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# Data-Driven Operational and Safety Analysis of Emerging Shared Electric Scooter Systems

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# DATA-DRIVEN OPERATIONAL AND SAFETY ANALYSIS OF EMERGING SHARED ELECTRIC SCOOTER SYSTEMS

by

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# ABSTRACT

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The rapid rise of shared electric scooter (E-Scooter) systems offers many urban areas a new micro-mobility solution. The portable and flexible characteristics have made E-Scooters a competitive mode for short-distance trips. Compared to other modes such as bikes, E-Scooters allow riders to freely ride on different facilities such as streets, sidewalks, and bike lanes. However, sharing lanes with vehicles and other users tends to cause safety issues for riding E-Scooters. Conventional methods are often not applicable for analyzing such safety issues because well-archived historical crash records are not commonly available for emerging E-Scooters.

Perceiving the growth of such a micro-mobility mode, this study aimed to investigate E-Scooter operations and safety by collecting, processing, and mining various unconventional data sources. First, origin-destination (OD) data were collected for E-Scooters to analyze how E-Scooters have been used in urban areas. The key factors that drive users to choose E-Scooters over other options (i.e., shared bikes and taxis) were identified. Concerning user safety tied to the growing usage, we further assessed E-Scooter user guidelines in urban areas in the U.S. Scoring models have been developed for evaluating the adopted guidelines. It was found that the areas with E-Scooter systems have notable disparities in terms of the safety factors considered in the guidelines. Built upon the usage and policy analyses, this study also creatively collected news reports as an alternative data source for E-Scooter safety analysis. Three-year news reports were collected for E-Scooter-involved crashes in the U.S. The identified reports are typical crash events

with great media impact. Many detailed variables such as location, time, riders' information, and crash type were mined. This offers a lens to highlight the macro-level crash issues confronted with E-Scooters. Besides the macro-level safety analysis, we also conducted micro-level analysis of E-Scooter riding risk. An all-in-one mobile sensing system has been developed using the Raspberry Pi platform with multiple sensors including GPS, LiDAR, and motion trackers. Naturalistic riding data such as vibration, speed, and location were collected simultaneously when riding E-Scooters. Such mobile sensing technologies have been shown as an innovative way to help gather valuable data for quantifying riding risk. A demonstration on expanding the mobile sensing technologies was conducted to analyze the impact of wheel size and riding infrastructure on E-Scooter riding experience. The quantitative analysis framework proposed in this study can be further extended for evaluating the quality of road infrastructure, which will be helpful for understanding the readiness of infrastructure for supporting the safe use of micro-mobility systems.

To sum up, this study contributes to the literature in several distinct ways. First, it has developed mode choice models for revealing the use of E-Scooters among other existing competitive modes for connecting urban metro systems. Second, it has systematically assessed existing E-Scooter user guidelines in the U.S. Moreover, it demonstrated the use of surrogate data sources (e.g., news reports) to assist safety studies in cases where there is no available crash data. Last but not least, it developed the mobile sensing system and evaluation framework for enabling naturalistic riding data collection and risk assessment, which helps evaluate riding behavior and infrastructure performance for supporting micro-mobility systems.

This thesis is dedicated to the proposition
that the harder you work, the luckier you get.

# ACKNOWLEDGMENTS

There are many people who have helped me successfully complete this dissertation. I extend many, many thanks to my committee members for their patience and hours of guidance on my research and editing of this manuscript. The untiring efforts of my major advisor deserve special recognition. I also want to thank my family and friends for their support. Hopefully I can continue with my research in the future.

# NOMENCLATURE

| | |
|---|---|
| *AADT* | *Annual Average Daily Traffic* |
| *AAP* | *American Academy of Pediatrics* |
| *BS* | *Bike Sharing* |
| *CBD* | *Central Business District* |
| *ED* | *Emergency Departments* |
| *E-Scooter* | *Electric Scooter* |
| *GPS* | *Global Positioning System* |
| *GWR* | *Geographically Weighted Regression* |
| *IMU* | *Inertial Measurement Unit* |
| *ITL* | *Individual Trip Level* |
| *MDA* | *Mean Decrease Accuracy* |
| *MDG* | *Mean Decrease Gini* |
| *MLR* | *Multinomial Logistic Regression* |
| *NACTO* | *National Association of City Transportation Officials* |
| *NHTS* | *National Household Travel Survey* |
| *OD* | *Origin Destination* |
| *OOB* | *Out of Bag* |
| *PCA* | *Principal Component Analysis* |
| *RUI* | *Riding Under Influence* |
| *SOD* | *Sum of Distance* |
| *VED* | *Vibration Event Density* |
| *VMT* | *Vehicle Mile Travelled* |

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# CHAPTER 1 – INTRODUCTION

## 1.1 RISE OF SHARED ELECTRIC SCOOTERS

Shared mobility systems have developed rapidly in recent years and have greatly changed the urban mobility landscape [1-4]. Like shared bicycles, electric scooters (E-Scooters) also quickly became an emerging form of micro-mobility mode providing flexible options to solve first-/ last-mile travel problems. As reported in the National Household Travel Survey (NHTS), nearly 60 percent of vehicle trips have a traveling distance of fewer than six miles FHWA [5]. The use of E-Scooters to serve short-distance trips has great potential to alleviate traffic congestion by reducing many trips made by vehicles. There are several E-Scooter companies such as Lime, Bird, and Jump started to provide shared E-Scooter rental services in 2017. The shared E-Scooters were accessible to wide spectrums of users and were rapidly spread out towards many urban cities in the United States. As shown in **Figure 1**, E-Scooters have been deployed in many states. Lime and Bird are the two main E-Scooter operators that dominate the market. As of December 2019, the numbers of cities in which Lime and Bird were deployed were 93 and 55 respectively, generating millions of trips. In contrast to the fast-growing trips, some initial deployments of E-Scooters were not strictly regulated by relevant rules or laws in many cities, which led to an emerging epidemic of E-Scooter injuries and fatalities. For example, a video was posted on May 16, 2019 showing recordings at the Mission Beach in San Diego [6]. The video shows numerous E-Scooter incidents that happened during both daytime and nighttime. After seven months of the pilot program, the San Diego City Council banned E-

Scooter operations at Mission Beach on December 16, 2019. Likewise, many other cities also face similar challenges in determining the destiny of their E-Scooter programs.

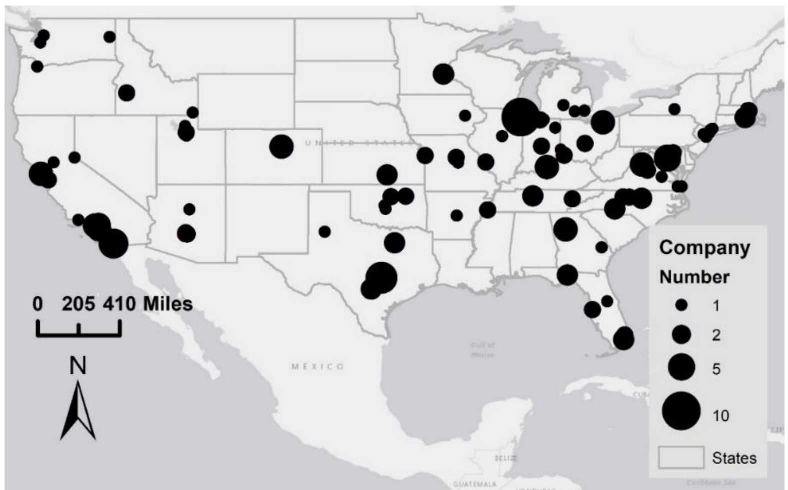



FIGURE 1. MANY CITIES WITH E-SCOOTER SYSTEMS.

## 1.2 DIVERSE POLICIES ON SHARED ELECTRIC SCOOTER GUIDANCE

Lacking crash data, many municipal governments introduced their guidelines/policies for the use of E-Scooters. However, the completeness, readability, and quality of the guidelines vary across cities, which can be controversial and problematic when applying to E-Scooter riders. For example, Arlington, VA allows E-Scooters to be ridden and parked on the sidewalks while neighboring Alexandria, VA prohibits E-Scooters from the sidewalks [7, 8]. This contradictory rule may confuse E-Scooter riders when traveling from one city to another. Moreover, whether riding on the sidewalks should be prohibited needs further analysis since many factors should be considered, such as device management, confliction with other modes, pavement condition, and safety. Despite the paramount importance of the user guidelines/policies, there is no existing research that has extensively examined current practices of E-Scooter policies across the country. A set of questions should be answered about the existing E-Scooter user policies/guidelines:

- What are the current municipal practices of E-Scooter guidelines across the country?
- Are there any unique patterns and differences among existing guideline practices?
- How can cities without E-Scooter guidelines benefit from existing practices?

## 1.3 LACK OF CRASH DATA FOR SHARED ELECTRIC SCOOTERS

When riding E-Scooters in various environments, crashes may occur that involve both E-Scooters and collisions with other users such as pedestrians, bicycles, vehicles, and fixed objects. Unlike vehicle-involved crashes, too few real-world E-Scooter-involved crash data are available. To overcome these issues, researchers attempted to gather indirect data from sources such as hospitals and surveys to probe the safety problems. For example, Beck, et al. [9] analyzed emergency department visit records to examine E-Scooter-involved injuries. They found that most injuries were attributed to vehicles. Meanwhile, 78% of patients were severely injured and required diagnostic radiology tests. Badeau, et al. [10] performed similar investigations with treatment records from two emergency departments. As reported, they found that 44% of incidents occurred on sidewalks, and most cases were minor injuries. Likewise, injury types and riders’ information were also analyzed in other relevant studies [11, 12]. Comparing the findings from these studies, it should be noted that the collision types and severity of injuries treated at emergency departments vary drastically among studies. This should be mainly attributed to the differences of the analyzed datasets. Typically, the emergency department visit data only cover local communities, which can be hardly applied to large-scale analyses. Similarly, the data quality of survey results is often questioned due to the subjective answers and/or biased responses. Therefore, these issues warrant the need for additional data to probe E-Scooter safety issues.

### 1.4 HAZARD RIDING BEHAVIORS FOR SHARED ELECTRIC SCOOTERS

While the policies, regulations, and laws lag behind the technology and practices, some debatable viewpoints can be systematically examined by using cutting-edge technologies. For example, many local authorities are still debating where to operate E-Scooters. Should there be speed regulation on sidewalks? Should riders wear helmets? Can E-Scooters use the vehicular lanes? Can users drink and ride, and so on? Such questions do not have unified answers, and current practices are inconsistent across jurisdictions due to the discrepancy in actions taken by local authorities. On the other hand, unlike motor vehicle facilities that often take a relatively comprehensive process for planning, construction, and operations, almost all existing infrastructures shared by E-Scooters are originally designated for other purposes (e.g., sidewalks for pedestrians and bike lanes for cyclists). Introducing E-Scooters to these facilities undoubtedly causes additional interferences between users, which makes it not only unsafe to E-Scooter riders but also others such as pedestrians and cyclists. For example, most off-the-shelf E-Scooters can have a top speed of 15 – 20 mph, which makes them dangerous roaming on busy sidewalks shared with pedestrians. Meanwhile, due to physical restrictions (e.g., limited width, roughness, etc.), many facilities may not be able to fully support the safe use of E-Scooters, which are often equipped with small wheels. Consequently, due to safety concerns, a number of places have/had banned the use of E-Scooters on certain facilities (e.g., sidewalks in Denver, Singapore, and Paris [13-15]) or in the entire jurisdiction (e.g., Alpharetta, GA and Elizabeth, NJ [16, 17]). The pressing safety risk of using E-Scooters warrants more in-depth investigation to understand the underlying crash mechanisms. Unfortunately, there were too few crash data to enable the probe of E-Scooter safety. Most existing studies [18-20] heavily relied on the injury records maintained by some emergency departments or hospitals. Unlike vehicular crashes that have relatively standard reporting procedures and databases, much smaller numbers of E-Scooter incidents were well documented and accessible for analytics [21, 22]. To understand the riding risk, more data-driven studies are necessary to extend the spectrum of the safety assessment associated with E-Scooters.

### 1.5 THESIS STRUCTURE

The dissertation is organized as follows: Chapter 2 provides the literature review for existing efforts on E-Scooter-related topics including usage, policy, and safety. Specifically, the safety topic will be mainly discussed in terms of (i) data vacuity and (ii) riding behaviors; Chapter 3 presents a mode choice analysis on how E-Scooters have been used in Washington D.C. along with bikes and taxis; Chapter 4 depicts the methods to review and summarize existing practices on E-Scooter guidelines in U.S. cities; Chapter 5 demonstrates a novel workflow to collect and analyze crash data through mining news reports; Chapter 6 designs and develops a portable platform for collecting E-Scooter riding behavior data. Chapter 7 further implements mobile sensing technologies to evaluate the wheel size’s impact on E-Scooter riding behaviors; conclusions regarding the aforementioned analysis on E-Scooters are provided at the end.

# CHAPTER 2 – LITERATURE REVIEW

As introduced in the previous chapter, we are going to focus on major points on E-Scooters including usage, policy, and safety. The literature review is arranged following that order as well.

## 2.1 ELECTRIC SCOOTERS USAGE

The emergence of shared E-Scooters has received growing attention from the research community and urban practitioners. A handful of early studies have attempted to leverage surveys for uncovering the intrinsic motivation of using E-Scooters. Crucial questions on demographics of E-Scooter riders, motivations, and patterns behind E-Scooter usage are frequently explored. For example, a survey by Fitt and Curl [23] of 591 people found that young people (58%), men (56%), and full-time employees (58%) were most likely to use E-Scooters. Besides, Laa and Leth [24] surveyed 166 E-Scooter riders in Vienna, Austria and found that E-Scooters were mainly used as an alternative for walking or public transit. In addition, a survey conducted by Eccarius and Lu [25] summarized previous riding experiences and trip purposes for E-Scooters among 129 student respondents. Their study indicated that the top three reasons for using E-Scooters are that they are environmental-friendly, cost-saving, and convenient. All in all, surveying methods are effective among small groups of respondents, which can be hardly extended to multi-mode analysis with a larger population. Alternatively, data-driven approaches can be applied when trip-related data are available. There are ongoing efforts exploring E-Scooter usage with origin-destination (OD) data. For example, Liu, et al. [26] analyzed the travel patterns and temporal usages of E-Scooters to guide long-term planning and resource allocations. It was noted that only 15% of E-Scooters were used for more than an hour per day. Orr [27] summarized user characteristics such as age, gender, and trip purposes from historical E-Scooter OD data in Portland. The study reported that Portland E-Scooter users are younger, more educated, and more likely to be male compared to the average statistics of the local population. Moreover, [28] examined 5-month OD trips in Austin, TX and found that E-Scooter users tended to ride at a slower speed for recreational purposes compared to when they ride for commuting purposes.

Existing studies with OD data have revealed that E-Scooters are competitive first-/last-mile options for trips between 0.5 to 2 miles according to Smith and Schwieterman [29]. Before the rise of E-Scooters, BS and taxis were two primary options for connecting riders to metro stations. E-Scooters may have disrupted the market by saving riders' walking and waiting time. As indicated by Zhu, et al. [30], E-Scooters were more frequently used between metro stations and campus in Singapore, where students/teachers were the primary riders. However, few studies have analyzed people's first-/last-mile options to metro stations with E-Scooters due to the following difficulties. Firstly, there are few publicly available shared E-Scooter data sets published by vendors/operators to support the study of shared E-Scooters. Many existing studies relied on the limited amount of data published by cities such as Austin [31], Chicago [32], and Washington, D.C. [33]. Some cities (e.g., Washington, D.C.) only publish real-time data instead of historical OD records, which requires more effort in data collection. Secondly, statistical models require well-formatted OD data, data from other modes (e.g., bikes and taxis) may not be simultaneously available for comparative studies.

Since adequate literature is unavailable for this newly emerging mode, previous mode choice research on BS and taxis can be referred. **Table 1** summarizes a few sample studies related to the comparative analysis of mode choices. The first/last mile attribute in the table indicates whether a paper has compared different modes connecting to stations of public transit. We can see that most of them rely on subjective surveys, which are limited by scales. Alternatively, OD data are most frequently used in mode choice analysis when well-formatted OD data are available for different modes. For example, Zhou, et al. [34] adopted a machine learning method using BS and taxi OD trips in Chicago. Distance, time, and speed are variables extracted from OD data and can reveal detailed traveling patterns. However, the method adopted in the study can be hardly extended to distinguishing E-Scooter and BS modes using only the traveling time and speed variables, without considering other variables such as location and land use. The most used method in **Table 1** is Multinomial logistic regression (MNL), which has been used in comparing three or more modes. For example, Ao, et al. [35] applied MNL model to survey data in rural areas in Sichuan, China. After modeling various modes including bikes, cars, and public transit, the result indicated that the mode choices are closely related to the built environments (e.g., bike lane, and pavement) in rural areas. After weighing the pros and cons of existing practices, this study intends to leverage MNL and well-formatted OD data for a comparative study of shared E-Scooter, shared bike, and taxis.

TABLE 1. SUMMARIZED SELECTED LITERATURE ON MODE CHOICE ANALYSIS

| Index | Reference | Mode | Method | Data | First/Last Mile |
|---|---|---|---|---|---|
| 1 | [35] | Bike, Car, Transit | Multinomial Logistic Regression | Survey | No |
| 2 | [36] | Bike, Taxi, Metro | Descriptive Analysis | OD | No |

| | | | | | |
|---|---|---|---|---|---|
| 3 | [37] | E-Scooter, Bike, Taxi, Transit | Nested Logit Model | Survey | No |
| 4 | [38] | Bike, Taxi | Spatial Lag Model | GPS & OD | No |
| 5 | [39] | Walk, Bike, Auto, Transit | Semantic Analysis | Social Media | Yes |
| 6 | [34] | Bike, Taxi | Random Forest Model | OD | No |
| 7 | [40] | Uber, Taxi, Transit | Semi-Compensatory Independent Availability Logit | Survey | No |
| 8 | [41] | Walk, Bike, Transit | Descriptive Analysis | Survey | Yes |
| 9 | [42] | Walk, Bike | Random Parameter Logit Model | Survey | No |
| 10 | [43] | Walk, Transit | Mixed Logit Model | Survey | Yes |
| 11 | [42] | Taxi, Transit | Descriptive Analysis | OD | No |
| 12 | [44] | Walk, Bike, Auto, Transit | Multinomial Logit Model | GPS | No |

## 2.2 ELECTRIC SCOOTER POLICIES

As a new form of micro-mobility mode, the distinct characteristics of E-Scooters have attracted increasing attention from researchers and users. Compared to other modes of transportation, E-Scooters are quite versatile and can be parked in many public right-of-way areas [45]. This feature has made the E-Scooter an alternative to a traditional passenger vehicle for short-distance trips (e.g., 0.5 to 2 miles) [46]. One common feature that is shared by ride-sourcing, bike-sharing, and shared E-Scooter is that smartphone applications can be used to easily access these vehicles. In addition, the use of GPS devices to locate a vehicle makes it very convenient to track the trajectory of each E-Scooter and to provide massive spatiotemporal data associated with user-generated trips. These data offer valuable insights for uncovering E-Scooter operational characteristics (trip distances, trip distributions, temporal patterns, etc.) with data-driven methods, similar to previous research on other shared mobility systems [2]. For example, Liu, et al. [26] analyzed the travel patterns and temporal usages of E-Scooters to guide long-term planning and resource allocations. It was noted that only 15% of E-Scooters were used for more than an hour per day. On the other hand, Caspi, et al. [47] compared weekday/weekend E-

Scooter usages in Austin, TX and found that commuting is not the main use of shared E-Scooter users. Orr, et al. [48] examined various topics on E-Scooter users in Portland, OR, such as age, gender, and trip purposes. It was reported that Portland E-Scooter users were younger than the population, more educated, and more likely to be male. Such findings can help guide the decision-making process regarding deploying E-Scooters in cities by scaling to different demographics.

The rapid expansion of E-Scooter systems across the country is also accompanied by increasing concerns about safety. Numerous E-Scooter-related injuries have been reported by hospitals, as well as being shown by data collected by emergency departments (ED) [22, 49]. For example, Badeau, et al. [10] identified eight E-Scooter-related injuries from June 15-November 15, 2017, and 50 cases from June 15-November 15, 2018, by using the ED records in Salt Lake City. Meanwhile, Beck, et al. [50] reported that no E-Scooter-related injuries occurred in Dunedin, New Zealand in 2018, but there were 55 cases in 2019. These studies suggest that there was a substantial increase in E-Scooter-related trauma after the deployments of E-Scooter programs in many cities worldwide. Similar conclusions were also derived in other research, using ED data [20, 51, 52]. Such data contains detailed information on E-Scooter-related injuries, which can help identify vulnerable riders by identifying characteristics of the victims. Nevertheless, it has also been admitted that there are many limitations to the adoption of ED data. Unlike well-documented vehicle crash data, attributes stored in ED data can vary in different cities. The study conducted by Trivedi, et al. [52] can be hardly scaled to other cities due to the inconsistency of different clinical variables. It should be noted that the small sample size of ED data may also lead to biased findings. For example, as reported by Beck, et al. [50], most injuries were associated with vehicles, and 78% of those involved were severely injured and required diagnostic radiology tests. On the other hand, Badeau, et al. [10] found that the majority of injuries (44%) occurred on sidewalks and, in most cases, were minor injuries only. Inconsistent conclusions were derived from similar analyses of ED data, and the summarized characteristics of E-Scooter-related injuries cannot represent system-wide issues because of the relatively small sample size.

E-Scooter-related injuries can be caused by the risky riding behavior of users. Many cities distributed surveys to solicit feedback on E-Scooter pilot programs and to collect opinions on E-Scooter safety. For example, APH [53] interviewed 125 E-Scooter riders about their safety concerns with regard to their riding experiences. Among the interviewed riders, 50% believed that surface conditions (like a pothole or crack in the pavement) contributed to their injuries, 29% were influenced by consuming an alcoholic beverage before being injured, and 37% reported that excessive scooter speed contributed to their injuries. Moreover, PBOT [54] conducted city-wide surveys of E-Scooter users in Portland. Helmet usage (29%) and unsafe riding on sidewalks (27%) were the two major types of reported safety concerns. The summarized safety concerns will help guide the launch of E-Scooter programs and the design of viable E-Scooter user guidelines.

Despite the growing pilot programs, many cities lack specific policies or regulations for guiding the use of E-Scooters. Such policies and regulations are closely associated with and are essential for the safety of E-Scooter riders. For example, in Auckland, New Zealand, there are no speed restrictions on E-Scooters, which may reach a risky speed of 27km/h [20]. As reported by Sikka, et al. [55], riding an E-Scooter on a sidewalk without regulations may result in injuries to pedestrians as well. Meanwhile, riding on high-speed roadways will put E-Scooter riders in vulnerable situations created by vehicles. Some cities that have developed guidelines may offer valuable references for cities without guidelines. For example, as stated by the City Council in Tempe, AZ, E-Scooters are restricted on roadways, by a speed limit of no more than 25 mph, although they may be ridden on sidewalks [56]. This statement defines where to ride an E-Scooter and will help mitigate conflicts between an E-Scooter rider and a high-speed vehicle. Nevertheless, practices in different cities can vary for a variety of reasons, such as demographic differences, environmental differences, etc. Therefore, investigating current practices in different cities can guide cities and help them learn the best practices of their peers. To the authors' best knowledge, no relevant research has systematically examined E-scooter policies and guidelines in cities in the United States. This study intends to shorten this information gap by analyzing E-Scooter guidelines in many U.S. cities with E-Scooter programs.

