03	1				0	
04	Project Monitoring and Control	2023-01-04	2023-01-04	1				0	
05	Project Closing	2023-01-05	2023-01-05	1				0	
06	Task 1.1	2023-01-06	2023-01-06	1				0	
07	Task 1.2	2023-01-07	2023-01-07	1				0	
08	Task 1.3	2023-01-08	2023-01-08	1				0	
09	Task 1.4	2023-01-09	2023-01-09	1				0	
10	Task 1.5	2023-01-10	2023-01-10	1				0	
11	Task 1.6	2023-01-11	2023-01-11	1				0	
12	Task 1.7	2023-01-12	2023-01-12	1				0	
13	Task 1.8	2023-01-13	2023-01-13	1				0	
14	Task 1.9	2023-01-14	2023-01-14	1				0	
15	Task 1.10	2023-01-15	2023-01-15	1				0	
16	Task 1.11	2023-01-16	2023-01-16	1				0	
17	Task 1.12	2023-01-17	2023-01-17	1				0	
18	Task 1.13	2023-01-18	2023-01-18	1				0	
19	Task 1.14	2023-01-19	2023-01-19	1				0	
20	Task 1.15	2023-01-20	2023-01-20	1				0	
21	Task 1.16	2023-01-21	2023-01-21	1				0	
22	Task 1.17	2023-01-22	2023-01-22	1				0	
23	Task 1.18	2023-01-23	2023-01-23	1				0	
24	Task 1.19	2023-01-24	2023-01-24	1				0	
25	Task 1.20	2023-01-25	2023-01-25	1				0	
26	Task 1.21	2023-01-26	2023-01-26	1				0	
27	Task 1.22	2023-01-27	2023-01-27	1				0	
28	Task 1.23	2023-01-28	2023-01-28	1				0	
29	Task 1.24	2023-01-29	2023-01-29	1				0	
30	Task 1.25	2023-01-30	2023-01-30	1				0	
31	Task 1.26	2023-01-31	2023-01-31	1				0	
32	Task 1.27	2023-02-01	2023-02-01	1				0	
33	Task 1.28	2023-02-02	2023-02-02	1				0	
34	Task 1.29	2023-02-03	2023-02-03	1				0	
35	Task 1.30	2023-02-04	2023-02-04	1				0	
36	Task 1.31	2023-02-05	2023-02-05	1				0	
37	Task 1.32	2023-02-06	2023-02-06	1				0	
38	Task 1.33	2023-02-07	2023-02-07	1				0	
39	Task 1.34	2023-02-08	2023-02-08	1				0	
40	Task 1.35	2023-02-09	2023-02-09	1				0	
41	Task 1.36	2023-02-10	2023-02-10	1				0	
42	Task 1.37	2023-02-11	2023-02-11	1				0	
43	Task 1.38	2023-02-12	2023-02-12	1				0	
44	Task 1.39	2023-02-13	2023-02-13	1				0	
45	Task 1.40	2023-02-14	2023-02-14	1				0	
46	Task 1.41	2023-02-15	2023-02-15	1				0	
47	Task 1.42	2023-02-16	2023-02-16	1				0	
48	Task 1.43	2023-02-17	2023-02-17	1				0	
49	Task 1.44	2023-02-18	2023-02-18	1				0	
50	Task 1.45	2023-02-19	2023-02-19	1				0	
51	Task 1.46	2023-02-20	2023-02-20	1				0	
52	Task 1.47	2023-02-21	2023-02-21	1				0	
53	Task 1.48	2023-02-22	2023-02-22	1				0	
54	Task 1.49	2023-02-23	2023-02-23	1				0	
55	Task 1.50	2023-02-24	2023-02-24	1				0	
56	Task 1.51	2023-02-25	2023-02-25	1				0	
57	Task 1.52	2023-02-26	2023-02-26	1				0	
58	Task 1.53	2023-02-27	2023-02-27	1				0	
59	Task 1.54	2023-02-28	2023-02-28	1				0	
60	Task 1.55	2023-03-01	2023-03-01	1				0	
61	Task 1.56	2023-03-02	2023-03-02	1				0	
62	Task 1.57	2023-03-03	2023-03-03	1				0	
63	Task 1.58	2023-03-04	2023-03-04	1				0	
64	Task 1.59	2023-03-05	2023-03-05	1				0	
65	Task 1.60	2023-03-06	2023-03-06	1				0	
66	Task 1.61	2023-03-07	2023-03-07	1				0	
67	Task 1.62	2023-03-08	2023-03-08	1				0	
68	Task 1.63	2023-03-09	2023-03-09	1				0	
69	Task 1.64	2023-03-10	2023-03-10	1				0	
70	Task 1.65	2023-03-11	2023-03-11	1				0	
71	Task 1.66	2023-03-12	2023-03-12	1				0	
72	Task 1.67	2023-03-13	2023-03-13	1				0	
73	Task 1.68	2023-03-14	2023-03-14	1				0	
74	Task 1.69	2023-03-15	2023-03-15	1				0	
75	Task 1.70	2023-03-16	2023-03-16	1				0	
76	Task 1.71	2023-03-17	2023-03-17	1				0	
77	Task 1.72	2023-03-18	2023-03-18	1				0	
78	Task 1.73	2023-03-19	2023-03-19	1				0	
79	Task 1.74	2023-03-20	2023-03-20	1				0	
80	Task 1.75	2023-03-21	2023-03-21	1				0	
81	Task 1.76	2023-03-22	2023-03-22	1				0	
82	Task 1.77	2023-03-23	2023-03-23	1				0	
83	Task 1.78	2023-03-24	2023-03-24	1				0	
84	Task 1.79	2023-03-25	2023-03-25	1				0	
85	Task 1.80	2023-03-26	2023-03-26	1				0	
86	Task 1.81	2023-03-27	2023-03-27	1				0	
87	Task 1.82	2023-03-28	2023-03-28	1				0	
88	Task 1.83	2023-03-29	2023-03-29	1				0	
89	Task 1.84	2023-03-30	2023-03-30	1				0	
90	Task 1.85	2023-03-31	2023-03-31	1				0	
91	Task 1.86	2023-04-01	2023-04-01	1				0	
92	Task 1.87	2023-04-02	2023-04-02	1				0	
93	Task 1.88	2023-04-03	2023-04-03	1				0	
94	Task 1.89	2023-04-04	2023-04-04	1				0	
95	Task 1.90	2023-04-05	2023-04-05	1				0	
96	Task 1.91	2023-04-06	2023-04-06	1				0	
97	Task 1.92	2023-04-07	2023-04-07	1				0	
98	Task 1.93	2023-04-08	2023-04-08	1				0	
99	Task 1.94	2023-04-09	2023-04-09	1				0	
100	Task 1.95	2023-04-10	2023-04-10	1				0	

Appendix F

Preprint of:

Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology

Nitesh R. Shah, Sameer Aryal, Yi Wen, Christopher R. Cherry

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Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology

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Abstract

Introduction:

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.

Method:

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.

Results:

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.

Conclusions:

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.

Practical Implications:

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.

Keywords: e-scooter, bicycle, PBCAT crash typology, micromobility, safety

1. Introduction

Cities across the world face common transportation issues like traffic congestion, air pollution (Kennedy, Miller, Shalaby, Maclean, & Coleman, 2005), collisions (NHTSA, 2008), and negative impacts on equity and social development (Cao & Zhang, 2015). Micromobility systems have aimed to fill a niche for short trips in cities by providing alternative options to low occupancy travel modes, which aim to reduce the physical and environmental footprint required for moving people quickly over relatively short distances (Maiti, Vinayaga-Sureshkanth, Jadliwala, & Wijewickrama, 2019).

This novel category of transportation modes includes vehicles such as e-scooters, e-bikes, and docked-bikes. In this paper, “e-scooters” refers to the ultra-lightweight, standard width, low-speed electric standing scooters that carry one rider according to the SAE International J3194 standard (SAE International, 2019). The National Association of City Transportation Officials (NACTO) has tracked and published the most definitive aggregate scooter ridership estimates across the U.S. in the past two years. E-scooters have proliferated in many cities of the United States in the last decade: 86 million trips were made with shared e-scooters in 2019, a more than 100% increase in trips compared to 2018 (NACTO, 2020). With e-scooters’ increasing popularity, one of the biggest challenges for decision-makers and transportation planners is to accommodate these emerging modes in the current transportation system.