## 2.3 ELECTRIC SCOOTER SAFETY – CRASH DATA

Even though the personal owned E-Scooter occurred as early as 2000 provided by Razor [57], vendors providing commercial and public E-Scooters such as Lime did not exist until January 2017. The first launch of a dockless E-Scooter sharing system quickly flooded streets in Santa Monica, California in September 2017. Then, mobility service providers (e.g., Bird, Lyft, Spin, and Lime) rapidly expanded E-Scooter systems in many metropolitan areas in North America and other international markets. The growing popularity of E-Scooters as a micro-mobility option has drawn increasing attention to the research community on various aspects of their use. For instance, based on an exploratory search with the key word "E-Scooter" OR "Electric Scooter" in the topic field of the Web of Science database, 5 relevant publications are found in 2017, followed by 9 studies in 2018 and 27 in 2019. In general, the state of the art regarding E-Scooters mainly focused on the analysis of system operations and characteristics of usage [26, 58]. Archived operational data, such as E-Scooter trips, were often used to perform the descriptive analysis for evaluating the appropriateness of commercial pilot programs. For example, Smith and Schwieterman [58] compared the travel time of E-Scooter trips in Chicago with other travel modes. The results indicate that E-Scooters have higher efficiencies in short-distance trips compared to walking and public transit. Later, Liu, et al. [26] analyzed the travel patterns and temporal usages of E-Scooters to guide long-term planning and resource allocations based on the archived data between September 4th and November 20th 2018 in Indianapolis. It was noted that only 15% of the scooters were used for more than an hour per day. Meanwhile, Orr, et al. [59] examined the E-Scooter relevant topics such as user age, gender distributions, and trip purposes in Portland. Females were found to be less likely to use E-Scooters compared with males, and young people used E-Scooters more frequently compared with elders. Such findings can help guide decision making when planning and operating shared E-Scooter systems in cities with different demographics and scales.

Other than the studies focused on the operations and usage aspects of E-Scooters, the safety issues associated with E-Scooters have also drawn significant attention over the rapid system expansion process. For example, Fitt and Curl [60] conducted a survey of Lime E-Scooter users in New Zealand cities. It showed that over 90% of 536 surveyed E-Scooter users had ridden on footpaths and the concerns about safety topped the list of reasons for not using E-Scooters. Some researchers have conducted surveys or observational studies to explore their impacts. For example, Fessler, et al. [61] conducted an observational study of helmet use among bicyclists and E-Scooter riders in two universities in Los Angeles. Later, Liew, et al. [62] reviewed the medical records of E-Scooter users from 2015 to 2016 at an emergency department in Singapore. It should be noted that only two of the 36 patient cases wore helmets. Such contributing factors (e.g., helmet) significantly affect E-Scooter related injuries but have not been well addressed with widespread consciousness. For example, Allem and Majmundar [21] analyzed 324 posts of Bird's official Instagram account collected from September 22nd, 2017 to November 9th, 2018, and found that posts rarely show E-Scooters being used with protective helmets. Therefore, more comprehensive explorations of such factors and their impacts are suggested to help transportation agencies and E-Scooter vendors to improve riders' safety awareness and reduce crash risks.

In addition to the safety concern among E-Scooter riders, the use of E-Scooters also triggers high safety risks when conflicting with other vulnerable road users (e.g., pedestrians). For example, Sikka, et al. [55] explored the impact of E-Scooter on pedestrian safety. Due to the limit of data, a case study of a sixty-year-old female pedestrian involved in a collision with an E-Scooter was conducted. Pedestrians are found to be prone to severe injuries when hit by an E-Scooter. Meanwhile, James, et al. [45] conducted a descriptive analysis of pedestrians and E-Scooters' view on E-Scooter parking and safety issues. The survey of 181 E-Scooter riders and non-riders in Rosslyn, Virginia revealed divergent responses regarding safety and sidewalk blocking perceptions. The additional observational study showed that 16% of 606 E-Scooters were not well parked while 6% blocked pedestrians. Thus, E-Scooters can expose pedestrians to crashes and the safety interactions between E-Scooters and other road users deserve more exploration.

Unlike vehicle crashes that have been widely studied with (relatively) standardized crash data (reports), the lack of crash data (reports) for E-Scooter-involved crashes (incidents) largely led to the shallowness of current E-Scooter safety analysis. Despite the efforts, early studies are mainly restricted to the use of some hospital reports and emergency department visit records.

Several researchers filtered such data and analyzed E-Scooter relevant injuries. For example, Nellamattathil and Amber [63] identified 54 E-Scooter related injuries from September 1st to December 1st 2018 via a radiology database. Injuries were found to predominantly affect the musculoskeletal system. Meanwhile, according to the examination by Beck, et al. [9] in Dunedin, New Zealand, no E-Scooter related emergency department presentations were identified in 2018, but there were 55 cases in 2019. The changes of E-Scooter-involved injuries before and after the boom of E-Scooter sharing systems reveals the notable safety impact of the growing deployment of E-Scooters worldwide. It should be noted that these studies typically relied on a specific database and are often limited by issues such as small sample size, potential regional differences, and unknown ratio of reported injuries against the total number of actual injuries. Therefore, alternative methods should be resorted to.

Previous studies have used media data for crash information and relevant safety research. Typically, injuries are analyzed through mining relevant news reports. For example, Yankson, et al. [64] conducted content analysis on newspapers in Ghana to complete crash reports with injury information. Goddard, et al. [65] re-wrote news contents of crash reports and analyzed the impact of their format from pedestrians' and drivers' perspectives. The validity of such collected injury data for safety research have been well illustrated. Like some other types of crashes, there exists plentiful news reports on E-Scooter related crashes with valuable injury information such as gender, age, and severity. It should be noted that such crashes reported by the news are typically the ones that have broader social and economic impacts. Reported E-Scooter related crashes, especially fatal injuries, can stimulate the modification of relevant polices and even trigger serious debate on the deployment of E-Scooter programs. For example, E-Scooter operational rules of a city (i.e., Tulsa, OK) were modified after the death of a 5-year-old boy in an E-Scooter involved crash [66]. Meanwhile, the E-Scooter program in Elizabeth City in New Jersey was shut down after the death of a teenaged E-Scooter rider [67]. Such representative news reports provide useful information and thus have the potential to facilitate E-Scooter safety research. However, to the best of our knowledge, no existing study has systematically utilized such data sources to analyze E-Scooter related crashes and their social and economic impacts. Therefore, a comprehensive review of existing E-Scooter crashes and relevant news reports is beneficial for facilitating the understanding of the unique safety problems, offering highlights for practitioners (e.g., transportation agencies and vendors) in deploying E-Scooters and raising safety awareness among the public.

In summary, there exist several issues that warrant further advancement of E-Scooter related safety studies: lack of comprehensive studies on potential contributing factors, the limited publicly available E-Scooter crash data, unclear interactions between E-Scooter riders and other road users, etc. Thus, this study intends to provide a unique analysis of the national E-Scooter safety issues in the United States with extensively collected information from news reports on E-Scooter-involved crashes and to provide some special insights for future E-Scooter deployments regarding their safety.

## 2.4 ELECTRIC SCOOTER SAFETY – RIDING RISK

The emergency of E-Scooters has drawn growing attention from the research community.

**Table** 2 provides a summary of the primary studies covering the following topics: (a) operations and usage; (b) riding behavior; (c) policy and guideline; and (d) safety and injury. Existing research on E-Scooters has made some efforts in providing insights into different aspects of this emerging micro-mobility mode using different data sources. For example, OD data containing summarized trip-based information are often collected by vendors, which provide valuable records to uncover trip characteristics (i.e., spatial distribution, distance, duration, start/end time, etc.) [68]. By summarizing and analyzing such OD data, Liu, et al. [26] revealed that only 15% of E-Scooters were used for more than an hour per day. Safety-related research on E-Scooters mainly rely on data sampled from local ED. Due to the sample size issues, sometimes contradictory findings can be seen among different studies. For example, Beck, et al. [50] reported that most E-Scooter-related injuries were associated with vehicles, and 78% of patients were severely injured and required diagnostic radiology tests. While according to Badeau, et al. [10], the majority type of injuries (44%) occurred on sidewalks and most victims experienced minor injuries. Despite the efforts by Yang, et al. [22] that examined 169 E-Scooter crashes through the mining of multi-year news reports, more safety-related data are needed to better depict various aspects of E-Scooter safety.

Existing studies on E-Scooter riding behavior mainly rely on the analysis of feedback from secondary data sources such as surveys and questionnaires. For instance, James, et al. [45] conducted a travel behavior and safety perception survey among 181 E-Scooter riders and non-riders. This study indicates that partial E-Scooters are parked improperly and may raise safety concerns by taking pedestrians' space while riding on sidewalks. APH [18] interviewed 125 E-Scooter riders about their safety concerns associated with their riding experiences. Among the interviewed riders, 50% believed that surface conditions like a pothole or crack in the pavement contributed to their injuries, 29% were influenced by an alcoholic beverage preceding their injuries, and 37% reported that excessive scooter speed contributed to their injuries. The subjective survey method on exploring riding behaviors is limited by many factors such as sample size, census of the respondents, and targeted groups/communities. As E-Scooters are equipped with a GPS device, the high-resolution trajectory data can be an alternative source for quantifying E-Scooter riding behavior [69]. Like other mobility modes (e.g., taxis, ride-hailing vehicles, shared bikes, etc.), such trajectory data can provide spatiotemporal records during each trip [2]. Based on these data, advanced analysis can be conducted such as route selection, speeding detection, and so on [70-72]. Unlike the OD data, which is available in several cities (e.g., Austin and Portland), few GPS data maintained by the vendors/operators are available to the public due to privacy or other business concerns. Consequently, there are notable gaps in quantitively understanding the riding behavior associated with different types of trips and different riders. Without accessing the massive trip records archived by vendors and systematically documented crash data, alternative data collection efforts will be needed to analyze riding behavior, safety facts, interactions with riding environment, etc.

In particular, earlier studies have shown that infrastructure characteristics will affect the crash risk of vulnerable road users (e.g., bicyclists and E-Scooter riders). For example, Prati, et al. [73] show that infrastructure characteristics such as type of road and type of segments will affect the severity of bicycle crashes. Likewise, Allen-Munley, et al. [74] imply that older pavement is more likely to lead to bicycle crashes with injuries. The mid-pilot report of an E-Scooter rental program in Calgary showed that E-scooter crashes resulted in 33 severe injuries (i.e., injuries serious enough to need an ambulance service) in a summer period and the top causes were speed, losing control, and hitting a pothole or a stationary object such as a pole [75]. Similarly, ten percent of injured E-Scooter riders reported uneven pavement as the reason for their falls [76]. These studies demonstrate the possible safety impact of riding environment on E-Scooter riders. Nevertheless, the quantitative data for describing the impact of riding environment (e.g., physical conditions of the riding facilities) are scarce. This motivates us to explore the safety issues associated with E-Scooters through the analysis of surrogate data gathered in this study.

TABLE 2. SUMMARY OF THE MAJOR STUDIES ON E-SCOOTER SYSTEMS

| Index | Reference | Topic | Method | Data | Sample Size & Location |
|---|---|---|---|---|---|
| 1 | Ao, et al. [35] | Usage | Spatial Analysis | 8-month OD | 2,430,806 trips (Austin, TX) |
| 2 | Zou, et al. [77] | Usage | Spatial Analysis | 5-week OD | 138,362 trips (Washington, D.C.) |
| 3 | Almannaa, et al. [78] | Usage | Descriptive Analysis | 6-month OD | 15,400 E-Scooters (Austin, TX) |
| 4 | Caspi, et al. [47] | Usage | Spatial Analysis (GWR) | 1-year OD | 11,358 trips per day (Austin, TX) |
| 5 | Jiao and Bai [79] | Usage | Spatial Analysis (Moran's I) | 11-month OD | 158,208 trips per month (Austin, TX) |
| 6 | Liu, et al. [26] | Usage | Descriptive Analysis | 3-month OD from two companies | 425,000 trips (City of Indianapolis) |
| 7 | Smith and Schwieterman [46] | Usage | Mode-Choice Analysis | Simulated OD | 10,000 trips per study area (Chicago, IL) |
| 8 | James, et al. [45] | Behavior | Survey & Questionnaire | Survey responses | 181 E-Scooter riders and non-riders (Washington, D.C.) |
| 9 | Todd, et al. [80] | Behavior | Descriptive Analysis | 3-month videos | 171 E-Scooters (Los Angeles & Santa Monica, CA) |
| 10 | Riggs and Kawashima [81] | Policies | Mannual | Mannual collections | 61 cities |
| 11 | de Bortoli and Christoforou [82] | Policies | Survey & Questionnaire | Survey responses | 445 responses (Paris, France) |
| 12 | Yang, et al. [22] | Safety | Descriptive Analysis | 3-year news reports on crashes | 169 news on E-Scooter-involved crashes |
| 13 | Bekhit, et al. [19] | Safety | Descriptive Analysis | 7-month ED | 770 patients (Auckland, New Zealand) |
| 14 | APH [18] | Safety | Descriptive Analysis | 3-month ED | 271 E-Scooter-related injuries (Austin, TX) |
| 15 | Sikka, et al. [55] | Safety | Descriptive Analysis | ED based on literature | Synthesis of literature |

| | | | | | |
|---|---|---|---|---|---|
| 16 | Allem and Majmundar [21] | Safety | Descriptive Analysis | 414-day Bird's Instagram posts | 324 posts |
| 17 | Mayhew and Bergin [20] | Safety | Descriptive Analysis | 4-month ED cases | 63 patients (Auckland City, New Zealand) |
| 18 | Schlaff, et al. [83] | Safety | Descriptive Analysis | ED | 5 patients (Washington, D.C.) |
| 19 | Badeau, et al. [10] | Safety | Descriptive Analysis | 10-month ED | 58 patients (Salt Lake City, UT) |
| 20 | Beck, et al. [50] | Safety | Descriptive Analysis | 2-year ED | 55 patients (Dunedin, New Zealand) |

# CHAPTER 3 – E-SCOOTER USAGE: CONNECTING URBAN METRO SYSTEMS

## 3.1 INTRODUCTION

The shared electric scooter (E-Scooter) systems have been rapidly adopted in many urban areas. Their focuses on short-distance travel have made E-Scooters a competitive option for the first-/last-mile problems. Compared to the formerly dominant modes of bikesharing (BS) and taxi, the portable and dockless characteristics of E-Scooters are favored by a large group of riders. However, its role in connecting to metro stations is still understudied. The lack of published data from vendors further prevents it from being compared with different modes of transport. The goal of this study is to develop mode-choice models that compare the use of E-Scooter, BS, and taxi modes in connecting to metro stations. Rather than focusing on surveying a small portion of the population, this study uses OD data extracted through the APIs provided by vendors. Then, To-Metro and From-Metro trips were defined based on spatial relationships. The formatted data were further analyzed with selected contextual data (e.g., land use, demographic, transportation) using multinomial logistic regression models to study how the mode choice varies within the context. The modeling results enrich our understanding of in what scenarios E-Scooters are preferred compared to shared bikes and taxis.

## 3.2 DATA PREPARATION

### 3.2.1 OD DATA FOR E-SCOOTER, BIKE SHARING, AND TAXI DATA

OD data have been widely used for analyzing urban mobility in many relevant studies. Many cities require vendor companies to publish their monthly OD data through public APIs.

For example, Lime is one of the predominant E-Scooter vendors whose data can be accessed through the dockless APIs hosted by DDOT [84]. The real-time locations for all parked E-Scooters are provided along with other attributes such as timestamps and ID. One E-Scooter's daily activities can be tracked by querying the API continuously with the same ID. As an example shown in **Figure 2**, an E-Scooter (plate: 349535) was parked at location A from 11:35:05 to 11:48:25 and then parked at location B from 12:13:25 to 13:11:55. The vacant time period from 11:48:25 to 12:13:25 belongs to a trip that moved the E-Scooter from location A to B. Trip duration is defined as the length of the vacant time and the Euclidean distance from point A to B is calculated as the trip distance. In that way, OD trips with attributes can be derived from E-Scooter parking data as reported by the real-time APIs. In October 2018, there were three major E-Scooter vendor companies: Lime, Bird, and Jump. Each company has a similar maximum number of E-Scooters distributed in Washington, D.C. Lime joined the market first on March 13, 2018, followed by Bird on March 28, 2018 and Jump on April 9, 2018. This study analyzed Lime data as the representative of E-Scooter mode.

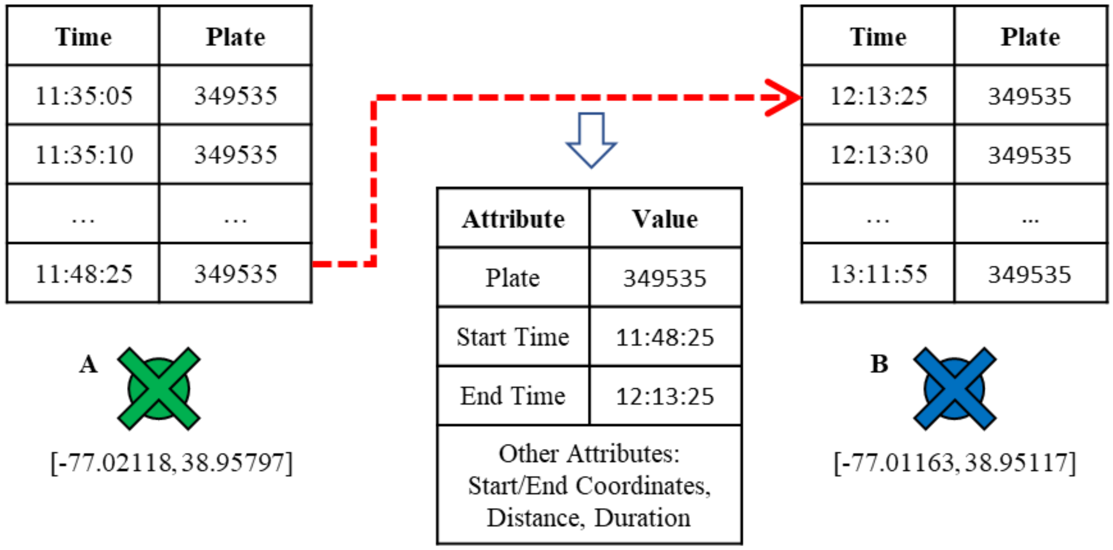



FIGURE 2. AN EXAMPLE OF TRIP FORMULATION.

Along with the processed E-Scooter OD data, BS data, and taxi OD data can be also downloaded separately from Capital Bikeshare [85] and Open Data DC [86]. To examine how these modes connect to metro stations, buffer rings are generated for each metro station downloaded from WMATA [87]. As shown in **Figure 3**, there are three categories of rings: (1) within 100 meters range, (2) 100~200 meters range, and (3) 200~300 meters range. The start and end points of each OD trip are joined spatially with the rings. Then the “To-Metro” and “From-Metro” trips are defined based on the spatial relationships as illustrated in the figure: (i) To-Metro trips are originated from outside metro rings and destinated in metro rings; (ii) From-Metro trips are originated from metro rings and destinated outside metro rings. In addition, since the weekday and weekend have different commuting patterns and we are interested in analyzing weekday patterns, only weekday data are extracted and analyzed in this study.

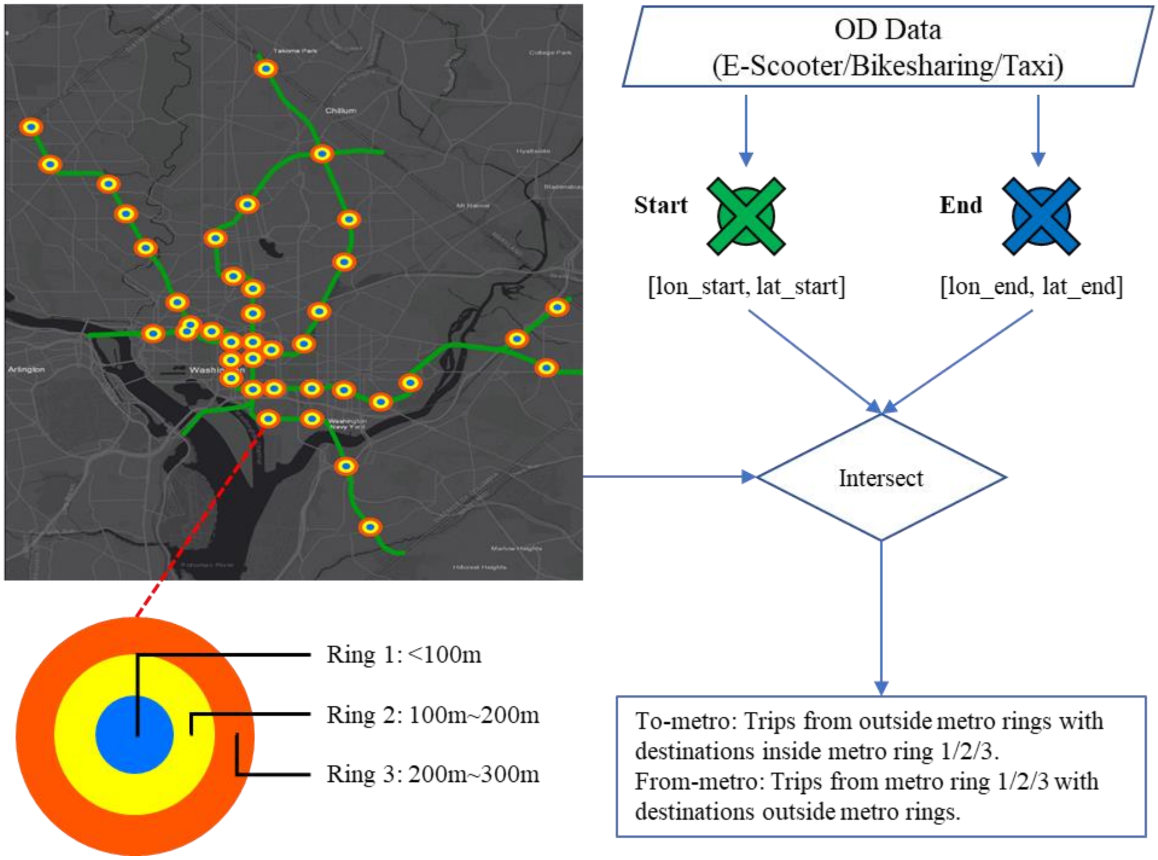



FIGURE 3. LINKING OD DATA TO METRO BUFFERS.

### 3.2.2 DESCRIPTIVE ANALYSIS OF TRIP DISTANCE

After filtering and extracting OD trips for To-Metro and From-Metro scenarios, their trip duration and trip distance attributes were calculated. It should be noted that the two variables are highly correlated. As the trip duration is less reliable and can be affected by the traffic, trip distance was selected as the candidate variable. **Figure 4** (a) and (b) show the density plots of trip distances for each mode. It can be observed that To-Metro and From-Metro share similar patterns that the E-Scooter and BS modes have shorter mean distances compared to the taxi mode. Considering that the first/last mile trips are short/median in distances, the trip distances are further categorized as (1) short (<1km); (2) median (1~2km); and (3) long (2~3km). Their proportional distributions are shown in **Figure 4** (c) and (d). We can clearly observe that more than three quarters of E-Scooter trips are fewer than 2 km; BS trips are quite balanced among the three categories; and long trips (2~3km) are the predominant type for the taxi mode.

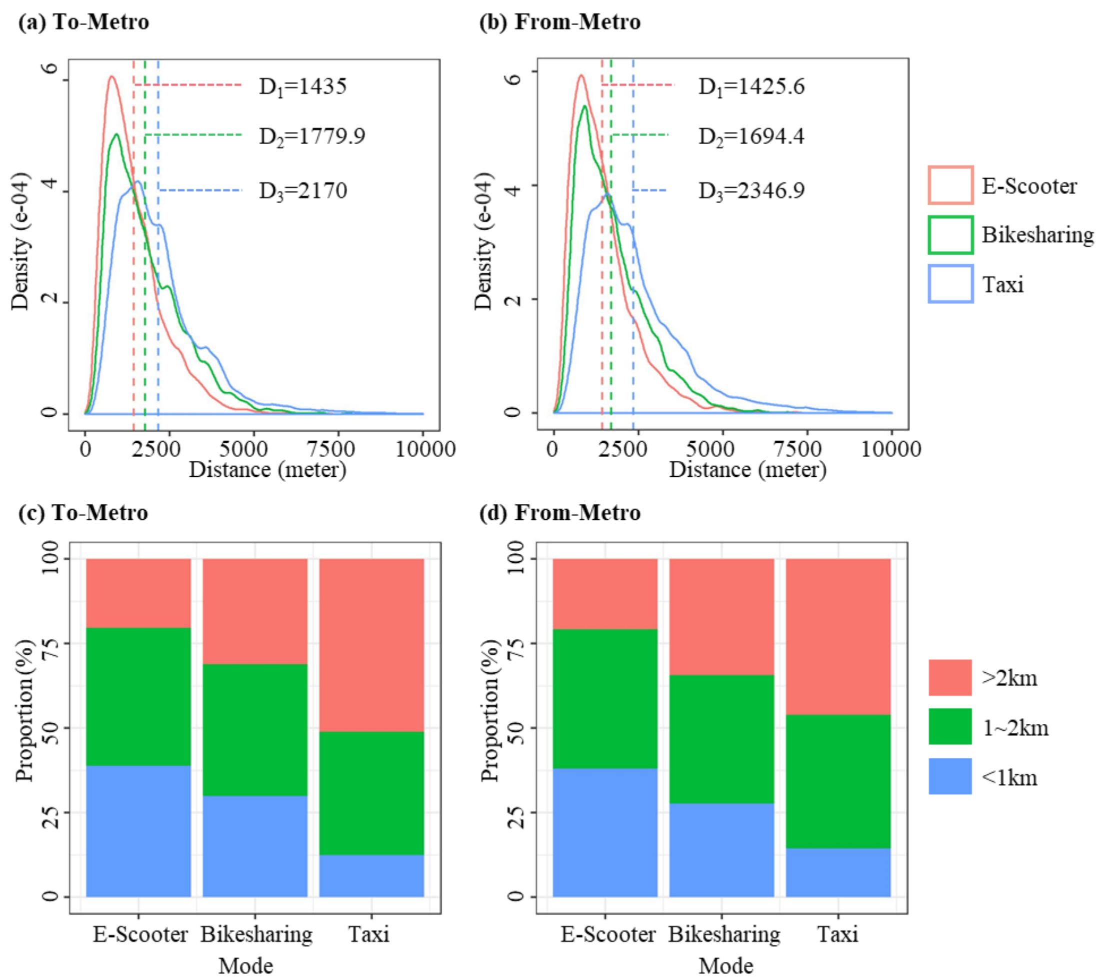



FIGURE 4. DENSITY PLOTS AND PROPORTIONAL DISTRIBUTIONS FOR TRIP DISTANCE.

### 3.2.3 GIS DATA

Limtanakool, et al. [88] states that the mode choices can be sensitive to land use data, which are closely related to the trip purposes. For example, a trip that starts/ends from school zones is likely to be related to the education purpose; a trip that starts/ends from a hospital can be associated with the medical demand. Considering the possible relationships with E-Scooters, the typical land use categories shown in **Figure 5** (a) are extracted from Open Data DC [89], which include (a) Park, (b) School, (c) Hospital, (d) Institution, and (e) Residential. As a trip can be associated with multiple types of land use, a 30-meter buffer is added to each type of land use. For example, **Figure 5** (b) shows a trip from point A to a metro station (point B). Point A is located in the overlapping areas of institution and park land use types. Both park and institution attributes are counted as “True” for this exemplar trip.

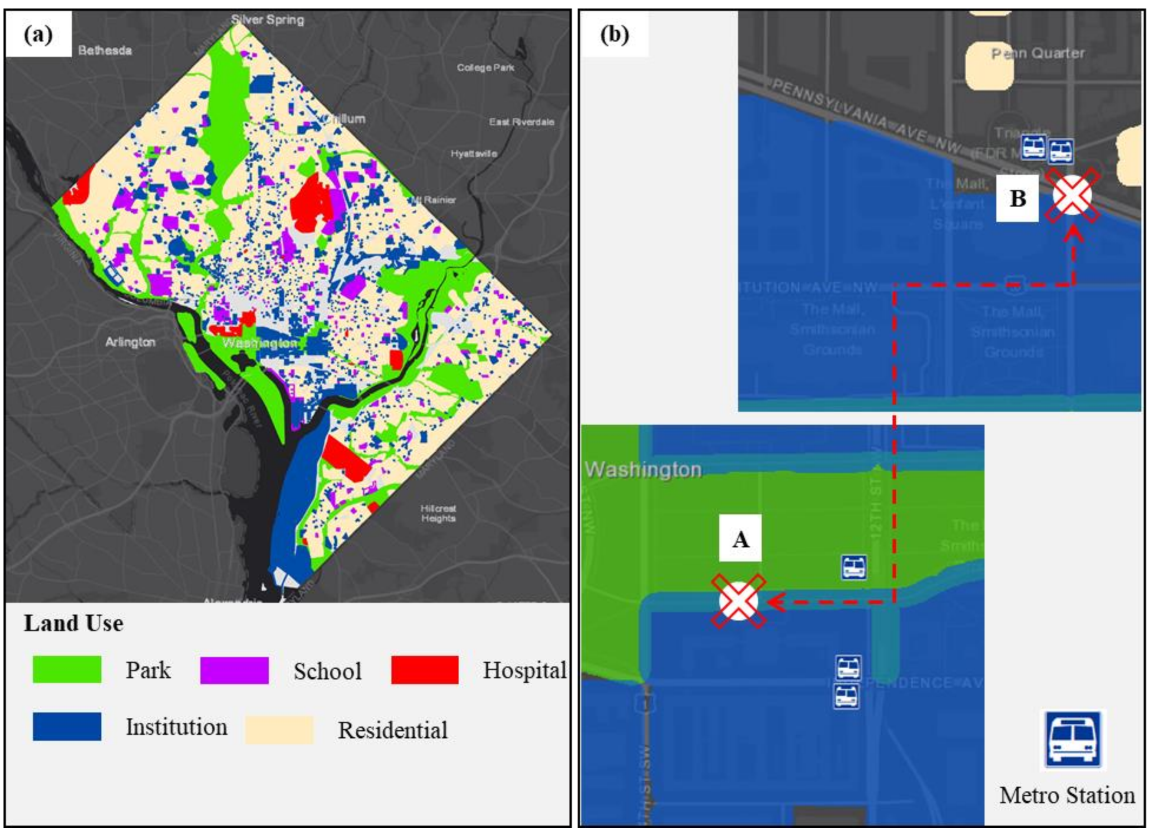



FIGURE 5. MAPS FOR LAND USE AND OTHER GIS DATA.

Besides the land use data, more GIS data are also prepared for the analysis. Restaurant data were downloaded and extracted from Open Street Map [90]. If a trip's O/D is located within 100 meters of a restaurant, its restaurant attribute will be counted as "True". Several other variables associated with census tracts are also included. This includes median household income [91], population [91], and Vehicle Mile Travelled (VMT). The VMT data for each census tract were calculated by aggregating the Annual Average Daily Traffic (AADT) in 2018 using the following equation.

$$VMT_j = \sum_{i=1}^{N_j} AADT_i \times Length_i \tag{1}$$

where, the $j^{th}$ census tract has $N_j$ road segments whose AADT values were aggregated by the length of each segment. It represents the intensity of activities for that census tract.

### 3.2.4 DESCRIPTIVE SUMMARY OF THE VARIABLES

The selected trips are between 6am and 8pm on weekdays from Monday to Friday. All trip durations are between 5 to 30 minutes and distances are between 0.3 to 3 kms. In total, 80,704 To-Metro trips and 79,300 From-Metro trips are used in our analysis. The descriptive statistics of the candidate variables are shown in **Table 3**.

TABLE 3. SUMMARY STATISTICS OF THE VARIABLES

| Trip Variables | Type | To-Metro | From-Metro |
|---|---|---|---|
| Mode | C | Scooter: 6,858; BS: 33,322; Taxi: 40,524 | Scooter: 6,751; BS: 31,639; Taxi: 40,910 |
| Duration (min) | N | Min: 5; Max: 30; Mean: 10.9; SD: 4.8 | Min: 5; Max: 30; Mean: 11.0; SD: 5.0 |
| Distance (km) | N | Min: 0.3; Max: 3; Mean: 1.7; SD: 0.6 | Min: 0.3; Max: 3; Mean: 1.7; SD: 0.6 |

| | | | |
|---|---|---|---|
| Time Period | C | Morning: 15,562; Middle Day: 32,620; Afternoon: 32,522 | Morning: 8,157; Middle Day: 30,527; Afternoon: 40,616 |
| Hospital (O/D) | C | 0: 77,340; 1: 3,364 | 0: 75,336; 1: 3,964 |
| Restaurant (O/D) | C | 0: 76,917; 1: 3,787 | 0: 75,189; 1: 4,111 |
| School (O/D) | C | 0: 75,635; 1: 5,069 | 0: 73,608; 1: 5,692 |
| Park (O/D) | C | 0: 72,162; 1: 8,542 | 0: 70,000; 1: 9,300 |
| Institution (O/D) | C | 0: 63,542; 1: 17,162 | 0: 61,992; 1: 17,308 |
| Resident (O/D) | C | 0: 61,800; 1: 18,904 | 0: 59,871; 1: 19,429 |
| Metro Ring | C | <100m: 30,190; 100~200m: 28,486; 200~300m: 22,028 | <100m: 25,206; 100~200m: 25,892; 200~300m: 28,202 |
| **Env. Variables** | **Type** | | |
| Population (O/D) | N | Min: 60; Max: 7,805; Mean: 3,519; SD: 1,405.9 | |
| Income (O/D) | N | Min: 13,750; Max: 250,001; Mean: 84,375; SD: 46,242.1 | |
| VKT (O/D) | N | Min: 8,249.2; Max: 3,874,473; Mean: 81,624.6; SD: 347,581.6 | |

Note: O/D represents origins for all To-Metro variables; and destinations for all From-Metro variables. C indicates categorical; N indicates numeric.

## 3.3 METHODOLOGY

### 3.3.1 SPATIAL ANALYSIS

Autocorrelation is frequently tested as the first step in examining spatial patterns in many relevant studies [1, 92]. Global Moran's I test and Local Indicators of Spatial Association (LISA) test were applied to measure the spatial autocorrelation for the origins of the To-Metro trips and the destinations of From-Metro trips.

Global Moran's I test [93] is widely applied to measure how the values of a variable are related to their nearby values, whose value can be calculated as the summation of LISA cross products [94]. LISA is often used to capture local patterns with detailed information. The local Moran's I for the $i^{th}$ entity is calculated using the following equation.

$$I_i = \frac{Z_i}{\left(\frac{\sum_i Z_i^2}{N}\right)} \sum_j W_{ij} Z_j \tag{2}$$

where, $Z_i$, $Z_j$ are the observations for the $i^{th}$ and $j^{th}$ entities. $N$ is the total number of spatial entities. The weight matrix $W_{ij}$ is used for determining the spatial relationship (1: neighbored; 0: not neighbored). In this study, census tracts are used as the spatial entities.

### 3.3.2 VARIABLE SELECTION USING RANDOM FOREST

Identifying relevant variables is the first and foremost step towards building a reliable model. Among the many variable selection methods, feature importance measures associated with the random forest model have proven to be robust in reducing dimensionality. In this study, we used two measures calculated from the random forest package in R to select important features, the Mean Decrease Accuracy (MDA) and the Mean Decrease Gini (MDG) (Hong Han et al., 2016; Louppe et al., 2013).

MDA is calculated by utilizing the out-of-bag (OOB) error of random forest. The value of a target variable is randomly permuted in out-of-bag samples, and the OOB error is calculated separately using original feature values and permutated feature values. The difference between the two OOB errors represents the decrease in accuracy when the target variable is randomized. If the target variable is important, randomizing the variable will result in a large decrease in accuracy. The differences between the two OOB errors are averaged across all trees and normalized by the standard deviation of the differences to represent the overall importance of a variable. The importance of a variable $x_j$ in tree $t$ is calculated using the following equation [95]:

$$VI^{(t)}(x_j) = \frac{\sum_{i \in OOB} I(y_i = f(x_i)) - \sum_{i \in OOB} I(y_i = f(x_i^j))}{|OOB|} \tag{3}$$

where $f(x_i)$ is the predicted class for observation $i$ before permuting the values of the variable $x_j$, and $f(x_i^j)$ is the predicted class for observation $i$ after the permutation. OOB is the out-of-bag sample for a tree $t$ where $t \in \{1, 2, 3, ..., n_{tree}\}$. The overall normalized importance of a variable across all trees is calculated using the equation $VI^{(t)}(x_j) = \frac{\mu(x_j)}{\sigma(x_j)}$, where $\mu(x_j)$ and $\sigma(x_j)$ are the mean and standard deviation values of $VI^{(t)}(x_j), t \in \{1, 2, 3, ..., n_{tree}\}$.

Mean Decrease Gini quantifies how much a variable can reduce the node impurity averaged across all trees in a random forest. If a variable significantly decreases the impurity of a node at a split, the feature is considered as important. The MDG index is calculated using the following equation [96].

$$VI(x_j) = \frac{1}{n_{tree}} \left[ 1 - \sum_{k=1}^{n_{tree}} Gini(j)^k \right] \tag{4}$$

To account for both the OOB error and the node impurity, we used the sum of both values (i.e., MDA + MDG) to represent the variable importance (Hong Han et al., 2016). A larger value of the sum indicates that a variable is more important.

### 3.3.3 MULTINOMIAL LOGISTIC REGRESSION MODEL

In an urban transportation system, travelers have multiple options for their last-mile problems before/after taking metro lines. Among these options, E-Scooter, E-Bike, and taxi are three frequently used modes post the emergency of various shared mobility solutions. Users may have different preferences due to various considerations such as trip purpose, price, speed, etc. To further understand possible relationships of such preferences, MNL regression models are applied in this study. Such models [97] have been frequently used to estimate odds ratios for mode choices of a trip associated with different attributes. The model can be expressed as follows:

$$\ln\left(\frac{\Pr(M=1)}{\Pr(M=3)}\right)=\beta_{1,0}+\sum_{p=1}^{P}\beta_{1,p}X_{1,p} \tag{5}$$

$$\ln\left(\frac{\Pr(M=2)}{\Pr(M=3)}\right)=\beta_{2,0}+\sum_{p=1}^{P}\beta_{2,p}X_{2,p} \tag{6}$$

where, $\Pr(M)$ is the probability of mode $M$ (1: E-Scooter; 2: BS; 3: taxi). $\beta_{mpc}$ is the coefficient of the mode $m$, $p^{th}$ parameter ( $p \in (1:P)$ ), and $c^{th}$ category ( $c \in (1:C)$ ). $X_{mpc}$ represents the corresponding individual trip level (ITL) explanatory variables. This model was implemented for both E-Scooter and BS modes compared to the taxi mode. Specifically, their performances on connecting to metro stations were estimated and compared.

## 3.4 RESULTS

### 3.4.1 SPATIAL AUTOCORRELATION EXAMINATION

The spatial analysis software GeoDa was applied in the spatial autocorrelation analysis [98]. Both global Moran’s I and LISA tests were conducted for the “From-Metro” and the “To-Metro” scenarios separately on the spatial units of census tracts. Specifically, the destinations of the “From-Metro” trips and the origins of the “To-Metro” trips were aggregated to census tracts by counting their frequencies. Then, the frequency values were used as inputs for the spatial autocorrelation analysis.

In general, all three modes were found to be positively autocorrelated for both To-Metro and From-Metro trips. The E-Scooter mode preserves the highest autocorrelation while the BS mode shows the lowest. The univariate LISA testing maps are shown in **Figure 6**. There are four types of local patterns between the value in each census tract with its neighbored census tracts: (1) high-high (in red); (2) low-low (in blue); (3) high-low (in light red); and (4) low-high (in light blue). Type (1) can be regarded as hotspots with relatively high-value tracts surrounded by high-value neighbors. Type (2) indicates the opposite low-value clusters. It can be observed that the Central Business District (CBD) areas of Washington, D.C. are the hotspots of high pick-up/drop-off activities; and the peripheral areas are less covered by activities connecting to the metro stations.

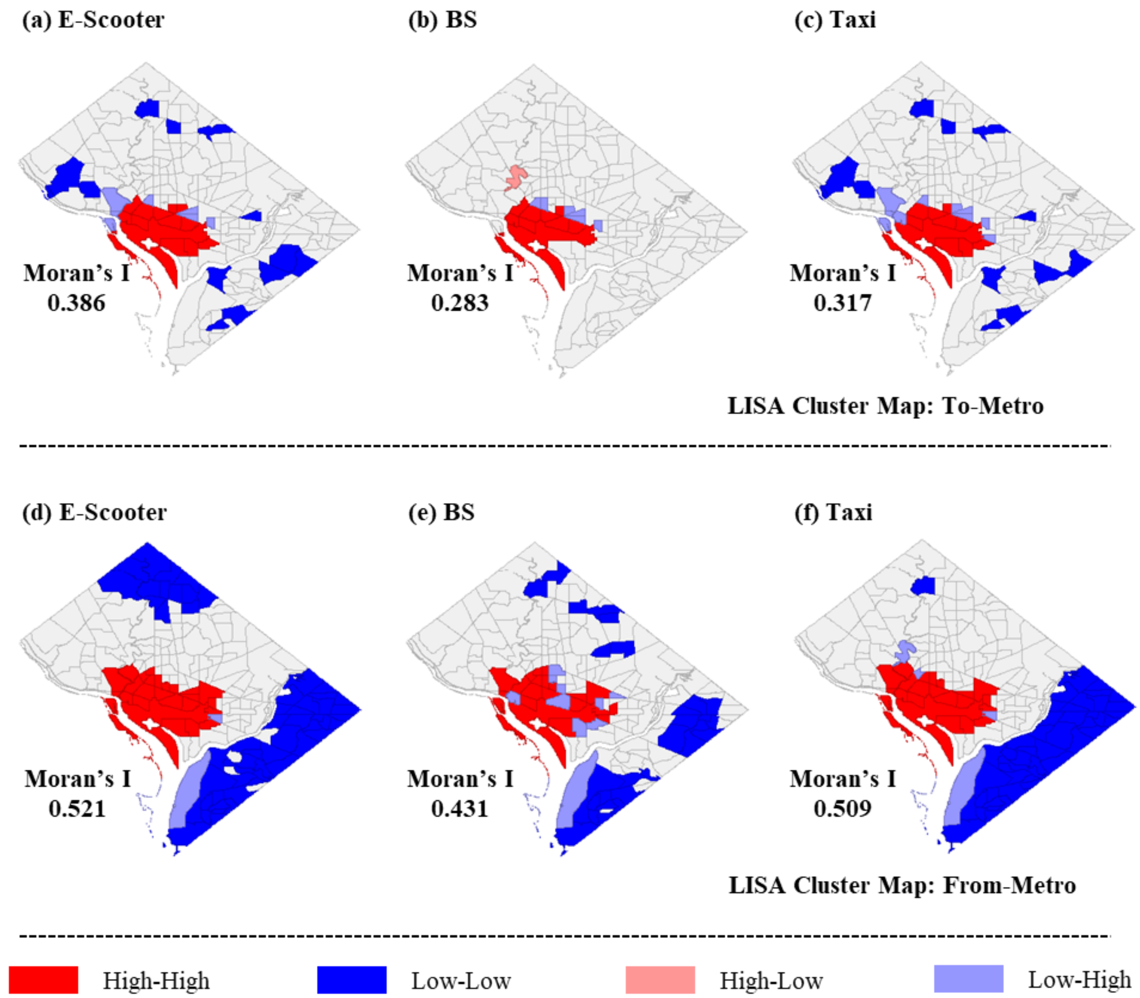



FIGURE 6. UNIVARIATE LISA CLUSTER MAPS.

### 3.4.2 VARIABLE SELECTION BASED ON FEATURE IMPORTANCE

**Table 4** shows the feature importance index calculated using the random forest model. Based on the feature importance index (MDA+MDG), the variables are ranked from 1 to 12. Duration, distance, VMT, income, and time period are the top five important variables for both From-Metro and To-Metro trips. The most significant difference between From-Metro and To-Metro trips is the ranking of the variable time period, which is the most important feature for To-Metro trips but the 5th most important feature for From-Metro trips. This result indicates that time period contributes more to the prediction of To-Metro trips than From-Metro trips. The ranking information was applied to select variables for the MNL model. The distance and duration variables are positively correlated with a coefficient of around 0.4 for both From-Metro and To-Metro trips. As the trip duration is less reliable and can be affected by traffic, idling, or other factors, trip distance was selected as the candidate variable.