The current literature lacks the understanding of e-scooter impacts, including safety. 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 of 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 paper.

1.1. 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 & Zubay, 2011; MacAlister & Zubay, 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 lighting, 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 paper 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.

1.2. 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, 2020). 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.

1.3. Research hypothesis

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 hypotheses of this study are as follows:

1. The general crash characteristics of bicycles or e-scooters colliding with a motor vehicle are different from each other.
2. The location as well as maneuver of bicyclists/e-scooter riders and motorists before the crash are different.

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

2. Method

The research hypothesis was evaluated by analyzing e-scooter and bicycle crash records using descriptive analysis and PBCAT crash typology. 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.

2.1. Crash Report Data

We 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, 2020). We 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, we 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 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. Although most reported injuries do not involve a motor vehicle, motor vehicle-involved crashes constitute about 80% of fatal crashes worldwide (Santacreu et al., 2020), emphasizing the importance of focusing on these conflicts to reduce severe injuries or death. The evaluation of such incidents is essential in developing countermeasures that reduce bicycle- and e-scooter-motor vehicle crashes.

We 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, we 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*. We 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, we 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, we 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. We extracted 79 bicycle crashes for the analysis.

We 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*. We also combined the *clear* and *cloudy* value of the weather condition field. Also, we 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.

2.2. 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, we also recorded other variables to compare e-scooter and bicycle crashes.

The framework uses a series of codes that enable comparison between modes (Table 1). 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.

Table 1 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

2.3. 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. We also converted continuous variables, like age and crash distance from home, into bins to further examine the distribution. We 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. We also used a t-test for continuous variables to evaluate the difference in means for e-scooter and bicycle crashes.

3. Results

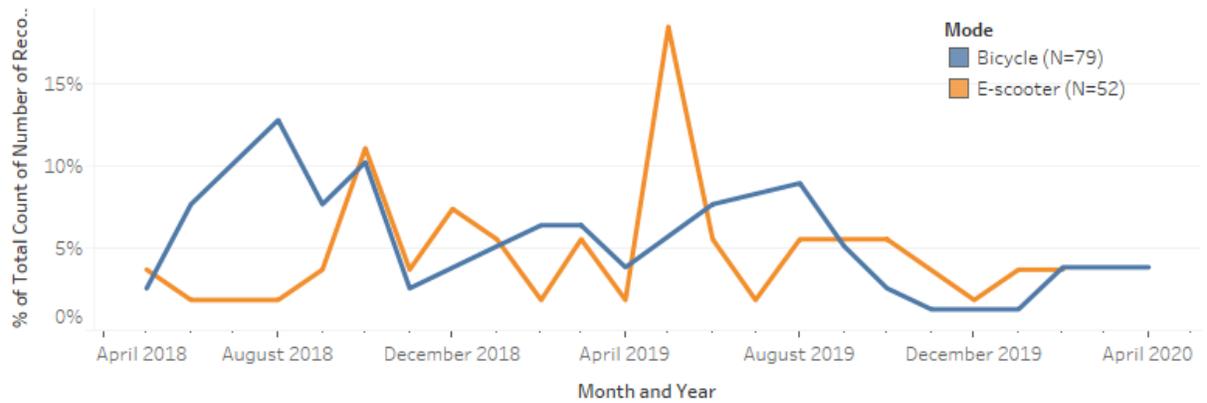
This section summarizes the key findings from the study, which are organized into two sub-section. The descriptive analysis of the crashes is presented in the first sub-section, followed by the crash typology in the next sub-section.