TABLE 4. FEATURE IMPORTANCE FOR “FROM-METRO” AND “TO-METRO” TRIP MODE CHOICES

| | From-Metro | | | | To-Metro | | | |
|---|---|---|---|---|---|---|---|---|
| Rank | Variables | MDA | MDG | MDA+MDG | Variables | MDA | MDG | MDA+MDG |
| 1 | Distance | 61.07 | 5471.16 | 5532.23 | Time Period | 128.23 | 7470.98 | 7599.21 |
| 2 | VKT (D) | 42.73 | 4172.49 | 4215.22 | Distance | 62.68 | 4606.01 | 4668.69 |
| 3 | Income (D) | 39.05 | 3779.87 | 3818.92 | VKT (O) | 40.22 | 4115.74 | 4155.96 |
| 4 | Time Period | 112.71 | 3672.77 | 3785.48 | Income (O) | 34.06 | 3480.60 | 3514.66 |
| 5 | Population (D) | 42.72 | 3515.51 | 3558.23 | Population (O) | 42.69 | 3399.56 | 3442.25 |
| 6 | Resident (D) | 51.67 | 1227.93 | 1279.60 | Resident (O) | 43.80 | 1115.32 | 1159.13 |
| 7 | Institution (D) | 42.24 | 935.85 | 978.09 | Institution (O) | 37.10 | 942.21 | 979.31 |
| 8 | Metro Ring | 34.55 | 800.02 | 834.58 | Metro Ring | 31.90 | 730.56 | 762.46 |
| 9 | Restaurant (D) | 49.43 | 667.20 | 716.63 | Park (O) | 35.73 | 634.73 | 670.46 |
| 10 | Park (D) | 37.62 | 571.45 | 609.07 | Restaurant (O) | 37.46 | 505.19 | 542.65 |
| 11 | School (D) | 37.65 | 564.49 | 602.14 | School (O) | 28.70 | 493.28 | 521.98 |
| 12 | Hospital (D) | 20.78 | 242.53 | 263.31 | Hospital (O) | 26.58 | 258.41 | 284.99 |

### 3.4.3 MODE CHOICE ANALYSIS

The mode choice analysis results using MNL models are shown in **Table 5**. Significant variables are presented for To-Metro and From-Metro scenarios, respectively. The taxi mode was taken as the base in comparison with the E-Scooter and BS modes. The coefficients describe the mode preferences and depict characteristics of trips traveling to/from metro stations using different modes. A positive coefficient indicates that the target mode is preferred compared to the taxi mode, whereas a negative coefficient means that the taxi mode is preferred compared to the selected mode. If both coefficients for E-Scooter and BS are positive, the mode with higher coefficient is preferred. Based on the coefficient of each variable, the preference of E-Scooter, BS is ranked under each variable and the results are shown in **Figure 7**. In general, the E-Scooter mode ranks first in the short-distance variable and ranks last in the long-distance variable. Those two variables are compared with the middle-distance trips (2~3km). This observation is consistent with the characteristics presented in **Figure 4**, that E-Scooters and BSs primarily serve shorter trips compared to taxis. More specifically, there are several unique characteristics that can be captured for the E-Scooter, BS, and taxi modes. Firstly, E-Scooter mode ranks first for both To-Metro and From-Metro trips in land use variables including school, park, and resident. It can be inferred that E-Scooters are often used for recreational purposes, travelling to schools by students, and travelling to metros from a residential area. The result is consistent with previous studies by [79, 99]. Secondly, BS mode is preferred during the morning peak and afternoon rush hours, indicating that BS mode is more likely to be used for commuting during weekdays. Third, the first (<100m) and second (100~200m) rings have the most taxi trips and the least BS trips compared to the third ring (200~300m). It can be inferred that taxi mode is good at picking-up/dropping-off passengers as close as possible to metro stations while BS mode finds it difficult to do so due to the fixed locations of bike stations.

| Variable | (a) To-Metro Rank: (1) | (2) | (3) | (b) From-Metro Rank: (1) | (2) | (3) |
|---|---|---|---|---|---|---|
| Time Morning (6-10am) | B | E | T | B | E | T |
| Time Afternoon (4-8pm) | B | T | E | B | T | E |
| Restaurant (O/D) | E | B | T | T | E | B |
| School (O/D) | E | B | T | E | B | T |
| Hospital (O/D) | B | T | E | T | B | E |
| Metro Ring (0.1 km) | T | E | B | T | E | B |
| Metro Ring (0.1 – 0.2 km) | T | E | B | T | E | B |
| Distance (short: < 1 km) | E | B | T | E | B | T |
| Distance (long: > 2 km) | T | B | E | T | B | E |
| Institution (O/D) | T | E | B | T | E | B |
| Park (O/D) | E | B | T | E | B | T |
| Resident (O/D) | E | T | B | E | T | B |
| Income (O/D) | B | E | T | B | E | T |
| Population (O/D) | B | E | T | T | B | E |
| VMT (O/D) | | | | | | |

Note:
O/D represents origins/destinations for all To-Metro/From-Metro variables.

E E-Scooter; T Taxi; B Bike-Sharing; (blank) Insignificant

FIGURE 7. MODE CHOICE RANK FOR TO-METRO AND FROM-METRO SCENARIOS.

TABLE 5. MULTINOMIAL LOGISTIC REGRESSION COEFFICIENTS

| Variables | Coefficients: To-Metro (E-Scooter) | Coefficients: To-Metro (BS) | Coefficients: From-Metro (E-Scooter) | Coefficients: From-Metro (BS) |
|---|---|---|---|---|
| Time Morning (6-10am) | 3.97 ± 6.7e-02 | 4.56 ± 5.4e-02 | 3.06 ± 5.7e-02 | 3.38 ± 4.9e-02 |
| Time Afternoon (4-8pm) | -0.61 ± 3.3e-02 | 0.25 ± 1.8e-02 | -0.93 ± 3.2e-02 | 0.44 ± 1.7e-02 |
| Population (O/D) | 0.28 ± 1.1e-01 | 0.31 ± 6.8e-02 | -0.47 ± 1.1e-01 | -0.28 ± 6.2e-02 |
| Income (O/D) | 0.24 ± 3.3e-02 | 0.31 ± 1.9e-02 | 0.14 ± 3.2e-02 | 0.29 ± 1.8e-02 |
| Metro Ring (100m) | -0.23 ± 3.4e-02 | -0.29 ± 2.1e-02 | -0.26 ± 3.5e-02 | -0.23 ± 1.9e-02 |
| Metro Ring (100-200m) | -0.46 ± 3.5e-02 | -0.65 ± 2.2e-02 | -0.24 ± 3.4e-02 | -0.46 ± 1.9e-02 |
| Distance (short: < 1000m) | 1.47 ± 3.3e-02 | 0.49 ± 2.4e-02 | 1.49 ± 3.3e-02 | 0.56 ± 2.3e-02 |
| Distance (long: > 2000m) | -0.85 ± 3.9e-02 | -0.34 ± 1.9 e-02 | -0.92 ± 3.9e-02 | -0.49 ± 1.8e-02 |
| Institution (O/D) | -0.16 ± 3.5e-02 | -0.52 ± 2.3e-02 | -0.44 ± 3.7e-02 | -0.62 ± 2.2e-02 |
| Park (O/D) | 0.82 ± 4.9e-02 | 0.66 ± 2.8e-02 | 0.56 ± 4.8e-02 | 0.38 ± 2.7e-02 |
| Resident (O/D) | 0.53 ± 3.3e-02 | -0.11 ± 2.2e-02 | 0.83 ± 3.2e-02 | -0.13 ± 1.9e-02 |
| Restaurant (O/D) | 0.34 ± 6.1e-02 | 0.29 ± 3.9e-02 | -0.13 ± 5.9e-02 | -0.14 ± 3.7e-02 |
| School (O/D) | 0.74 ± 5.2e-02 | 0.57 ± 3.7e-02 | 0.65 ± 4.7e-02 | 0.24 ± 3.0e-02 |
| Hospital (O/D) | -0.31 ± 9.7e-02 | 0.22 ± 4.2e-02 | -1.11 ± 8.9e-02 | -0.65 ± 4.2e-02 |

Note: O/D represents origins for all To-Metro variables; and destinations for all From-Metro variables.

### 3.5 SUMMARY AND DISCUSSION

E-Scooters have emerged on the streets of cities across the country in the past few years. As a relatively new mobility option, the dockless and portable characteristics make it a unique and competitive choice for first-/last-mile trips. Unfortunately, unlike the BS and taxi modes that have been extensively studied, there are few mode choice studies focused on E-Scooters. This study contributes to the research community by developing mode choice models using multinomial logistic regressions. The characteristics of E-Scooter mode have been systematically analyzed and described compared to those of BS and taxi. The result showed that E-Scooters are primarily used for recreational purposes and short-distance trips connecting to recreational land use such as parks. Meanwhile, E-Scooters are favored near schools, providing great convenience for students and teachers. On the other hand, E-Scooters are not preferred for some circumstances compared to BSs and taxis. Fewer people select E-Scooters as the transport mode for commuting to work compared to BSs. Besides, E-Scooters can be picked up/dropped off further from metro stations compared to taxis. However, it should be noted that there can be other variables not fully considered in this study. For example, riders' information such as income level is not included due to lack of available data. When more exposure data are available in the future, more factors can be considered, and further casual inference can be explored to understand riders' mode choice preferences.

This research has included E-Scooter, BS, and taxi modes, which is limited by data accessibility. There are also other transportation modes such as Uber/Lift serving as first-/last-mile solutions. When the corresponding OD data are available, other modes can also be included in the mode choice framework developed in this study.

# CHAPTER 4 – E-SCOOTER POLICY: EXAMINING MUNICIPAL USER GUIDELINES

## 4.1 INTRODUCTION

The emerging shared E-Scooters as a new micro-mobility mode have drawn significant attention from local governments in many urban areas. Despite the fast growth in trips, current policy and guidelines for using E-Scooters consistently experience lag. Existing guidelines in some cities are also vague and vary drastically by area. This study aims to analyze current municipal guidelines on the use of E-Scooters in the United States. Specifically, official E-Scooter user guidelines in 156 cities were collected, reviewed, and synthesized. Through the descriptive analysis, cross-tabulation, and quantitative categorization, the distinct characteristics of E-Scooter user guidelines were highlighted. A total of 16 key attributes were identified and two categorizing procedures were developed. The comparative results show the information completeness and similarities among cities. The findings suggest that municipal agencies need to introduce more thorough, consistent, and actionable guidelines and policies regarding the use of E-Scooters in urban areas.

## 4.2 RESEARCH DESIGN AND METHODOLOGY

In general, several types of E-Scooter regulations can be found on a number of cities' official websites in the format of ordinances, pilot programs, agreements, permits, and guidelines [100]. As shown in **Figure 8**, the permits, pilot programs, agreements, and ordinances mainly clarify how E-Scooters can be properly operated by vendors while the E-Scooter guidelines are primarily prepared for riders. E-Scooter guidelines can be found on cities' webpages, which are advised to be referred to by riders prior to their E-Scooter trips. This study examines 156 cities that have/had E-Scooter systems to study their practices of E-Scooter user guidelines. These cities are identified through the collaborator lists of different E-Scooter service providers (e.g., Bird, Lime, etc.). Through searching the cities' webpages, the studied cities are divided as cities with/without E-Scooter guidelines. Then, the detailed text descriptions about E-Scooter guidelines are manually reviewed and summarized as the basic dataset in this study. The following sections describe our research design and specific research approaches.

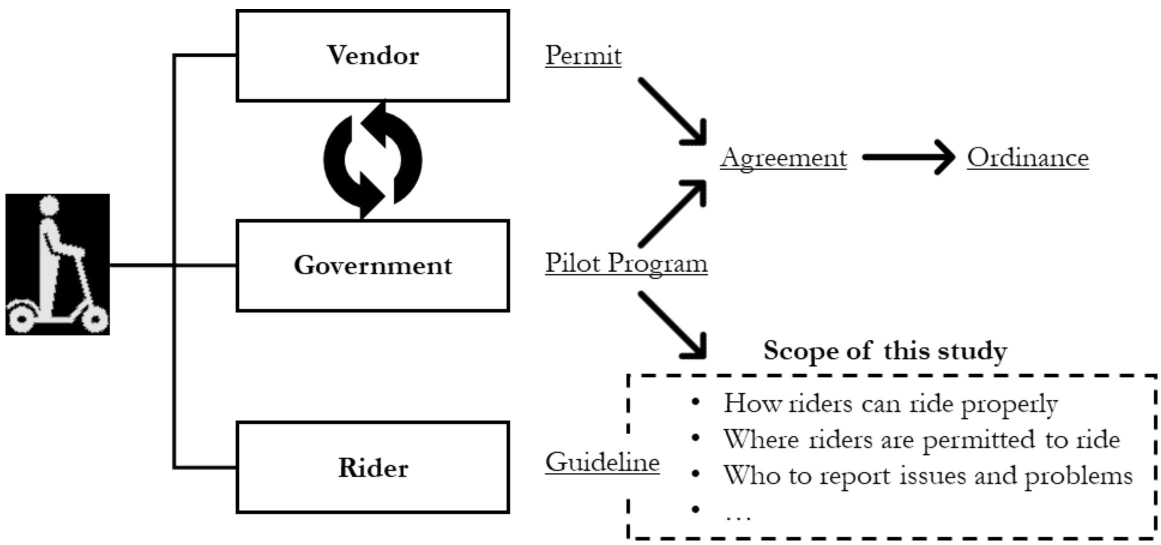



FIGURE 8. RESEARCH PROBLEM DEFINITION.

#### 4.2.1 E-SCOOTER CITY CATEGORIZATION & SPATIAL DISTRIBUTIONS

Firstly, the spatial patterns of the present adoption status of E-Scooter guidelines among all cities is examined. Based on whether guidelines and laws on E-Scooter use are available, cities can be categorized into four groups, as shown in **Table 6**. Since many cities collected residents' opinions on E-Scooters by distributing surveys, we assume that the policies can be mainly affected by residents' feedback. In particular, the reasons why E-Scooter operations were banned are going to be summarized through mining news reports, which can be mainly described as:

- Operational concerns;
- Safety concerns;
- Nuisance by communities;
- Blocking traffic/pedestrians; and
- Blocking disabled people/public infrastructures.

TABLE 6. CATEGORIZING CITIES ON E-SCOOTER POLICIES

| Name | Description |
|---|---|
| Cities with law | Besides E-Scooter guidelines, relevant ordinances are available. |
| Cities with guidelines | E-Scooter guidelines are provided for E-Scooter riders. |
| Cities without guidelines | No E-Scooter guideline is available. |
| Banned cities | Cities where E-Scooters are prohibited. |

### 4.2.2 KEY ATTRIBUTES OF E-SCOOTER GUIDELINES

Different cities may focus on different aspects of the safe use of E-Scooters. In order to generalize the guidelines of different cities, this study uses a set of variables to characterize the adopted guidelines in each city. **Table 7** shows the variables that depict E-Scooter guidelines closely related to E-Scooter use. The variables frequently mentioned or discussed by other studies are selected. For example, more than 75% of the studied cities mention the locations to ride and park E-Scooters. Helmet usage is also an important variable since many head injuries were reported by emergency departments while the E-Scooter victims did not wear helmets. Moreover, an age requirement may help protect children from potential E-Scooter injuries. As mentioned earlier, the vague definitions of E-Scooter guidelines may lead to conflict with other transportation modes. Pedestrians can be vulnerable in front of speedy E-Scooters on sidewalks. Thus, prohibiting E-Scooters on sidewalks or defining guidelines on how to properly ride on sidewalks should be important components in E-Scooter guidelines. On the other hand, improperly parked E-Scooters may block the entrances/exits of vehicles. Whether there is a way to report such issues can be an important consideration in E-Scooter guidelines. The coverages and completeness of E-Scooter guidelines are different among cities and may or may not be associated with the cities' sizes or populations. For example, it is notable to see that the guidelines in some big cities like San Diego, CA only mentioned a few variables, whereas cities with a smaller population such as Scottsdale, AZ (with a population of 0.25 million) have more detailed E-Scooter guidelines. The collected attributes will be descriptively analyzed using grouped circular bar plots.

TABLE 7. KEY ATTRIBUTES FOR E-SCOOTER POLICY COLLECTIONS

| Variable | Categories | Description |
|---|---|---|
| Where to park | right of public/specific locations | Where E-Scooters should be parked. |
| Where to ride | any roads/specific roads | Where E-Scooters can be ride. |
| Sidewalk restriction | no/partial/yes | Whether E-Scooters are prohibited to be ride on sidewalks. |
| Helmet usage | suggested/teen required/all required | Whether helmets are suggested, required, or partially required while riding E-Scooters. |
| Report reckless E-Scooters | no/yes | How to report reckless E-Scooter riding behavior. |
| Report E-Scooter incidents | no/yes | How to report E-Scooter incidents. |
| Report improper parking | no/yes | How to report improperly parked E-Scooters. |
| Age requirement | no/yes | Minimum age to ride E-Scooters. |
| Speed limit | no/yes | Whether speed limits are defined for E-Scooter devices. |

| | | |
|---|---|---|
| Geo-fencing | no/yes | Whether specific regions are mentioned to ride E-Scooters. |
| Weather condition | no/yes | Whether E-Scooters are prohibited to ride in raining or snowing days. |
| Double riding restriction | no/yes | The maximum riders one E-Scooter can have. |
| Curfew restriction | no/yes | Whether a city has curfew for riding E-Scooters. |
| Alcohol impacts | no/yes | How E-Scooter riders are treated when riding with alcohol. |
| Educational materials | no/yes | Whether educational materials (e.g., fliers, videos) are provided on the websites. |
| Driver license | no/yes | Whether a driver license is required to ride E-Scooters. |

### 4.2.3 ANALYZING THE RELATIONSHIP BETWEEN VARIABLES

Among the characterized variables of E-Scooter guidelines, some variables may appear simultaneously. For example, helmet requirements for children often come along with guidelines on age requirements. These two variables mainly help protect child riders that are vulnerable victims in E-Scooter-related injuries. On the other hand, if riding on the sidewalk is restricted, the city is more likely to have specific guidelines on where to ride E-Scooters. To examine whether a pair of extracted variables $x$ and $y$ are associated, contingency tables will be constructed by listing all the levels of one variable as rows in a table and the levels of the other variable as columns, then finding the join or cell frequency for each cell of the table. Statistically, Chi-square test is performed on contingency tables. The equation of Chi-square test is shown as below:

$$\chi^2 = \sum_{i,j} \frac{(f_{i,j} - e_{i,j})^2}{e_{i,j}} \tag{7}$$

where, $f_{i,j}$ is the observed frequency count of events belonging to the $i^{th}$ category of $x$ and $j^{th}$ category of $y$. Also $e_{i,j}$ is assumed to be the corresponding expected count if $x$ and $y$ are independent. Then, p-value is compared with the significance level $\alpha$ to determine whether or not to reject the non-hypothesis that $x$ and $y$ are independent.

#### 4.2.4 CATEGORIZING IMPLEMENTED GUIDELINES

<u>(A) Categorizing by Completeness</u>

The completeness of guidelines is defined based on their covered variables. For example, Coral Gables, FL has a low completeness score since its guideline only mentions where to park and how to report incorrectly parked E-Scooters. On the other hand, Charlotte, NC provides a more thorough guideline by covering eight variables. A score will be calculated for each city to describe the completeness. Among the 16 variables summarized in **Table 7**, if one variable is discussed in the guideline, the score will add one point. In total, a city's policy may receive up to 16 points if all variables were considered. The calculated scores will then be grouped into four categories using the quantile method. The categories from small to large scores are: (i) general, (ii) median-general, (iii) median-detailed, and (iv) detailed. Such categories can be further used for describing the overall quality of E-Scooter guidelines.

<u>(B) Categorizing by Similarity</u>

To further characterize guideline patterns based on the similarities between variables, rather than individually considering these variables, this study proposes to use the principal component analysis (PCA) and K-means clustering to jointly consider multi-dimensional information for discovering E-Scooter guideline patterns. PCA has been frequently used for the purpose of dimensionality reduction, which is suitable to be applied to quantitatively formulate E-Scooter guidelines. The collected 16 variables for the cities are constructed as a binary matrix consisting of 0 or 1 for each variable. The overwhelming number of dimensions make it challenging to extract important information. Thus, PCA will be firstly adopted to find the primary and secondary principal components. Through this method, the cities' guidelines will be fitted into 2-dimensional space, which is easier for further analysis using K-means clustering. The first step is to define the linear function as $z = a'x$ where, $x$ is a vector of $p$ variables and $a'$ is a vector of $p$ constants. As described by Rencher [101], the sample variance of $z$ has no maximum if $a'$ is unrestricted. Therefore, a Lagrange multiplier $\lambda$ is employed to maximize the variances, which satisfies the following vector equation:

$$a'\bar{x} = \lambda\bar{x} \tag{8}$$

where, $\lambda$ is an eigenvalue of the matrix $[a']$, and the vector $\bar{x}$ represents an eigenvector of $[a']$. To find the eigenvalues and eigenvectors, the following characteristic equation is used:

$$D(\lambda) = \det(a' - \lambda I) = 0 \quad . \tag{9}$$

With the help of the PCA packages in R software, the problem can be simply solved by plugging in the data and both primary and secondary principles can be obtained. Thereafter, the data will be further categorized using a K-means clustering approach.

In general, K-means clustering is frequently used for such categorizing purposes in a high-dimension space. Suppose there are $n$ cities in the 2-dimensional space consisting of the primary and secondary principle components as obtained earlier, the problem is to find $M$ points named centers $C_m(m \in (1, 2, \ldots M))$ , to minimize the sum of Euclidean distances from each observed point to a nearest center [102]. The sum of distance (SOD) can be calculated with the function below:

$$SOD = \sum_{m=1}^{M} \left[ \sqrt{\sum_{g=1}^{G} \left( (P_g^1 - C_m^1)^2 + (P_g^2 - C_m^2)^2 \right)} * I_{m,g} \right] \quad (10)$$

where, $M$ denotes the total number of clusters, $G$ represents the total number of cities, $P_g^d \ (g \in (1,2,...,G), d \in (1,2))$ is the point representing each city in the dimension $d$ and $I_{m,g} (m \in (1,2,...,M), g \in (1,2,...,G))$ is used to determine whether the center $C_m$ is the nearest center for point $P_g$ $(Yes: I_{m,g} = 1;\ No: I_{m,g} = 0)$.

(C) Cross Tabulation with Other factors

Many factors such as terrain and weather will affect the development of policies for using E-Scooters in a specific area. Among these factors, population is frequently considered. Population is a typical demographic feature reflecting the sizes and activities of cities. Many policymakers often determine guidelines by referring to other cities of similar sizes [103]. As a way to comparatively analyze the guidelines among different areas, this study cross tabulates the obtained guideline categories with populations for the cities with E-Scooter guidelines to illustrate discovered patterns from another perspective. The results will be visualized using spiral bubble plots ordered by population with increasing bubble sizes. Meanwhile, the previously determined categories will be presented with distinguished colors from light to dark. In this way, the existing distribution of E-Scooter guidelines among studied cities can be better illustrated. Other than population, if analysts would like to explore the guidelines considering other factors such as weather condition, a similar approach can be considered.

### 4.2.5 REFERENCE SYSTEM FOR SHARING E-SCOOTER GUIDELINES

Previous steps have characterized typical features of E-Scooter guidelines. The well-summarized knowledge can be used for guiding cities without E-Scooter guidelines. Based on the common practice that cities may refer to peer cities with similar populations for designing guidelines, we categorize all the cities with E-Scooter deployment on the following levels: (i) 0~50,000; (ii) 50,000~100,000; (iii) 100,000~200,000; (iv) above 200,000. Then, a web-based reference system will be developed to help the unregulated cities find their similar-sized cities interactively. By simply clicking the targeted city, all similar cities will show up with detailed practices of E-Scooter guidelines. This provides cities a convenient tool for quickly understanding the key information of E-Scooter guidelines established in other peer cities. It should be noted that if other factors such as weather and terrain are considered the system can be further extended to support multi-dimensional comparisons other than population.

## 4.3 RESULTS

### 4.3.1 PRACTICES OF E-SCOOTER GUIDELINES AMONG CITIES

Among the 156 cities that have/had E-Scooters distributed, 61 (39%) have E-Scooter guidelines, 19 (12%) have both guidelines and specific laws, 47 (30%) have no guidelines, and 29 (19%) have banned E-Scooters after their pilot programs. Their spatial distributions are shown in **Figure 9**. It can be observed that cities with E-Scooter guidelines are mainly distributed in eastern, southern, and western areas in the United States. Fewer cities in northern and central areas have established E-Scooter user guidelines.


FIGURE 9. SPATIAL DISTRIBUTION OF CATEGORIZED E-SCOOTER PRACTICES (N=156).

In particular, after reviewing the relevant reports for banning E-Scooter usages among the 29 banned cities, **Figure 10** (a) shows the temporal distributions of the starting dates of E-Scooter bans. Most of the bans took place from winter 2018 to spring 2019. **Figure 10** (b) shows the frequencies of cities associated with the main categorized reasons to ban E-Scooter use. It should be noted that a safety concern that represents excessive E-Scooter-related injuries or death is the predominant factor with the highest number of cities among all the factors. For example, as reported by Tucker, GA, E-Scooters were banned since more fatalities occurred in nearby cities [104]. Meanwhile, there are nine cities that expressed their operational concerns by mentioning that there was no guideline for operating E-Scooters properly; thus, they were not yet prepared for the march of E-Scooters. In particular, massive and frequently updated E-Scooter devices may generate waste and carbon emissions (e.g., due to need of charging), which can be harmful to the sustainability of cities [105].

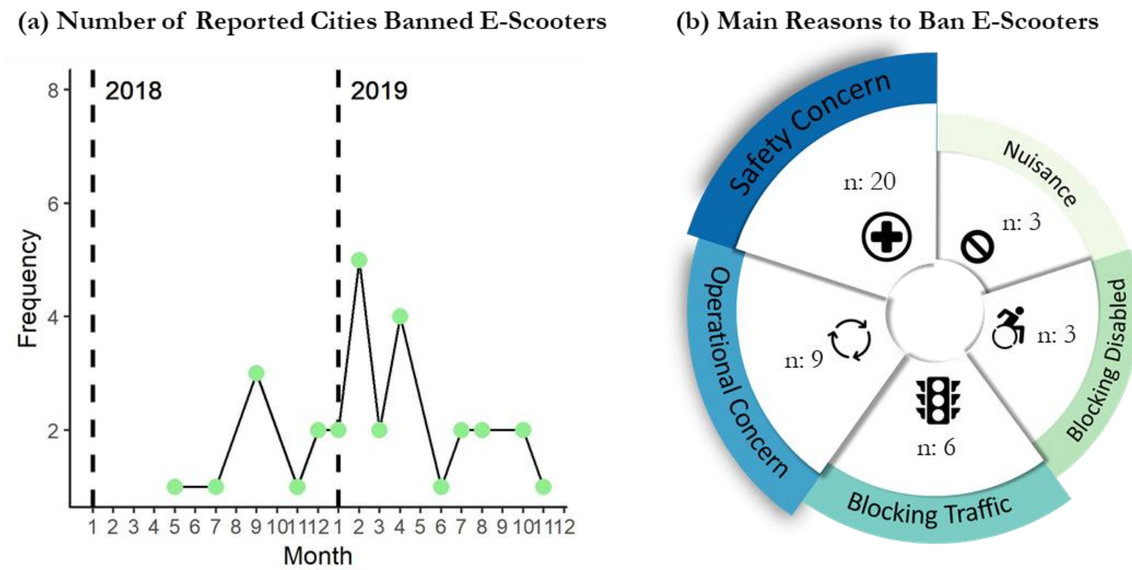



Figure 10. Temporal Distributions and Categorized Reasons for Banning E-Scooter Use.

### 4.3.2 KEY CHARACTERISTICS OF EXISTING GUIDELINES

**Figure 11** shows the proportional distributions of key attributes on E-Scooter guidelines among the 80 cities with guidelines. It should be noted that some of the attributes are not mentioned in some cities, whose number is labeled as “missing”. From the circular bar plots, several distinct characteristics of the attributes can be found:

- More general guidelines on how to park E-Scooters: most suggest parking in right-of-public places;
- More detailed guidelines on how to ride E-Scooters, such as roadways with speed limits less than 25 mph;
- Most of cities prohibit riding E-Scooters on sidewalks;
- Helmets are suggested by most of cities for E-Scooter riders while around 30% cities do not mention helmet usage in their guidelines;
- 43.8% of cities provide guidelines on how to report displacements of E-Scooters; and

- Other considerations such as age requirements, double-riding, speed limit, and educational resources are offered by some of cities.

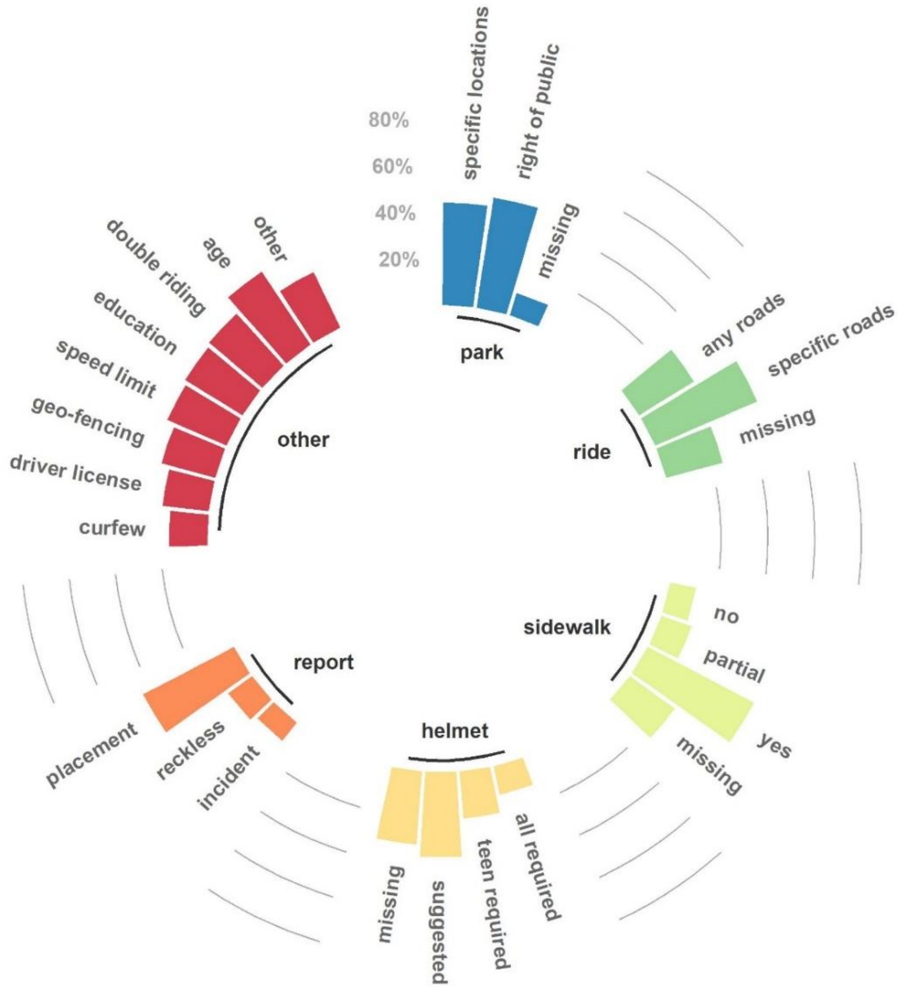



FIGURE 11. KEY ATTRIBUTE ANALYSIS OF E-SCOOTER GUIDELINES.

### 4.3.3 RELATIONSHIP BETWEEN SELECTED VARIABLES

After applying Chi-square test to examining the relationships between all selected variables, two pairs are closely associated with each other. As shown in **Table 8** and

**Table** 9, (i) helmet usage and age requirement; (ii) sidewalk restrictions and where to ride are the associated two pairs with their contingency tables and Chi-squared testing results presented. Both p-values are less than the significance level of 0.05, which indicates that the Chi-squared test's non-hypothesis is rejected, and both pairs of variables are considered to be associated with each other. In other words, there are some patterns observed from these testing results. Specifically, among cities with E-Scooter guidelines, helmet usage often comes along with an age requirement. Meanwhile, when it is prohibited to ride on sidewalks, detailed explanations about where to ride E-Scooters are likely to be provided as well.

TABLE 8. HELMET USAGE *VS* AGE REQUIREMENT.

| **Age Requirement** / **Helmet Usage** | **Yes** | **Unknown** |
|---|---|---|
| **All required** | 6 | 4 |
| **Child only** | 6 | 10 |
| **Recommend** | 15 | 15 |
| **Unknown** | 3 | 21 |
| $\chi^2$: 10.56; p-value: 0.014; Non-hypothesis: Rejected | | |

TABLE 9. SIDEWALK RESTRICTION *VS* WHERE TO RIDE.

| **Where to Ride** / **Sidewalk Restriction** | **Unknown** | **Roadway Only** | **Multiple Choices** | **Specific Roadway** |
|---|---|---|---|---|
| **Yes** | 8 | 10 | 16 | 7 |
| **Partial** | 2 | 1 | 1 | 7 |
| **No** | 1 | 2 | 5 | 1 |
| **Unknown** | 9 | 3 | 6 | 1 |
| $\chi^2$: 22.95; p-value: 0.006; Non-hypothesis: Rejected | | | | |

### 4.3.4 POLICY CATEGORIZATION

In this study, we have categorized the E-Scooter guidelines considering two aspects: (a) completeness and (b) similarities, as discussed in Section 3.4. Then the cities were sorted by their populations using spiral bubble plots as shown in **Figure 12**. The population variable has been selected as the sorting dimension because it is closely related to the E-Scooter market and potential users. Among the 60 E-Scooter cities examined by Riggs and Kawashima [81], cities with higher populations have more E-Scooter devices distributed. Meanwhile, the population size is proportional to the number of potential E-Scooter riders. Therefore, the population variable is the first one examined in this study. It should be emphasized that based on the research interests, many other variables such as climate, geography, and economics can be also considered. As shown in **Figure 12** (a), the cities are colored based on completeness scores using the quantile method: (i) 0~2: general; (ii) 3~4: median-general; (iii) 5~7: median-detailed; and (iv) 8~16: detailed. The higher completeness scores, the more detailed variables covered on E-Scooter policies, which represent better qualities. It can be inferred that the qualities of E-Scooter guidelines are not consistent with the population sizes of the cities. Big cities such as Dallas, TX and San Diego, CA provide E-Scooter guidelines covering only 3~4 perspectives, which are very limited compared to some cities with less populations. The other categorizing results using PCA and k-means clustering are shown in **Figure 12** (b) where four categories are derived based on similarities. The cities in one category share more E-Scooter policies in common. One interesting observation is that most of the cities in the 3$^{rd}$ category are coastal cities located in California or Florida. In such cities, many E-Scooters are often distributed at tourist attraction sites (e.g., oceanfront areas). By sharing similar facilities, their E-Scooter policies cover similar topics.

The analysis results are helpful for planners in two primary ways. First, cities with large populations lacking E-Scooter polices are identified. More effort should be applied to improving policy for those cities with more existing/potential E-Scooter demand. Second, although depicting E-Scooter policies by similarity may not be directly used for evaluating performances, it helps planners to fast match cities that might share similar E-Scooter-related characteristics (e.g., have E-Scooter deployed on Beach sidewalks).

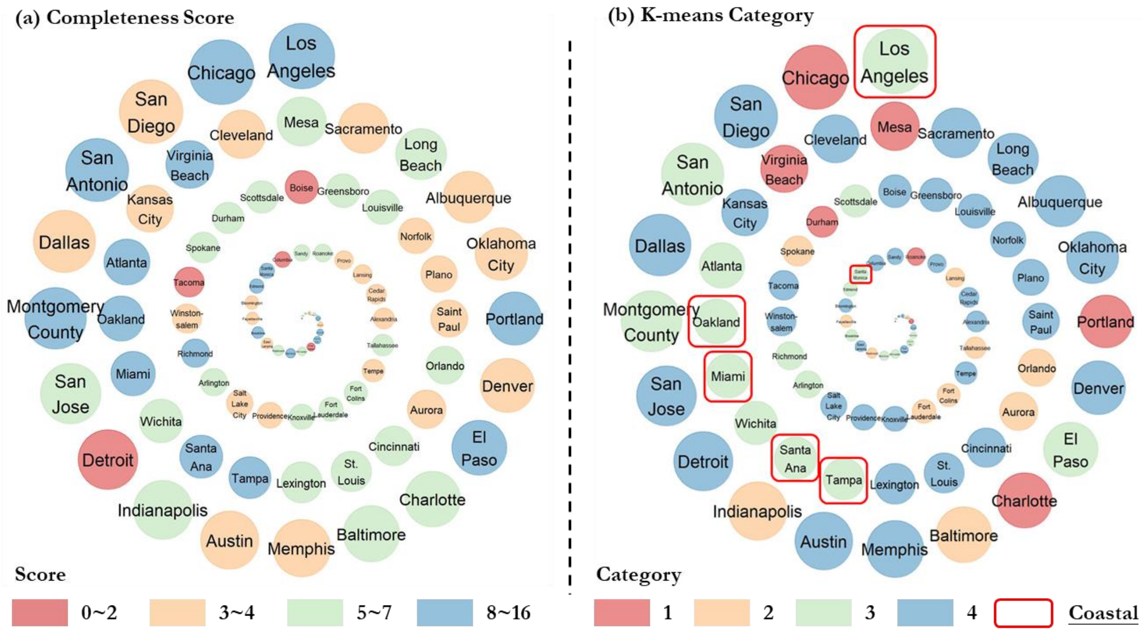



FIGURE 12. E-SCOOTER POLICY CATEGORIES AMONG CITIES WITH DIFFERENT POPULATIONS.

### 4.3.5 SHARING PRACTICES

Despite existing practices among many cities, it is often difficult for a city to identify and learn the best practices of E-Scooter use from peer cities. This is largely attributed to the diverse formats and structures of the guidelines of different municipalities. A unified platform that helps sharing the practices will be helpful. Apart from the quantitative analysis, this study introduces an example of such platforms to facilitate the examination of the studied guidelines. Specifically, a web-based mapping portal, named E-Scooter Ruler, has also been developed and published[1]. Cities without E-Scooter guidelines can find reference cities with similar population sizes by simply checking on the platform. As the examples shown in **Figure 13** (a) indicate, the map displays the cities currently having E-Scooter programs. The ones with user guidelines are indicated by the green flags, whereas the others without E-Scooter guidelines are shown in red. After selecting one of them, Las Cruces, NM as an example, whose population is estimated to be 96,005 in 2019, the reference cities with populations ranging from 50,000 to 100,000 are displayed on the map in **Figure 13** (b). Meanwhile, the reference cities' names are listed on the sidebar. Detailed information will pop up when users click on any of the cites. The website also provides interaction controls. By clicking on the "Back" button on the sidebar, users can move one step back to the menu so that they can re-select other reference cities. With the E-Scooter Ruler platform, E-Scooter guidelines development can be more efficient for peer cities with emerging E-Scooter programs. Currently, this website visualizes data collected by January 2020, which can be extended by updating new policies or adding additional cities. This platform by no means replaces any city's guidelines. Instead, it illustrates how the policy information may be shared among different cities conveniently.

[1] source: http://senselane.com/od/scooter_ruler

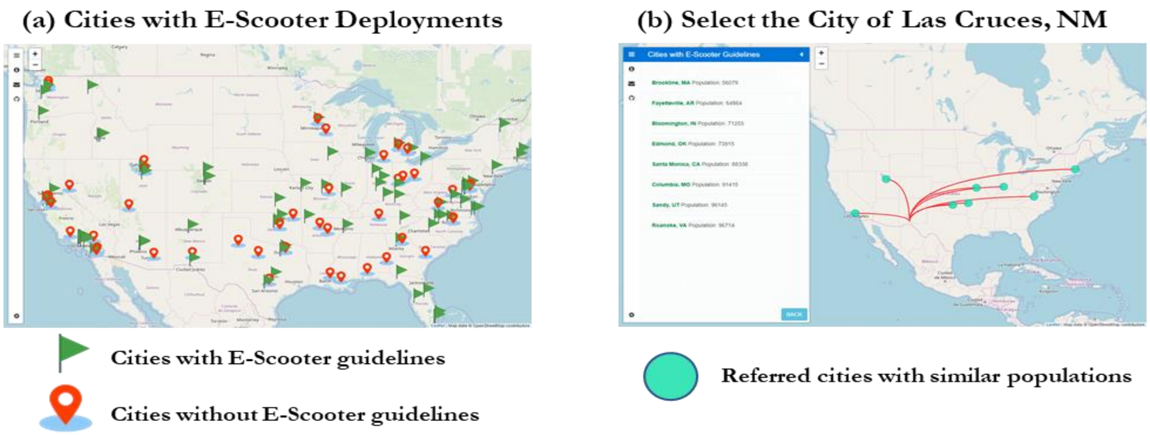



FIGURE 13. INTERFACES AND FUNCTIONS OF E-SCOOTER RULER WEB PORTAL.

## 4.4 DISCUSSION

The examination of existing E-Scooter guidelines warrants discussing several important issues while running E-Scooter programs in urban areas.

### 4.4.1 DATA GAP IN DEVELOPING GUIDELINES FOR THE USE OF E-SCOOTERS ON DIFFERENT FACILITIES

Where to use the E-Scooters is very important to guide users. One distinguishing characteristic of E-Scooters is that they can be ridden on a variety of road facilities, including sidewalks. Contrary to the flexible route choices and convenience, riding E-Scooters on sidewalks can be hazardous due to uneven pavement or conflicts with pedestrians. Unlike bicycles with well-specified paths in many cities, E-Scooters are allowed to be used freely on sidewalks without further restrictions in nearly half of the examined cities with guidelines (39 out of 80). There are many reports that E-Scooter riders fell off and were injured due to poor pavement conditions of some sidewalks [10, 54, 55].

The quality of riding facilities significantly impacts E-Scooter use. **Figure 14** shows some examples of sidewalks with a good surface (**Figure 14** (a)) and with cracks (**Figure 14** (b)). As illustrated, an ES-scooter was ridden on the two sidewalks separately with accelerometers to measure vibrations. The corresponding vibration curves shown in **Figure 14** (c) and (d) capture the vibrations during the rides on the sidewalks, whose vibration strengths can be represented by three accelerometer dimensions. $X$ is along with the heading direction of the E-Scooter with low vibrations while riding at a steady speed. $Y$ and $Z$ are another two dimensions vertical to dimension $X$. In general, low vibrations were observed during the ride on a good pavement surface; a strong vibration event was detected in $Y$ and $Z$ dimensions at the cracks. Clearly, riding E-Scooters on a sidewalk in **Figure 14** (b) is more challenging and riskier due to the frequent pavement cracks or potholes. The cracked pavement can get E-Scooters' small wheels stuck and result in crashes. Currently, no data are available for assessing the facility conditions, whereas such information is necessary for guiding cities in planning riding facilities with good quality for safely using E-Scooters. If condition indexes, such as poor, median, good, and excellent, are provided for each riding facility, cities will be able to determine whether to set up geo-fences prohibiting E-Scooter riders from using uneven sidewalks or encouraging riders to ride on locations with relatively good facility conditions.

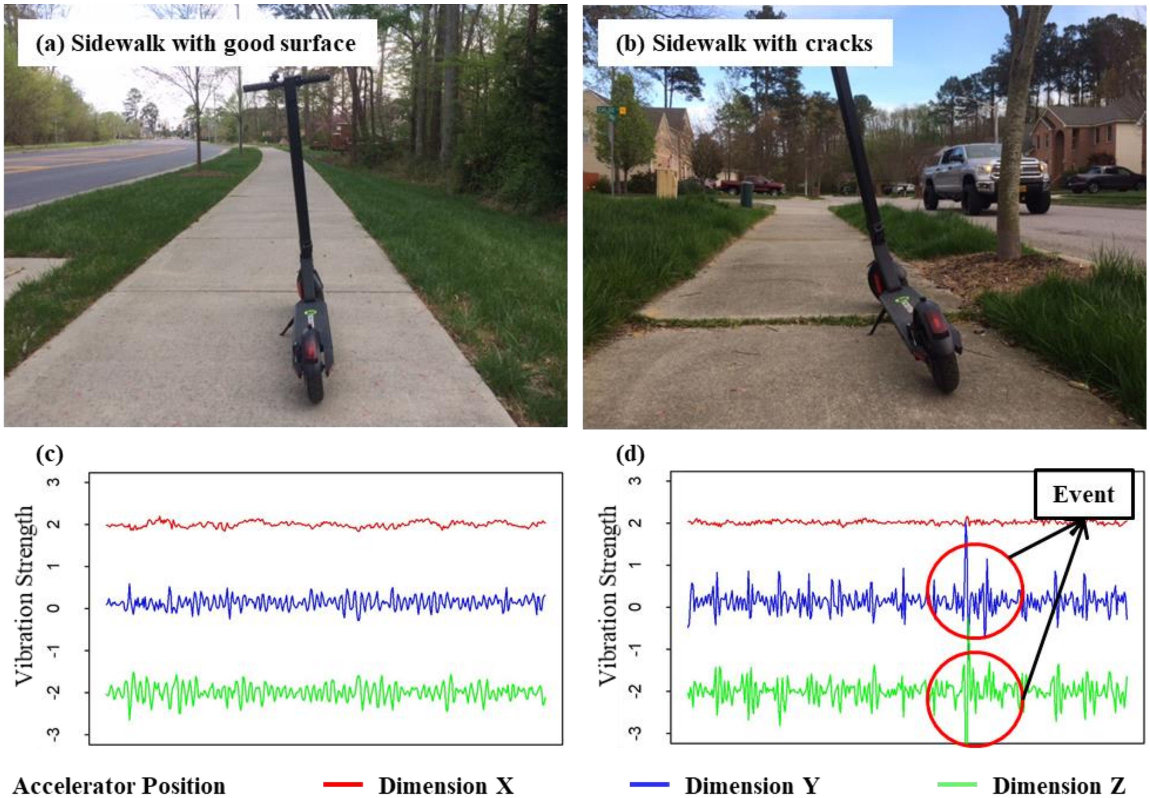



FIGURE 14. SIDEWALKS WITH DIFFERENT QUALITY.