3.1. Descriptive Analysis of Crashes

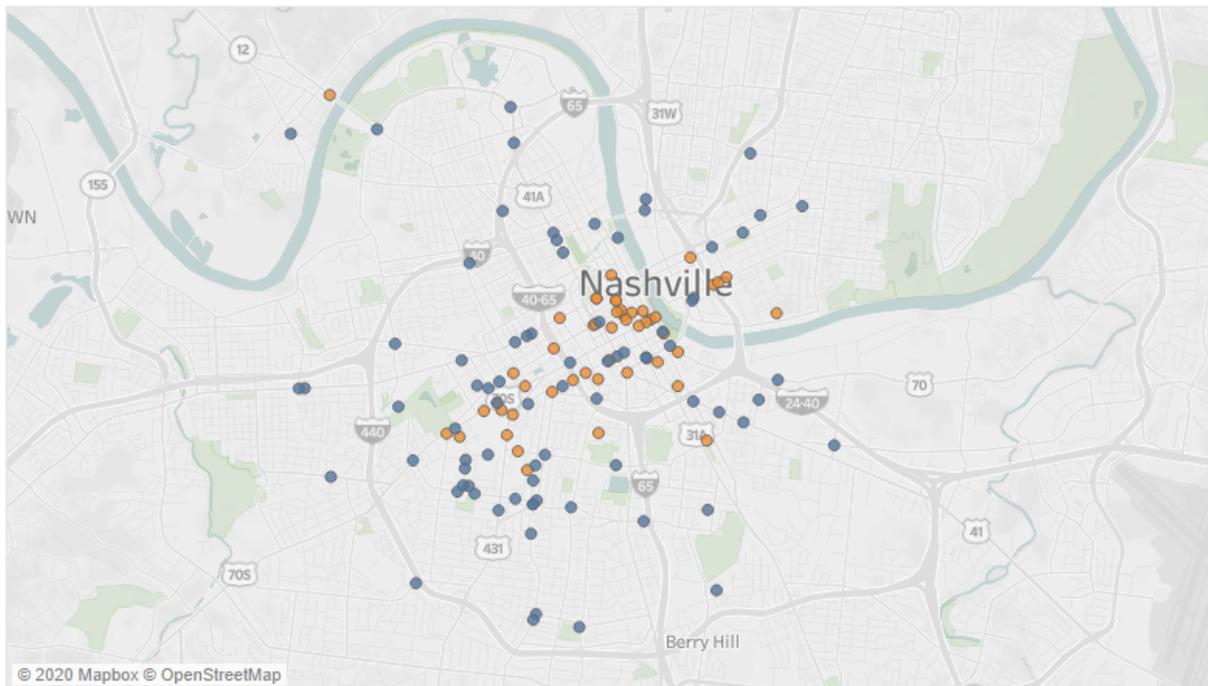
We evaluated the differences in the characteristics of e-scooter and bicycle crashes that are not inherently included in the PBCAT crash typology. This sub-section summarizes the descriptive analysis of such characteristics.

3.1.1. Temporal and Spatial Distribution

Figure 1 (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 1 (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 1 (b) illustrates that the e-scooter crashes were mostly concentrated in the city center of Nashville, whereas the bicycle crashes were more spatially dispersed.



(a)



(b)

Figure 1. Temporal and spatial distribution of bicycle and e-scooter crashes: (a) Temporal distribution, (b) spatial distribution

3.1.2. Crash Characteristics and Demographics

Figure 2 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 2 (a) and Figure 2 (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 2 (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 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). We found only 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). 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. In most of the police reports tests were not administered and the responding officer relied on visual or behavioral cues to assess intoxication, limiting the definitive assessment that scooter riders or drivers were not impaired. 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. We 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 2 (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 2 (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).