Besides the sidewalk example, E-Scooters can also be ridden on facilities with different types of pavement such as bike lanes with concrete and asphalt pavement. To assess such pavement conditions scientifically, several key variables are to be collected, such as speed, acceleration, and vibration. All those variables should be monitored continuously while riding an E-Scooter. This requires additional efforts for cities to develop appropriate solutions for data collection. Like other vehicles, any motion-related data can be collected using relevant sensors and GPS devices so that spatiotemporal data can be retrieved. It is worthwhile to mention that mobile sensing devices can also be used to detect nearby obstacles on the sidewalks, such as trees, transportation infrastructures, and pedestrians. As there are many complaints that E-Scooters can easily collide with other roadway users, quantitative ways to measure such possible conflicts as well as the environmental constraints will be helpful to guide the planning and design of riding facilities. Besides, surveys can also be distributed to collect opinions on riding on different facilities to support the design or modify existing guidelines. For example, Fitt and Curl [106] conducted a survey of Lime E-scooter users in cities in New Zealand. It showed that over 90% of 536 surveyed E-scooter users had ridden on sidewalks and the concerns about safety topped the list of reasons for not using E-scooters. This valuable feedback from citizens will be helpful to develop more appealed guidelines in practice.

### 4.4.2 VARIATIONS OF E-SCOOTER GUIDELINES AMONG CITIES

Different E-Scooter guidelines present in different cities may confuse E-Scooter riders. One awkward situation is that E-Scooter riders may be required to follow different rules while riding in different cities. For example, in Virginia, E-Scooter riders can ride on sidewalks (with limitations) in Arlington, whereas they are prohibited from sidewalks in neighboring Alexandria. Similar contradictory policies exist in many nearby cities. **Figure 15** shows several examples of such neighbor cities, whose policies for E-Scooters can be quite different or even without any rules guiding E-Scooter riders. According to Riggs and Kawashima [81], many factors such as climate, geography, and land use may contribute to the establishment of different E-Scooter requirements for cities. Therefore, it is suggested that cities improve their E-Scooter guidelines by referring to others with good practices and sharing similar characteristics (e.g., population, climate, and geography).

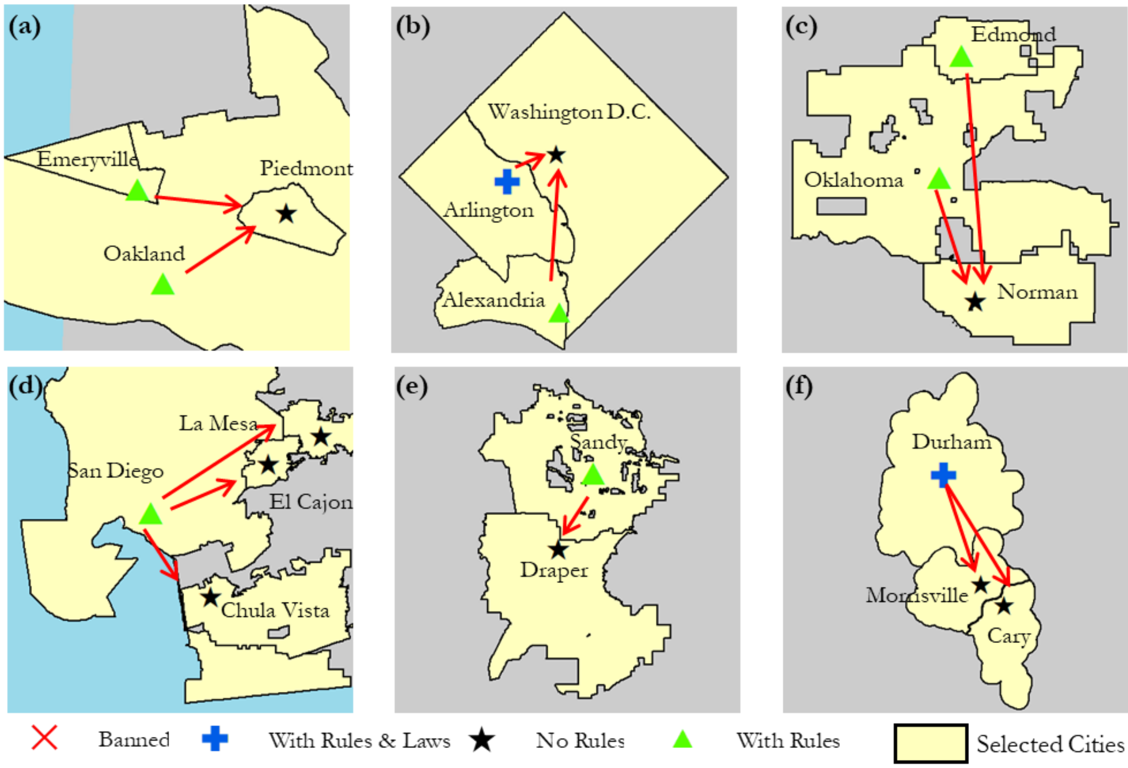



FIGURE 15. REFERRING TO GUIDELINES IN NEIGHBORED CITIES.

### 4.4.3 POST-EVALUATION OF MUNICIPAL GUIDELINES ON E-SCOOTER USE

After implementing E-Scooter guidelines, their effectiveness on the operations and safety needs to be further evaluated. Such post-evaluations will be critical to refine guidelines. However, since this newly established mode has a short history, historical crash records are often unavailable and cannot be used to timely assess the effectiveness of E-Scooter guidelines. Therefore, alternative data are required to conduct post-evaluations. One possible source of E-Scooter-related crash data is the news, which usually covers E-Scooter incidents with significant impacts [22]. The contexts of news reports are often well-organized in similar formats containing key attributes such as place, time, and victim's information. Goddard, et al. [65] validated the quality of news reports by applying them to modeling the safety of pedestrians and vehicles.

Similarly, news reports can also be applied to post-evaluating the E-Scooter guidelines. To better describe the safety of E-Scooters, several attributes should be considered to answer some important questions as shown in **Table 10**. For example, after the tragic death in an E-Scooter-related accident in Denver City, CO, the city's government prohibited E-Scooters from sidewalks and encouraged riders to wear helmets [107]. After that, if similar tragedy happens, the policies should be further improved. The performances and treatment effects of E-Scooter guidelines can be monitored and evaluated with additional quantitative information from a variety of channels.

Certainly, other than the news, other detailed information from additional sources such as emergency rooms and health centers on E-Scooter injuries can be leveraged for assessing the effects of the specific guidelines as well.

TABLE 10. SUMMARIZING NEWS REPORTS ON E-SCOOTER-RELATED CRASHES

| **Question** | **Possible Attribute(s)** |
|---|---|
| Who was the E-Scooter rider? | Age; Gender; Helmet usage; Alcohol usage |
| Where and when was the accident? | Place (Street/Intersection/Sidewalk/Campus); Day/Night |
| How did the accident happen? | Collision Type (Falling off/Hit vehicle/Hit pedestrian) |
| How was the injury severity? | Severity (Slight/Severe/Dead) |

**4.5 SUMMARY**

With the rapid expansion of E-Scooter programs, many cities have established guidelines to regulate E-Scooter riding behavior. This emerging mobility mode has brought convenience for first-/last-mile trips by its portability and flexibility. Meanwhile, it has also sparked discussion about operation, economy, and safety. To better facilitate the planning and operations of E-Scooters in urban areas, it is valuable for city governments to provide effective E-Scooter guidelines. However, among the 156 U.S. cities with E-Scooter systems deployed, only 80 cities provide guidelines on their websites, and those qualities vary notably. To better understand current policy practices in the U.S., this study collected and synthesized E-Scooter guidelines for all cities with E-Scooter deployments. With both descriptive analysis and in-depth categorizing approaches, important characteristics of E-Scooter guidelines have been revealed. First, it was found that the cities with E-Scooters have a clustered pattern in space, and the top-frequent variables concerning the implemented guidelines include where to park, where to ride, helmet requirement, sidewalk restrictions, and how to report issues. Second, completeness scores were introduced to describe the levels of details of the E-Scooter guidelines. Moreover, another categorizing method using PCA and K-means clustering was applied to categorizing E-Scooter guidelines based on similarities. Both categorizing results were tabulated and visualized with respect to population. It was found that most cities in one category are coastal cities. In addition, a web-based map portal was developed and published to help cities without E-Scooter guidelines explore existing practices in other cities with similar sizes. Finally, several key issues concerning the implementation of E-Scooter guidelines in neighboring cities, the critical data gap, and post evaluation of the guidelines were also highlighted in this study. Based on these findings, it can be concluded that municipal agencies need to introduce more thorough and actionable guidelines and policies regarding the use of E-Scooters in urban areas. The consistency of the guidelines across different municipalities are also important to positively promote the use of E-Scooters as a micro-mobility solution.

While there can be different ways of summarizing E-Scooter guidelines or categorizing the summarized results, this study provides a thorough examination of current practices by municipalities in the U.S. The synthesized results are expected to support research communities and practitioners by providing information about the status quo of policy/guidelines of E-Scooter use. By knowing current practices and issues, peer cities can learn lessons for solving similar problems. It should be mentioned that many cities are also actively updating their guidelines and thus revisiting and exploring the existing guidelines. Policies deserve continuous efforts in supporting the planning and operating of E-Scooter programs in urban areas. In addition, it is highly advised to perform more quantitative assessments of the impact of different guidelines with the use of real-world facility information, E-Scooter system operational metrics, and safety data.

# CHAPTER 5 – E-SCOOTER SAFETY: MINING CRASH DATA FROM NEWS REPORTS

## 5.1 INTRODUCTION

Dockless E-Scooters have emerged as a popular micro-mobility mode for urban transportation. This new form of mobility offers riders a flexible option for massive first-/last-mile trips. Despite the popularity, the limited regulations of E-Scooters raise numerous safety concerns among the public and agencies. Due to the scarcity of well-archived crash data, it is difficult to understand and characterize current state quo of E-Scooter-involved crashes. This study aims to shorten the gap by analyzing a set of reported crash data to describe the patterns of crashes related to E-Scooter use. Specifically, massive media reports were searched and investigated for constructing the crash dataset. Key crash elements such as rider demographics, crash type, and location were organized in an information table for analysis. From 2017 to 2019, there were 169 E-Scooter-involved crashes identified from the news reports across the country. Through the descriptive analysis and cross tabulation analysis, the distinct characteristics of these reported crashes were highlighted. Overall, reported E-Scooter-involved crashes were unevenly distributed among the states. The distribution of the crashes across different groups of users, facilities, time periods, and severity levels also showed skewed patterns towards a subset of categories. The quantitative analyses also provide some supportive evidence for warranting the discussion on key issues, including helmet use, riding under influence (RUI), vulnerable riders, and data deficiency. This study highlights the importance of public awareness and timely developing safety countermeasures to mitigate crashes involving E-Scooters.

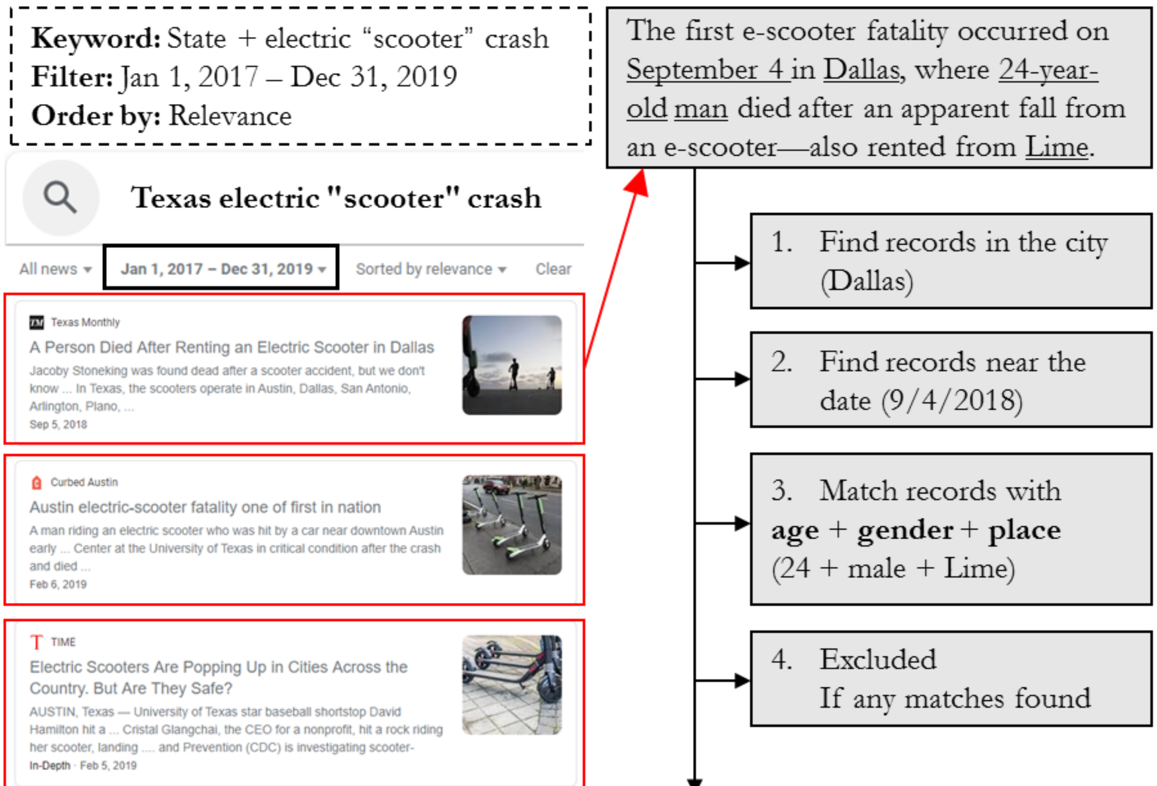
## 5.2 METHODOLOGY

Unlike traffic crashes that have well-established reporting procedures and well-archived crash data for analysis (Yang et al., 2014; Xie et al., 2017), no relatively standardized crash records associated with E-Scooter riders exist. Some agencies are considering the modification of crash reports to include a specific category for labeling E-Scooter-involved crashes. Even with the modified crash reports, it is highly likely that only a small portion of crashes that involve E-Scooters will be archived, which will also not occur until crash forms are modified and implemented. Crashes involving only E-Scooters will be less likely to be documented in crash databases managed by public agencies (e.g., Departments of Motor Vehicles). The lack of rich crash data creates hurdles for researchers and public agencies trying to advance knowledge on the safety impact of E-Scooter use. To facilitate the understanding of current injury status, this study designs an alternative approach that leverages the massive media data for characterizing some unique safety patterns of E-Scooters. Specifically, we took advantage of a primary search engine (i.e., Google News) to gather media reported crash information and build a surrogate crash database for analytics. According to Trivedi et al. (2019), collected text information can be duplicated, vague, or even biased under different contexts. Therefore, a systematic process for collecting, screening, and classifying media reports is necessary for identifying appropriate news records from massive searching results. Moreover, due to the possible subjective influence of the news collectors, a validation process should also be included to ensure the reasonable coverage and correctness of the collected data. Further, the collected data need to be well structured to facilitate subsequent analyses.

### 5.2.1 DATA COLLECTION

(A) Targeted News Reports

Many E-Scooter sharing companies have launched their systems across the country, with Lime and Bird being the two major players dominating a large portion of the market. These two operators both were founded in 2017 and then spread out to many U.S. cities. Since then, public safety concerns have arisen regarding E-Scooter safety, sparking extensive discussion across the country. A new trend of E-Scooter crashes emerges ─ more shared E-Scooters were involved in crashes as their usage surpasses the personal-owned E-Scooters posted the launch of many shared E-Scooter systems across the country. Therefore, the searching period in this study is from January 1, 2017 to December 31, 2019. As of December 2019, there are 40 States with E-Scooter sharing systems. Based on the spatial entities, E-Scooter-involved crash reports were searched manually using keyword combinations for each state. As shown in **Figure 16**, one of the most efficient keyword combinations was experimentally selected, where the names of States were replaced in each searching loop. In general, there are 200-400 news stories presented for each state. We are aware that the same event can be reported repeatedly by multiple media and each report may cover some of the key information about the event. We only target crash reports containing essential components including date, location, victim description, and crash facts (e.g., type). Such professional news reports are usually well documented by professional journalists, and they are often archived online for post retrieval. Self-produced contents on social media platforms such as Twitter, Facebook, and YouTube videos are excluded for consideration in this study.




| ID | City | State | Date | Age | Gender | Place | Severity | Collision type | Day/night |
|---|---|---|---|---|---|---|---|---|---|
| 89 | Dallas | Texas | 9/4/2018 | 24 | Male | Street | Died | Falling off | Day |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |

FIGURE 16. IDENTIFYING NEWS FOR ELECTRIC SCOOTER INVOLVED CRASHES.

(B) Development of Information Table

In order to extract useful information from the news reports, an information table is needed to capture the key information associated with the reported events. Like vehicle crash data, the information table should consist of different attributes of the riders and the incidents. The key attributes are identified through the manual review of each news report. First, age and gender attributes are collected for depicting E-Scooter riders' characteristics. Such information may help understand the unique characteristics of different user groups. For example, according to Krizek and McGuckin [108], males are more likely to use E-Scooters and the major users are adults whose ages are from 18 to 50. Due to such differences, many questions can be explored. For example, will there be any different crash patterns among these different users? As there were no unified regulations for operating E-Scooters on specific infrastructures, E-Scooter crashes may take place at various locations, such as streets, sidewalks, intersections, and so on. Recording the locations can be helpful when developing safety countermeasures by different scenarios. Furthermore, injury severity, collision type, and occurrence time are also key attributes describing crash events from different perspectives (e.g., temporal pattern, outcome, etc.). The table illustrated in **Figure 16** summarizes the attributes as the foundation for further analysis in our study.

<u>(C) Data Reduction and Enrichment</u>

As mentioned earlier, one crash event may be reported by different media. The searching results may include some redundant reports. In addition, different media may cover/depict different attributes of the same crash event. Synthesizing multiple media on the same crash event can enrich the collected data. Thus, the preparation of the information table needs special attention for such issues. As shown in **Figure 16**, a data reduction and enrichment process is applied when adding a candidate news report to the information table. Existing news collections are sorted by cities and dates. If existing collections are matched with a date the same as the candidate news report in the same city, detailed attributes including age, gender, and place are going to be cross-checked. If the targeted news matches any of the existing collections, it will be excluded post the conflation of data elements. Otherwise, the candidate news reported will be incorporated to extend the records of the information table.

### 5.2.2 DATA VALIDATION

The collected news reports should be validated since the attribute identifications were manually reviewed by researcher A, which can be subjective. Meanwhile, it is also critical to know the efficiency and reliability of the proposed keyword combinations. Thus, an additional two researchers B and C are asked to independently collect E-Scooter-involved crash reports for three randomly picked states (i.e., North Carolina, Florida, and Colorado) using more keywords as listed below through Google's search engine directly. All the searching processes are filtered by time period from 1/2017 to 12/2019.

- Researcher A: State name + electric "scooter" crash (e.g., Florida electric "scooter" crash)
- Researcher B: State name + e scooter "accident" (e.g., Florida, e scooter "accident")
- Researcher C: State name + E-Scooter Safety Report (e.g., Florida, E-Scooter Safety Report)

These independent news collections are compared with initial data constructed through Google News by researcher A. Any crashes missed in the initial dataset will be added. Another way to validate our collected data is to compare the data with other published data sources. Specifically, NBC4 I-Team [109] published a map showing 16 E-Scooter-involved deaths between September 2018 and August 2019, which is used as a reference for data validation in this study.

### 5.2.3 DATA ANALYSIS

E-Scooter-involved crashes have distinguishing features that can be summarized from relevant news reports. Since the news reports typically reflect major events with notable impact among communities, the analysis of the news collections will be helpful for characterizing vulnerable E-Scooter riders and revealing current E-Scooter safety situations. This study mainly takes advantage of two analytical approaches, namely descriptive analysis and cross tabulation analysis, for quantitatively uncovering the underlying significance tied to E-Scooter safety.

(A) Descriptive Analysis

Firstly, the temporal and spatial patterns will be highlighted. Specifically, a monthly frequency curve plot will be presented to describe the temporal distribution of news collections. Then, a state-based map will be generated to show the spatial distributions of the news collections. It should be noted that Alaska and Hawaii will be excluded from the map since no E-Scooters were deployed at the time of analysis. Second, grouped circular bar plots will be constructed to visually present the categorical distributions for each attribute of the identified crashes. These descriptive analyses will focus on answering the following questions of E-Scooters:

- How are E-Scooter crashes evolving along with the expansion of E-Scooter services across the country?
- What are the spatial distributions of the reported E-Scooter crashes?
- Who is likely to be injured and what levels of injury severity do they have?
- What are the main types of E-Scooter crashes?

(B) Cross Tabulation Analysis

As each news report contains multiple attributes, some of the attributes may be related to each other. For example, will there be more falling-off crashes at night due to low visibility of the environment? Will victims be more prone to severe injuries in certain types of crashes? Cross tabulation analysis will be used to examine such questions through mining collected data. Two variables are compared in each time of analysis. The analysis method varies based on the variable types. If both variables are continuous numbers, scatter plots will be drawn to highlight their relationship; if one variable is continuous and the other variable is discrete, boxplots will be selected; and if both variables are discrete categories, proportional bar charts will be suitable.

In addition, we also design a virtual transportation scene to illustrate the crash distributions among different scenarios, such as sidewalks, bike lanes, travel lanes, and intersections. The quantitative information is extracted based on the "Place" variable in the information table. Also, the frequencies of major types (>30%) of collisions are presented for each scenario. This diagram cross-tabulates the "Place" and "Collision Type" variables so that the distributions of collisions can be visually illustrated.

## 5.3 RESULTS

### 5.3.1 DATA COLLECTION AND VALIDATION

In total, 169 E-Scooter-involved crashes were identified through the mining of news reports during the study period from January 1, 2017 to December 31, 2019. It should be noted that these crashes may involve some personally owned E-Scooters other than the shared E-Scooters operated by renting companies such as Bird and Lime.

<u>(A) Validation with Keywords Searching</u>

As shown in **Table 11**, researcher A used Google News to identify E-Scooter-involved crashes and the other two researchers (B and C) independently conducted news searching tasks for Florida, North Carolina, and Colorado using more keyword combinations such as State-name + E-Scooter + Safety + Report through Google's search engine directly. Researcher A conducted the news searching tasks with keyword combinations adopted in this study, whereas researcher B and C used other expanded keywords freely. Taking all searching records as the whole set, researcher A has the highest coverage of 82.14%. Therefore, more than 80% of the news collections can be sampled using the searching method in this study.