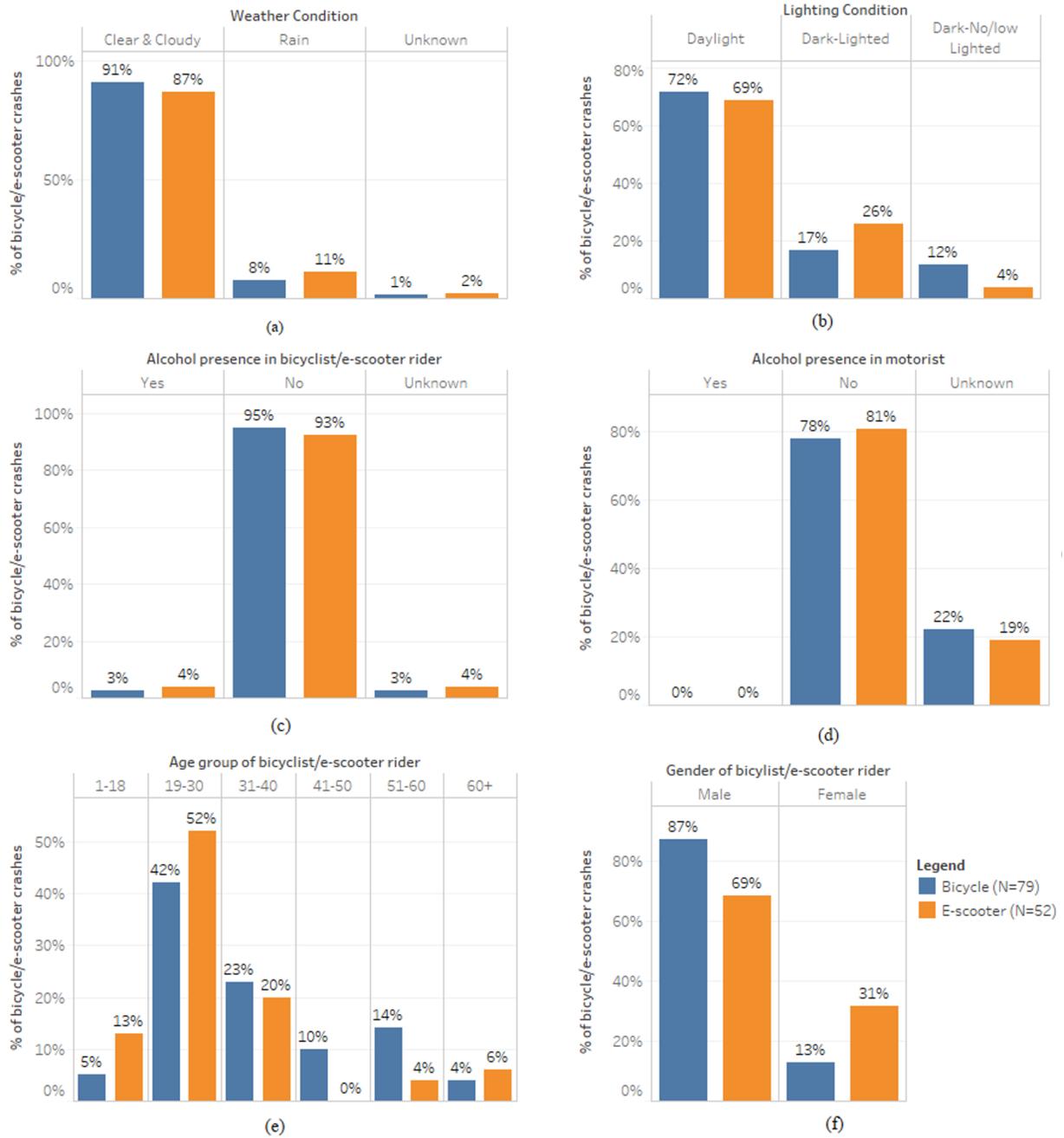
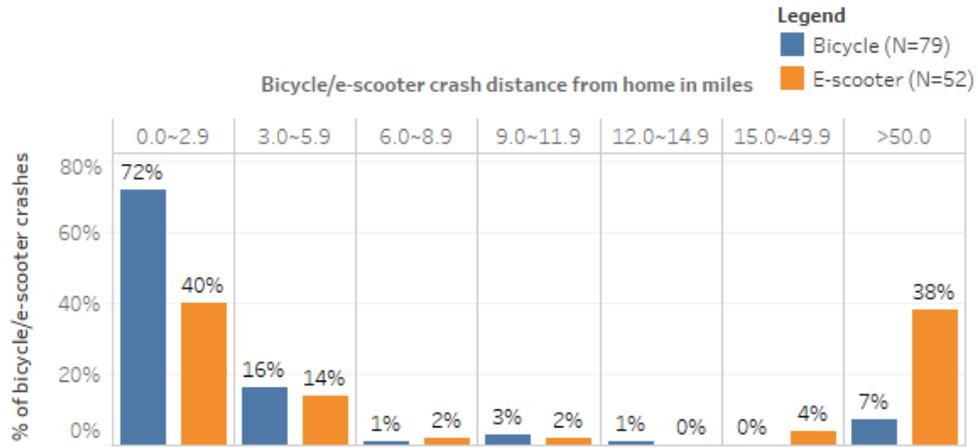