TABLE 11. VALIDATION RESULTS USING DIFFERENT KEYWORDS

| **State** | **Florida** | | | **North Carolina** | | | **Colorado** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Researcher** | **A** | **B** | **C** | **A** | **B** | **C** | **A** | **B** | **C** |
| Event 1 | Yes | No | No | Yes | No | No | Yes | Yes | Yes |
| Event 2 | Yes | No | No | Yes | No | No | Yes | No | No |
| Event 3 | Yes | Yes | Yes | Yes | No | No | Yes | Yes | Yes |
| Event 4 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Event 5 | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes | No |
| Event 6 | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Event 7 | No | Yes | Yes | Yes | No | No | No | Yes | No |
| Event 8 | No | No | Yes | Yes | No | No | --- | --- | --- |
| Event 9 | No | Yes | No | --- | --- | --- | --- | --- | --- |
| Event 10 | Yes | No | No | --- | --- | --- | --- | --- | --- |
| Event 11 | Yes | No | No | --- | --- | --- | --- | --- | --- |
| Event 12 | Yes | Yes | No | --- | ***Researcher*** | | ***A*** | ***B*** | ***C*** |
| Event 13 | Yes | No | No | --- | ***Coverage:*** | | ***82.14%*** | ***57.14%*** | ***46.43%*** |

(B) Validation with Other Data Source

As shown in **Figure 17**, we compared these published fatal crash data with our news collections. Among the same study period, we found 32 fatal crashes individually reported by different media, 16 of which are consistent with the mapped ones by the NBC4-Team. Therefore, the news collections in this study have more coverage of the fatal crashes.

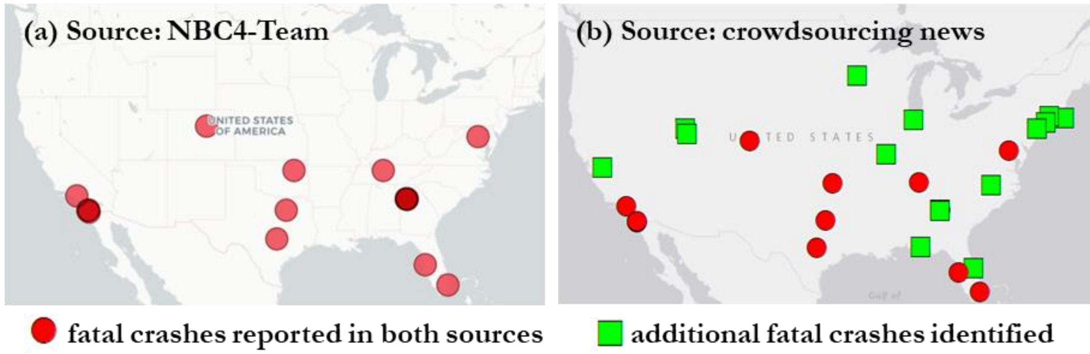



FIGURE 17. VALIDATION OF FATAL CRASHES USING AN INDEPENDENTLY PUBLISHED DATA SOURCE.

It should be noted that additional validation can be further conducted if other well-structured data were available. For example, we are aware that some existing studies examined the emergency visit records at some health/medical organizations. The hospital/emergency service records may offer a good source to verify the identified events. However, one should expect that these data may have large disparities due to the uncovered minor events in news reports.

### 5.3.2 CHARACTERIZATION OF E-SCOOTER-INVOLVED CRASHES

(A) Descriptive Analysis

The temporal and spatial distributions of the collected E-Scooter crashes are shown in **Figure 18** (a) and (b), respectively. Overall, it can be seen from the temporal curve that the number of reported crashes is increasing after 2018, with a majority of them being reported in 2019. In 2019, the summer months are associated with higher frequencies than the rest of the year. This observation is consistent with the reported growing E-Scooter ridership. For example, in 2018, riders took 38.5 million trips on shared E-Scooters, which surpassed the 36.5 million station-based bike-share trips, 6.5 million E-Bike trips, and 9 million dock-less bike-share trips

[110]. According to Srivastava [111], Bird and Lime E-Scooter users increased drastically in 2018. The installation of their smartphone applications quickly increased from 30k and 100k to 479k and 405k during the time period from January 2018 to July 2018. On the other hand, **Figure 18** (b) shows the spatial distribution of E-Scooter-related crashes and demonstrates the crash occurrences across the country, where California, Indiana, Texas, Florida, and Georgia are the top five states with the highest numbers of reported crashes by media. This can be highly related to the growing ridership in these states. For example, the monthly E-Scooter trips in Austin, TX increased from 36,710 in April 2018 to 246,810 in February 2019 [79]. If detailed crash data and ridership information were available, we suggest further quantifying the relationship between the crash fact and the growing E-Scooter sharing systems among the cities.

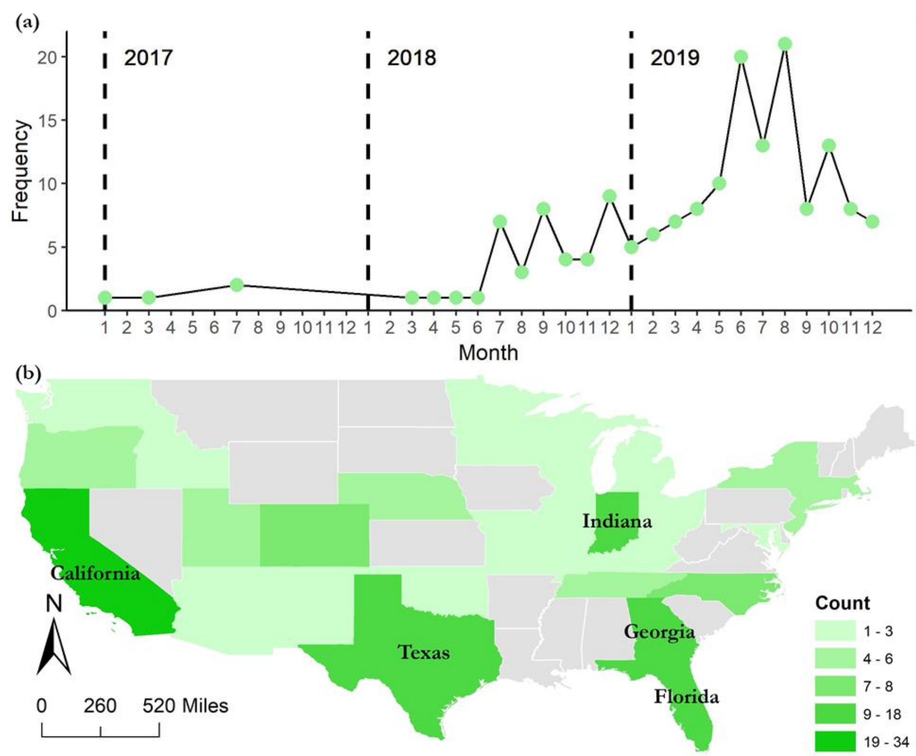



FIGURE 18. TEMPORAL TRENDS AND STATE-BASED DISTRIBUTIONS OF E-SCOOTER CRASHES IDENTIFIED FROM NEWS REPORTS.

Besides the general temporal and spatial patterns as described, the proportional distributions of detailed attributes are shown in **Figure 19**. From the circular bar plot, we can see several distinct characteristics of the reported E-Scooter-involved crashes:

- The reported number of crash-involved riders are unproportionally distributed among male and female users, with more reported crashes involving male E-Scooter riders;
- Most of the identified crashes involved E-Scooter riders ranging in age from 18 to 40; and about 20% of the reported crashes involved riders with under 18;
- The majority of reported crashes happened on streets, intersections, and sidewalks;
- More than half of the reported victims were severely injured or even dead; and
- The major collision types of the identified E-Scooter crashes were collisions with vehicles and falling-off events.

The extracted patterns are consistent with other relevant studies on E-Scooter usage. For example, subsequent analysis by researchers at Portland State University discovered that only 34 percent of trips were made by women and gender non-conforming folks [112]. The female riders involved in E-Scooter crashes are proportional to the number of users, which take 28 percent according to our analysis results. On the other hand, E-Scooter riders are more exposed on arterials/streets than intersections [113], which may lead to more crash occurrences as reported on these facilities.

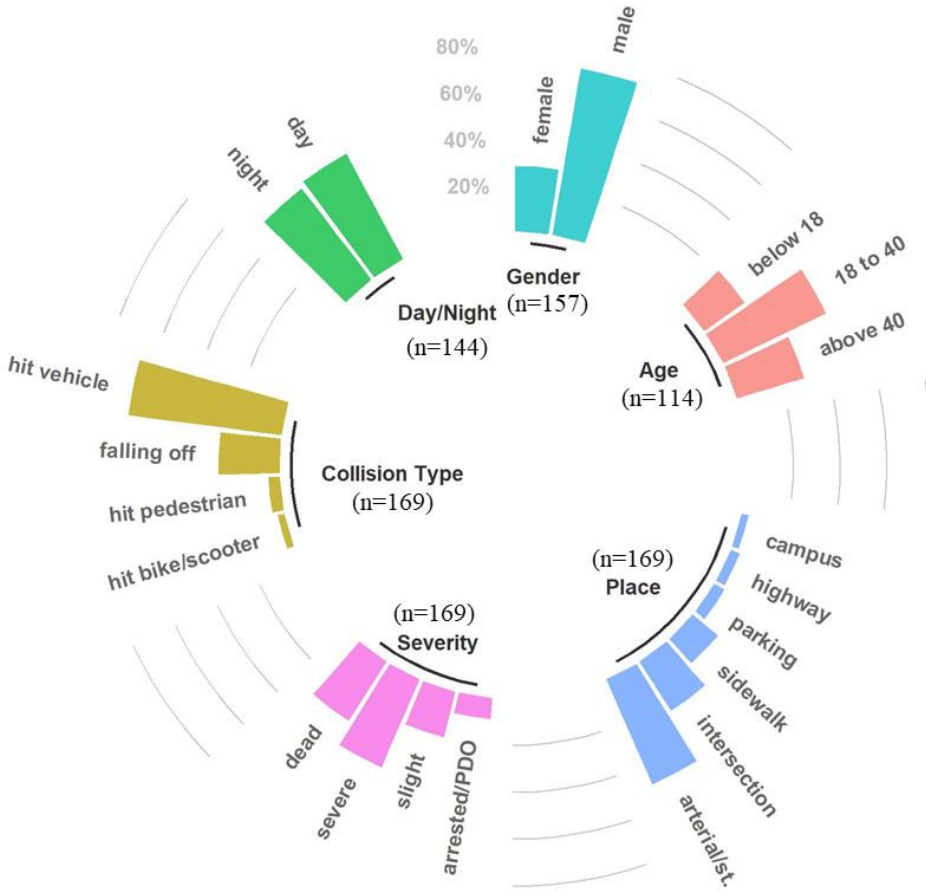



FIGURE 19. KEY ATTRIBUTE ANALYSIS OF E-SCOOTER CRASHES IDENTIFIED FROM NEWS REPORTS.

<u>(B) Cross Tabulation Analysis</u>

Other than performing the analysis of individual attributes, this study particularly explored the interactions between some critical variables.

**<u>Age and Severity</u>**

**Figure 20** shows the age distributions of E-Scooter riders whose crashes led to slight injuries, severe injuries, and deaths. We can see that the victims who were severely injured or dead range in age from 5 to 88, whereas slightly injured victims are mainly young people whose ages are between 18 and 40. The dashed line indicates 18 years old. In particular, children and teenagers are vulnerable in E-Scooter crashes since the majority of such incidents ended with severe injuries or even deaths. This finding is consistent with many other studies discussing children's safety while riding scooters [114]. To protect children, some organizations such as the American Academy of Pediatrics (AAP) recommend that children under 16 should not operate or ride on E-Scooters [115]. Meanwhile, there are new rules announced by some city governments prohibiting children under 16 from riding E-Scooters. Taking advantage of our news collections, the efficiencies of such rules can be examined. For example, some children-involved in E-Scooter crashes were reported after the launch of rules prohibiting children from riding E-Scooters. This suggests that the implementation of the rules is not successful and additional enforcements are necessary. More details will be discussed on this topic in the discussion section.

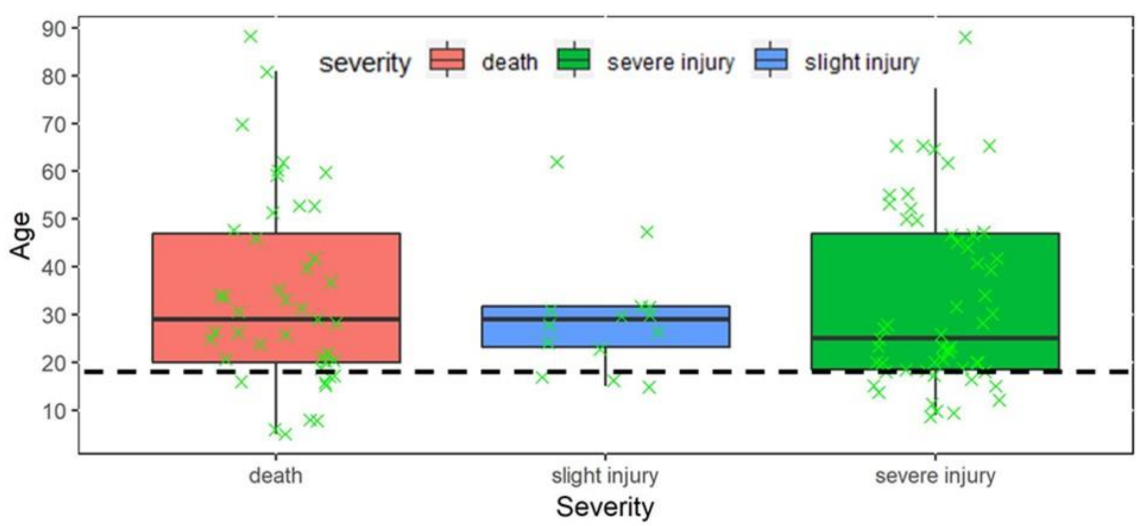



FIGURE 20. AGE DISTRIBUTION UNDER DIFFERENT LEVELS OF SEVERITY.

**<u>Day/Night, Gender, Severity, and Collision Type</u>**

**Figure 21** (a) shows daytime and nighttime comparative results for the crash outcomes in terms of severity and collision type. According to González-Gómez and Castro [116], the time of day (daytime and nighttime) and light conditions have a high impact on pedestrians' and E-Scooter riders' safety. Similar results are found in the present study; a higher proportion of reported fatal crashes occurred at nighttime. Meanwhile, fatal crashes (42.9%) during the nighttime are also higher than the daytime (30.4%). Likewise, E-Scooter riders may easily collide with inanimate objects at night due to the low visibility of the riding environment. Although the frequencies of the reported falling-off crashes are similar between daytime and nighttime, the injuries associated with these crashes at night are noteworthy. As reported by the National Association of City Transportation Officials (NACTO), in 2018, the majority of E-Scooter trips were generated during the daytime (6:00AM - 6:00PM). Therefore, it can be inferred that the injury rate during the nighttime tends to be higher considering the number of trips as the exposure.

**Figure 21** (b) shows the comparisons between male and female riders that were identified in E-Scooter-involved crash reports. The comparisons are mainly on the severity and collision type. Female riders were involved in a lower proportion of fatal crashes compared to male riders in the reported crashes. E-Scooters can be deadly when crashing at high speeds (e.g., 15+ mph). Some studies stated that "Males are more willing to give up safety considerations on account of speed or quickness" [117]. However, there are other factors that affect safety, such as driving skills, reception, reaction times, etc. Extra efforts and data are necessary to derive more strict inferences.

**Figure 21** (c) shows the comparisons between day and night riders with different collision types. The falling offs during the daytime (21.9%) are similar with the nighttime (19.7%). However, as previously mentioned, there are significantly more riders during the daytime than the nighttime; thus, falling off may be more likely to happen for riders during their night trips. On the other hand, a higher proportion of falling-off injuries were reported among female E-Scooter riders in **Figure 21** (d). Female riders generate fewer trips and can be less adept in riding E-Scooters compared to the male riders [118]. Regarding these distinct features, more customized trainings are necessary to improve the safety of different riders when riding E-Scooters.

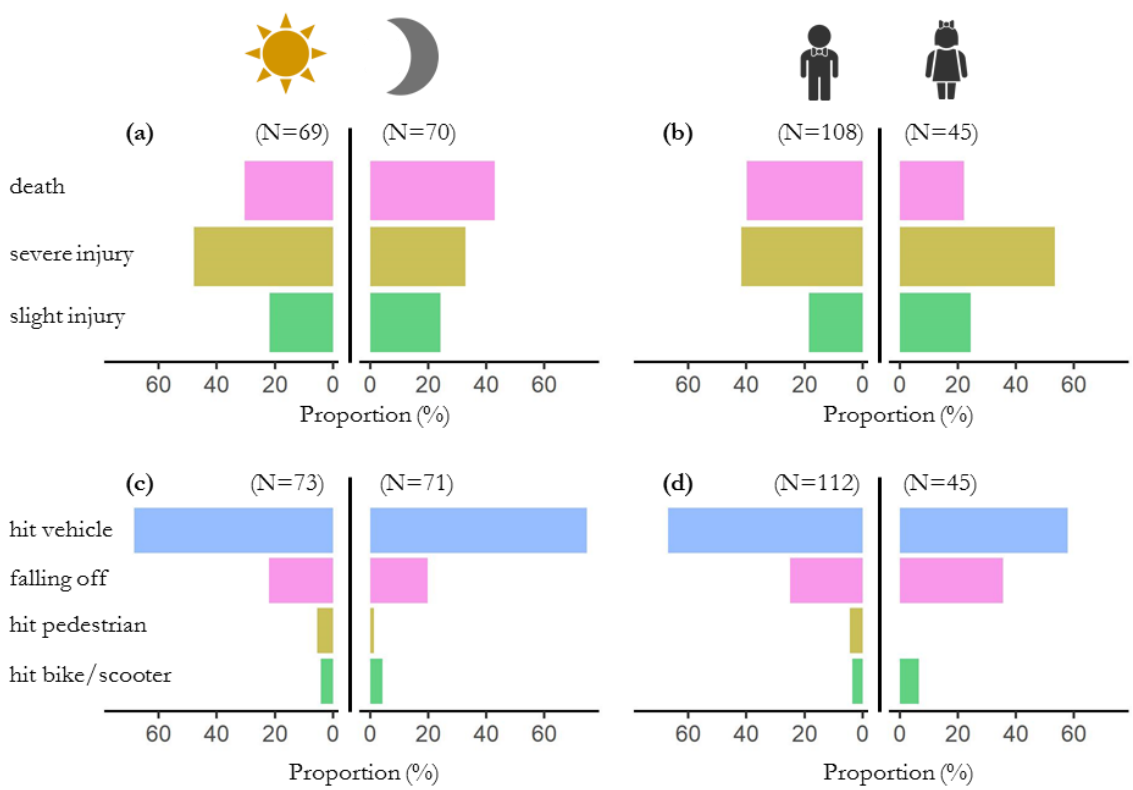



FIGURE 21. COMPARATIVE ANALYSES OF SELECTED VARIABLES.

**Crash Location and Collision Type**

**Figure 22** shows the major types of E-Scooter collisions distributed under different transportation scenarios. E-Scooter collisions with vehicles are mainly on arterial roads / streets and intersections. E-Scooter riders fell off on both sidewalks and arterial roads/streets that can be caused by multiple factors such as riding on uneven pavement, avoiding fixed objects (e.g., trees), conflicts with pedestrians and vehicles, etc. No crash was reported in bike lanes, which indicates that riding E-Scooters in a dedicated lane may have fewer conflicts with other transportation modes. The planning of facility for E-Scooters should consider the crash patterns.

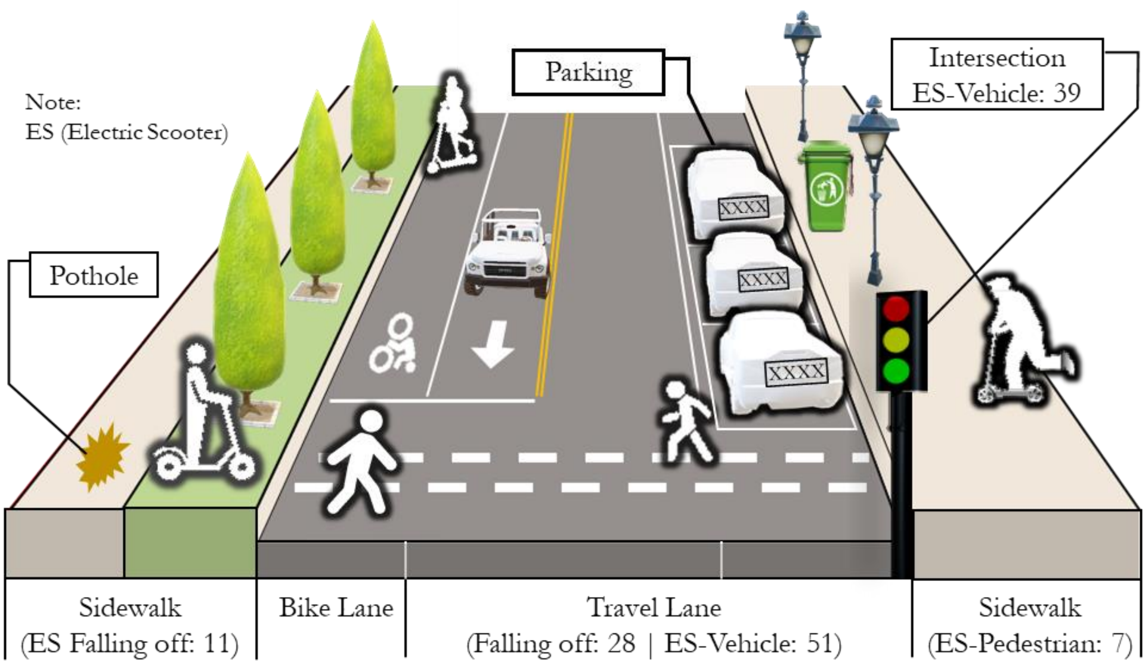



FIGURE 22. E-SCOOTER CRASH DISTRIBUTIONS UNDER MULTIPLE SCENARIOS.

Our findings are consistent with observations reported by Austin Public Health [114], which summarized E-Scooter-involved injuries by interviewing 271 persons. In that report, the injury places and the types of collisions were described separately: more than half (55%) of the riders were injured in the travel lanes; one-third (33%) were injured on the sidewalk. Collisions with vehicles and falling off are the two major types of collisions. Besides the numeric summaries, more detailed information such as the relationship between main collision types and places can be found from this diagram. The results can be informative for designated countermeasures or programs to improve the safety of E-Scooters. For example, several cities such as Denver and Atlanta banned E-Scooters from sidewalks in 2019 [119]. As seen from **Figure 22**, hitting pedestrians and falling off are the major types of injuries on sidewalks. Through banning E-Scooters from sidewalks, the crash risk for E-Scooters conflicting with pedestrians can be reduced.