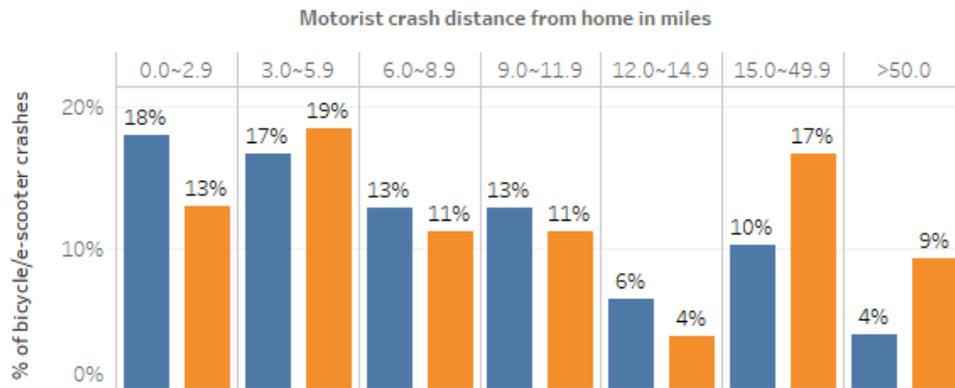
Figure 2. General characteristics of bicycle and e-scooter crashes: (a) weather condition, (b) light condition, (c) bicycle/e-scooter rider intoxication, (d) motorist intoxication, (e) age distribution of bicyclist and e-scooter riders, (f) gender distribution of bicyclist/e-scooter rider

3.1.3. *Crash distance from home*

Figure 3 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 3 (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 3 (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. We did not find a statistical difference in motorist's crash distance crashing with an e-scooter or bicycle (Fisher's Exact test $p\text{-value} = 0.747$). 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.



(a)



(b)

Figure 3. Crash distance from home: (a) bicyclist/e-scooter riders; (b) motorists

3.2. PBCAT Crash Typology

We 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 4 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.

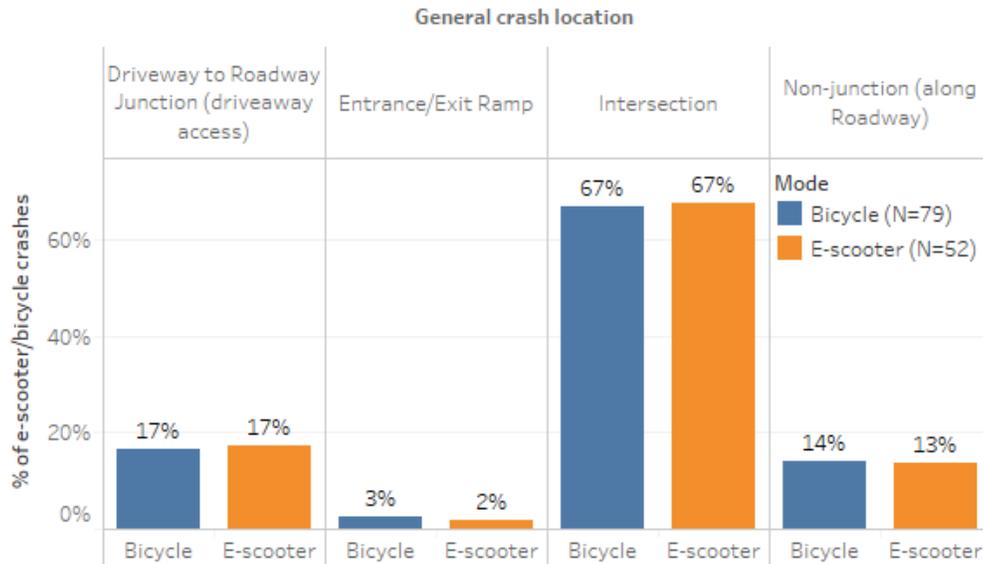


Figure 4. PBCAT typology – location

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

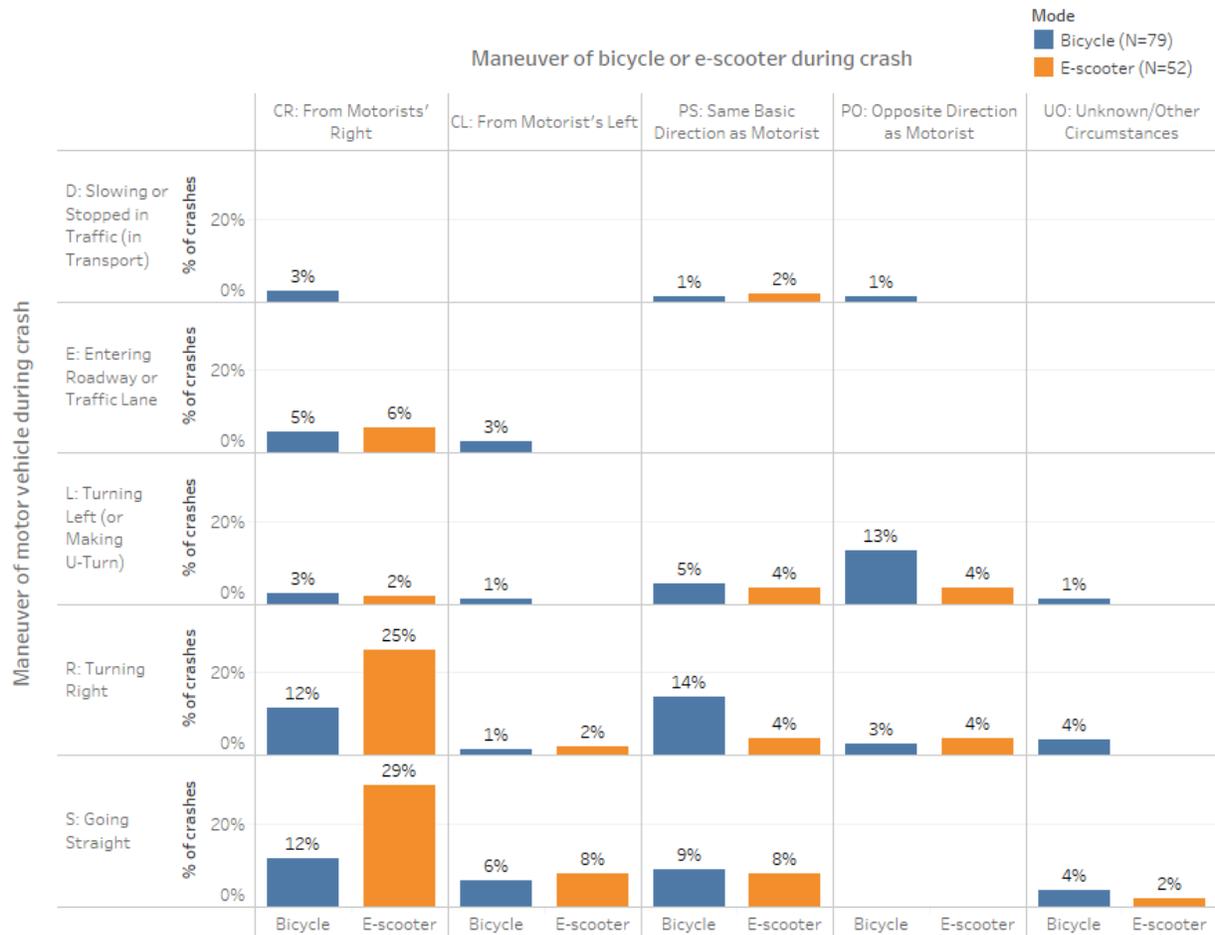


Figure 5. PBCAT typology - maneuver

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 5. 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.

3.2.1. Intersection Crashes

Since more than 60% of the bicycle and e-scooter crashes occurred at an intersection, we 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 2 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*.

Table 2 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

As shown in the table, 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 6 (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 were S-CL, where a motor vehicle was moving straight and an e-scooter collided from the left of the motor vehicle.

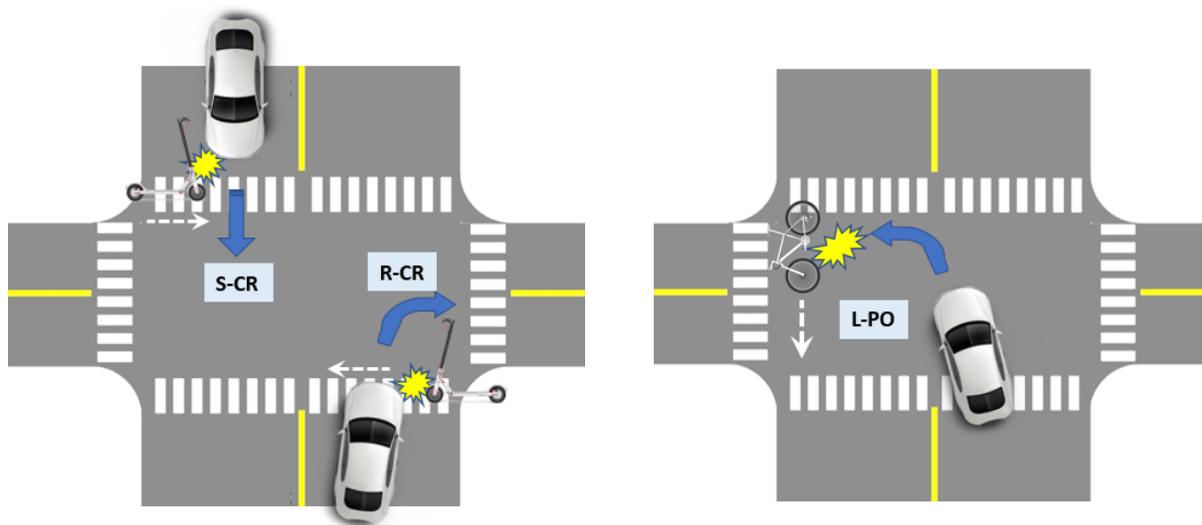


Figure 6. Most common PBCAT crash typology at intersection: (a) e-scooter; (b) bicycle

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 6 (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.

3.2.2. *Severity Levels of Crash Typology*

Approximately 1 in 10 e-scooter- and bicycle-motor vehicle crashes led to a reported 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). We reviewed one bicycle crash 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.

4. Discussion

Based on the findings of bicycle- and e-scooter-motor vehicle crashes in Nashville, Sections 4.1 – 4.4 provide a discussion on the general crash characteristics of bicycles or e-scooters colliding with a motor vehicle. Sections 4.5 and 4.6 emphasize the location and maneuver of bicyclists/e-scooter riders and motorists before the crash, while section 4.7 ends with the limitations of the study and a discussion on future research.

4.1. Temporal and spatial distribution of crash

We 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 (Shah, 2019) 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 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; Shah, 2019). 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.

4.2. 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 (Shah, 2019), 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.

4.3. 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.

We 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.

4.4. 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, 33% 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-scooter riders 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.

4.5. Crash locations

We 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. We 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).

4.6. 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. We 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.

4.7. Limitations of the study 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 city. This study is based on evaluation e-scooter and bicycle crashes with motor vehicles in Nashville, Tennessee. Other cities have different rider and driver norms and behaviors and likely have different policies. Third, we 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.

5. Conclusions

We 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. We 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, we did not find an apparent difference concerning the locations by road type of the crashes. Additionally, we 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.

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