## 5.4 DISCUSSION

### 5.4.1 VULNERABLE E-SCOOTER RIDERS

Children and elderly riders were found to be vulnerable in E-Scooter-involved crashes. **Figure 23** summarizes E-Scooter laws based on age and helmet use in each state synthesized from the reported information in UNAGI INC [120]. Forty-eight states allow E-Scooters to be used on streets. The laws in 16 states have clarified the minimum age of legal E-Scooter riders, which is either 16 or 18 years old. Some of them require juveniles to wear helmets when riding E-Scooters. According to our collected data, there are 15 crashes with juveniles and children with ages under 16. Six of them were dead and eight of them were severely injured. Their located states are also highlighted on the map. We can see that California, Utah, Oklahoma, Florida, and Washington D.C. have already established relevant laws while no specific law exists in Nebraska, Indiana, Massachusetts, and Georgia. The practices among experienced states can be assumed to improve the safety of vulnerable E-Scooter riders. For example, it is reported that

Georgia plans to explore E-Scooter rules in other states [121]. A follow-up study that compares the differences of the practices in different states will be valuable.

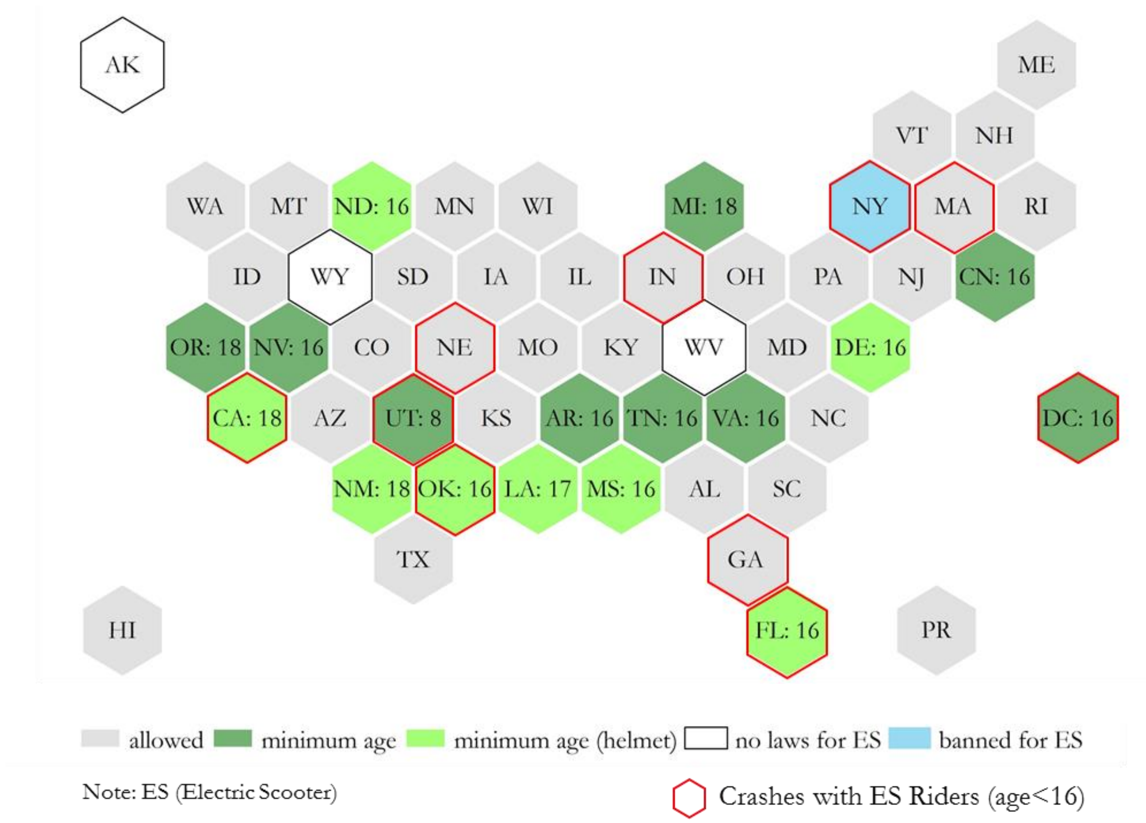



FIGURE 23. ELECTRIC SCOOTER LAWS WITH AGE CONCERNS IN UNITED STATES.

### 5.4.2 DATA LIMITATIONS AND IMPROVEMENTS

Despite our extensive data collection efforts, the E-Scooter-involved crashes identified from news reports remain limited since the media report activities vary from state to state. For example, the emergency service departments documented 65 patients with injuries related to E-Scooters in Virginia Beach [122]. However, no news report was found relating to any of these incidents. Due to the extent of the crash outcome and/or self-visits of emergency service departments, these crashes may not be known to local media in Virginia Beach. We should be cautious to derive any inference or conclusion without considering the impact of other crash-related factors and rider demographic information such as speed, driving skills, perception, reaction times, etc. Moreover, the exposure data measuring the intensity of E-Scooter travel should also be accounted for. Nevertheless, the analysis based on the news report collections are informative by listing typical incidents that have great impacts in both local communities and nationwide. Besides the E-Scooter-involved crashes, hazardous riding behavior should also be considered for complementing the safety study. **Figure 24** illustrates some risky E-Scooter riding behavior observed by our researchers in three cities. Notably, none of these E-Scooter riders wore a helmet. The first three cases illustrate that riders were riding in some compelling traffic environments such as a traffic circle, crowded crosswalk, and travel lane with mixed functions. The **Figure 24** (d) showed that two riders inappropriately "shared" one E-Scooter. These types of risky behaviors are often difficult to control. More observational studies are suggested to gather relevant information for examining the behavioral issues. For augmented studies, dangerous riding behavior found from news reports can also be utilized. For example, tourists were fined for riding E-Scooters on a Wisconsin highway in August 2019 [123]. Since news reports keep updating, our existing news collections can be extended by following the similar process with a focus on behavioral factors. In addition, it would be valuable to develop an open data platform to allow other contributors to add more event cases on E-Scooter-involved crashes. The crowdsourced database can be available for other researchers and practitioners to conduct E-Scooter studies.

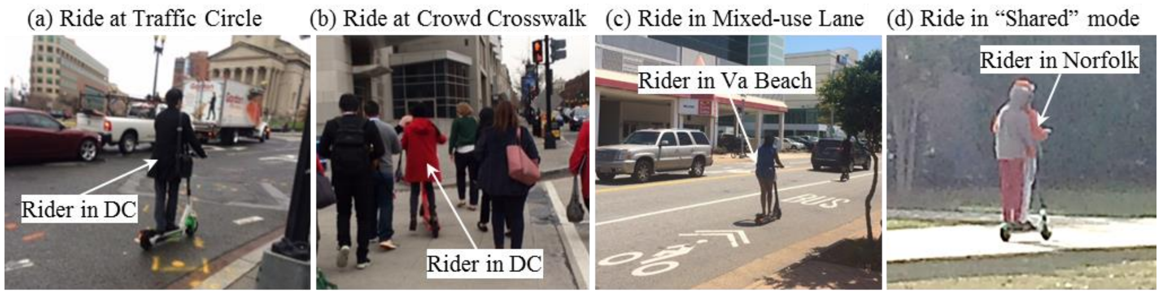



FIGURE 24. EXAMPLES OF RISKY E-SCOOTER RIDING.

### 5.4.3 THE NEED OF WEARING HELMETS

Riding without protective helmets can increase the risk of severe injuries to the brain and head when involved in a crash. It was reported by the Austin Public Health Department (APH) in a study that 15% of riders suffered from brain injuries, while less than 1% of the identified 190 injured riders wore a helmet [114]. The concerns for helmet usage were also frequently discussed in our collected news reports. 17.8% (30 out of 169) of news clearly stated that the riders did not wear a helmet, among which 76.7% (23 out of 30) of the involved E-Scooter riders were severely injured or dead. Thus, it is strongly advised to wear a helmet while riding E-Scooters. Some E-Scooter vendors like Bird are willing to mail free helmets to riders, but it is often impractical for riders (e.g., a visitor) to bring a helmet during their occasional use of a scooter. To be realistic, riders would be more willing to wear a helmet if it were easily accessible or mandatory. The introduction of mandatory laws can be controversial since it may discourage E-Scooter usage by adding cost and/or inconvenience. For example, before January 1, 2019, all E-Scooter riders in California were required to wear a helmet. The rules were modified by bill AB2989 that only requires riders under 18 to wear a helmet [124]. Otherwise, if shutting down all riders without a helmet, 99% of the ridership may disappear [125]. It is expected that E-Scooter vendors, transportation agencies, and or local communities may cooperate to develop more deployable programs that encourage riders to wear helmets and reduce the safety risk. For example, in Queensland, Australia, riders must wear a helmet when using E-Scooters [126]. To enable the use of helmets, one countermeasure provided in Brisbane, Australia is that people can find some scooters with a helmet hanging on the handlebars for convenience. This will largely facilitate those who do not have their own helmet at the time of renting an E-Scooter.

### 5.4.4 PREVENTING RIDING UNDER THE INFLUENCE (RUI)

Like driving under the influence (DUI), riding under the influence (RUI) prevents riders from making appropriate and timely decisions. Consequently, RUI was found to be a notable issue by increasing the risk of crashes. In earlier studies, some data collected at emergency departments included alcohol testing results for the patients. For example, Kobayashi, et al. [12] analyzed 103 patients involved with E-Scooter crashes. Among the 79% tested for alcohol, 48% of them were affected. The alcohol rate can be influenced by many factors, such as (i) location of emergency department; (ii) screening rate (rate of patients conducted alcohol tests); (iii) sample size. Based on our collected data, only 4.1% (7) of 169 crashes reported that riders were found to have had alcohol.

The small numbers of such news reports associated with E-Scooter RUI crashes can be attributed to the vague definitions of relevant laws and the availability of such RUI information (e.g., RUI indicator in crash reports). Some states directly apply DUI laws to E-Scooter riders. For example, an E-Scooter rider in Santa Monica, CA was charged with a DUI when he was passing by a policeman [127]. Compared with laws that clearly forbid DUI for vehicle operations, there is a still a lack of unified regulations/laws about RUI in E-Scooter riders. This situation also occurs in use of bicycles and skateboards [128, 129]. More educational efforts and clearer policies and regulations are needed to raise the safety awareness and reduce the RUI risk of E-Scooter riders.

### 5.5 SUMMARY

The safety concern has arisen regarding E-Scooter safety as the shared E-Scooter systems gain popularity across the United States in the last two to three years. As an emerging mobility mode that flexibly roams around streets, E-Scooters' convenience for first-/last-mile trips is also accompanied by an alarming crash risk. This has sparked much discussion on the deployment of such micro-mobility systems among transportation agencies and the public. To better facilitate the planning and safe operation of E-Scooter systems in urban areas, it is valuable to examine safety facts associated with E-Scooters. Nevertheless, the success of timely uncovering the safety issues requires more thorough examination of relevant crash records. Unfortunately, unlike motor vehicle crashes that have been relatively well archived for in-depth analytics, there were no well-documented crash records for E-Scooters. To shorten the gap, this study contributed to the research community by offering an alternative way to probe the safety issues of E-Scooters. In particular, it leveraged massive up-to-date media reports as a surrogate to successfully collect data for analyzing E-Scooter-involved crashes. The collected data have provided much credible information regarding the E-Scooter safety problem. With both descriptive analysis and cross tabulation analysis, important crash characteristics have been revealed. First, it was found that both children and senior riders are prone to severe injuries in the reported crashes. Second, based on the comparative analysis, fatal crashes and falling-off crashes are more likely to occur during nighttime. In addition, the crash outcome is highly likely to be related to gender difference, with female riders being involved in more falling-off crashes and fewer fatal crashes. The nonuniform distribution of E-Scooter crashes among different facilities also suggests the heterogeneity of crash outcome as an interaction between E-Scooters and riding environments. However, it should be noted that this study is limited to the analysis of reported news without accounting for exposure differences. For example, the higher proportion of male riders may be associated with more reported male-involved crashes. In this study, the findings mainly reflect statistical comparisons, indicating different patterns mined from news reports. When the exposure data are available in the future, further casual inference can be explored to reveal the relationships between E-Scooter crashes and different factors.

While vulnerable E-Scooter riders and risky places can be highlighted through mining news reports on E-Scooter-involved crashes, it deserves mention that the interpretation of the results should be performed with caution. This is largely due to the shortcomings associated with the nature of the collected data: (i) The coverage of news reports varies city by city; (ii) Many E-Scooter crashes with minor impact may not be reported; and (iii) Mining the news is time-consuming for individual screening. Thus, the results of this study are appropriate in the context of the analyzed cases only and their consistence with findings based on well-archived crash data was not examined as no enriched crash dataset was publicly available for performing the comparisons at the current stage.

For further augmenting our understanding of the safety issues associated with E-Scooters, additional research efforts are expected from both practitioners and research communities. For example, efforts are needed for consolidating fragmented data from different sources for more data-driven analysis of the safety issues. One may establish an open data platform to collect data from individual reporters as well as public agencies such as hospitals and emergency service departments. In addition, a synthesis of existing safety practices among the cities with E-Scooter programs will be valuable for guiding more applications in other places. It is expected that with more efforts from practitioners and research communities, more stakeholders will be more aware of the potential risk of riding E-Scooters and benefit from more dedicated safety countermeasures.

# CHAPTER 6 – E-SCOOTER SAFETY: RIDING RISK ANALYSIS FROM MOBILE SENSING DATA

## 6.1 INTRODUCTION

The emergence of shared E-Scooter systems offers a new micro-mobility mode in many urban areas worldwide. These systems have rapidly attracted numerous trips on various types of facilities such as sidewalks and bike lanes. After their burst of popularity, there are also growing safety concerns about E-Scooter riding. Consequently, a few cities have banned or temporarily suspended E-Scooters as severe crashes occurred. As an emerging micro-mobility mode, its safety performance is significantly understudied compared to other travel modes such as cars and bicycles. The lack of crash records further prevents understanding the underlying mechanisms that drive the occurrences of E-Scooter crashes. The overarching goal of this study is to probe the safety risk when riding E-Scooters. Specifically, it aims to study the interactions between e-scooter riding and the environment settings through naturalistic riding experiments. Rather than focusing on the analysis of individual riders' heterogeneous behavior (e.g., swinging, hard braking, etc.) and rider characteristics (e.g., age, gender, etc.), the naturalistic riding study examines the riding process in different riding circumstances. A mobile sensing system has been developed to collect data for quantifying the surrogate safety metrics in terms of experienced vibrations, speed changes, and proximity to surrounding objects. The results from naturalistic riding experiments show that E-Scooters can experience notable impacts from different riding facilities. Specifically, compared to bicycle riding, more severe vibration events were associated with E-Scooter riding, regardless of the pavement types. Riding on concrete pavement was found to create a multiple times higher frequency of vibration events when compared to riding on asphalt pavement of the same length. Riding on both sidewalks and vehicle lanes can both encounter high-frequency close contacts in terms of proximity with other objects. These experimental results suggest that E-Scooters are subject to increased safety challenges due to the increased vibrations, speed variations, and constrained riding environments.

## 6.2 METHODOLOGY

The large number of E-Scooters roaming streets can be disruptive and risky for both riders and other road users. As discussed earlier, more explicit data are necessary to facilitate the understanding of E-Scooter riding behavior and safety. In particular, the examination of E-Scooters' riding conditions is understudied. Unlike other transportation modes that often have well-planned facilities, the emerging e-scooters systems are typically allocated to share the right of ways with existing pedestrians, cyclists, and/or vehicles without sufficient assessment. The overall policy/guidance (if it exists) in different municipalities that suggests where to use E-Scooters is usually lagging due to the inexperience of running the programs. It is highly likely that not all the facilities are appropriate for E-Scooters. For example, some sidewalks may be too narrow to ride, or pavement conditions are not acceptable. Such facilities with capacity/quality deficiencies will raise more challenges for E-Scooter users. According to the 125 E-Scooter riders interviewed by APH [18], 50% believed surface conditions like a pothole or crack on the pavement contributed to their injuries. E-Scooter riders are more likely to feel strong-strength vibrations when riding across potholes, which may impact their comfort and health [130]. Meanwhile, different types of (fixed/non-fixed) obstacles are often present in complex riding environments. For example, pedestrians, trees, electricity poles, and mailboxes are frequently seen during a ride on sidewalks and riders should pay special attention to moving/parked vehicles in lanes. In these cases, nearby obstacles can be a significant variable relating to E-Scooter collisions. Thus, understanding the impact of different riding environments on E-Scooter riding experience and identifying hazardous riding facilities are helpful in mitigating potential crashes. The present study developed a mobile sensing system to collect data for examining the following questions: (i) Where are the facilities with deficient riding conditions? (ii) How do E-Scooter riders experience the vibration impact of different facilities? and (iii) What are the possible interactions with surrounding environments while riding? The collected data are not aimed at providing a direct quantitative assessment of E-Scooter riding safety in terms of crashes or riders' risky behavior. Instead, it emphasizes providing surrogate measurements for depicting possible risky factors attributable to riding facilities.

### 6.2.1 DEVELOPMENT OF THE MOBILE SENSING SYSTEM

The research team at Old Dominion University (ODU) developed a mobile sensing system to record naturalistic riding data for each trip by E-Scooter riders. **Figure 25** (a) illustrates the architecture of the system design and **Figure 25** (b) shows the final developed system equipped on an E-Scooter. The mobile sensing system leverages the sensing and computational capabilities of a set of low-cost sensors and mobile computing units. Four types of data can be collected from the sensing systems: (i) detailed trajectory logs with timestamp and coordination information acquired by the global positioning system (GPS); (ii) motion sensor measurements – an inertial measurement unit (IMU) combining a 3-axis gyroscope and a 3-axis accelerometer to measure dynamic acceleration forces. The gyroscope measures rotational velocity or rate of change of the angular position over time, along the X, Y, and Z axes. The accelerometer measures gravitational acceleration along the 3 axes. Combing the accelerometer and gyroscope data, one can track the motion status of the E-Scooter; (iii) cloud points acquired by a LiDAR Scanner that performs 360-degree omnidirectional laser-range scanning for measuring the distance to surrounding objects. It has a typical measurement range of up to 12 meters, a typical scan frequency of 5.5 Hz, and a measurement frequency up to 8,000 Hz. The scanner facilitates the accurate distance measuring between an object (e.g., a pedestrian or a tree on sidewalks) and the running E-Scooter; and (iv) real-time video recording through a portable camera for post review, if necessary.

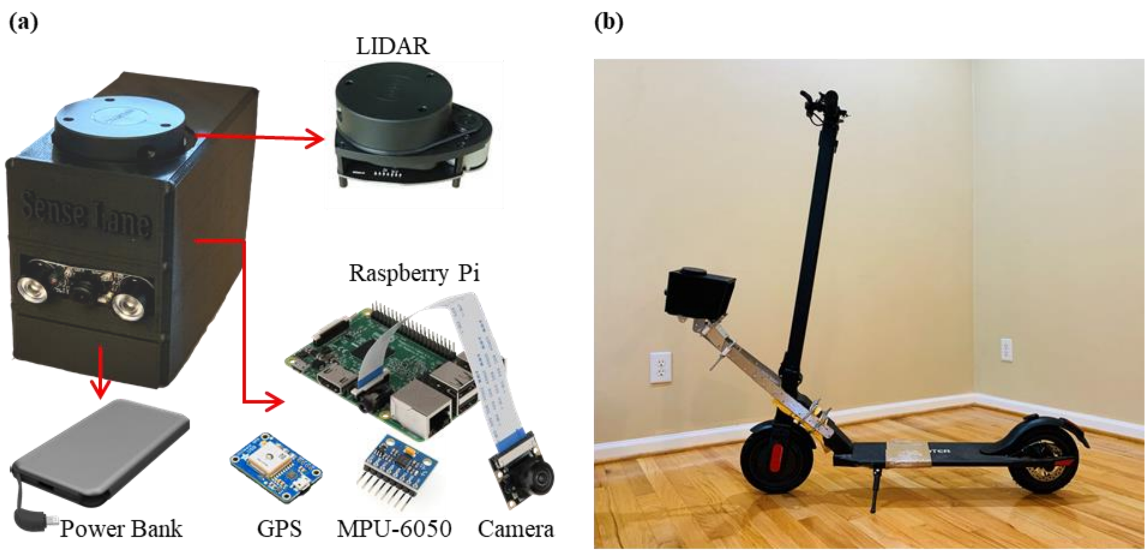



FIGURE 25. E-SCOOTER MOBILE SENSING SYSTEM FOR NATURALISTIC RIDING DATA COLLECTION.

In order to make the system more portable in field data collection, all sensors are connected with a Raspberry Pi platform for data acquisition, processing, and storing. They are powered by a portable low-voltage (5V) battery pack. As shown in **Figure 25 (b)**, the developed sensing system was assembled and installed on a customized mounting structure so that the data can be collected without interrupting normal riding. For example, the motion sensors were fastened horizontally for maintaining a relatively static status with respect to the standing deck of the E-Scooter, which allows the measurements to directly reflect the E-Scooter's motion. The LiDAR sensor was mounted in such a way that it is independent of the handlebar rotation as well. Its position is also relatively static with respect to the E-Scooter deck. This will help avoid the unstable measurements caused by the frequent swinging operations of the handlebar. All sensor output can be stored in a MicroSD card attached to the Raspberry Pi. The stored data can be downloaded wirelessly through a customized program developed by the research team.

### 6.2.2 QUANTIFYING THE PROXIMITY WITH SURROUNDING ENVIRONMENTS

Unlike other vehicles that are typically running in designated lanes, E-Scooters do not have dedicated facilities for traveling. The shared use of existing roadway facilities (e.g., sidewalks, bike lanes, etc.) with other users undoubtedly creates interference between E-Scooters and the surrounding environments. For example, riding on a sidewalk, an E-Scooter rider may encounter both moving pedestrians and static objects such as trees, electricity poles, and trash cans. There have been many reports on E-Scooter collisions with such objects, ending in severe injuries or fatalities [22, 75]. Also, because of the non-fixed riding paths and the changing built environments, the interference will drastically change as E-Scooters roam different urban streets and sidewalks. As a preventive risk assessment approach, the research team borrowed some ideas from roadside safety audits and inspections and proposed a data-driven evaluation framework to depict the interactions of E-Scooters with surrounding environments. Rather than directly relating any crash facts to environmental factors, it intends to uncover the complicated riding circumstance as surrogates for describing potential riding risk due to proximity. Specifically, the evaluation framework leverages the integrated LiDAR sensor of our developed mobile sensing system to provide instantaneous measurements of proximity to all objects around a running E-Scooter. Due to the relatively high accuracy, resolution, and frequency, the distance to objects such as pedestrians, vehicles parking at curbside, etc. can be successfully sensed both at low and high riding speeds. Assembling all collected cloud points will provide a full spectrum of the surrounding environment while riding an E-Scooter.

**Figure 26** shows the overall data-driven evaluation framework to capture the interactions between a running E-Scooter and surrounding environments. Specifically, the measurements from the LiDAR sensor will be extracted from our mobile sensing system wirelessly after each field test. The extracted data organized in the .CSV format include timestamps and the corresponding detected direction and distance measurements with respect to the longitudinal motion of an E-Scooter. This study introduces a risk map $g(d,\theta)$ as illustrated in **Figure 26** (b) to further analyze the data. The risk map is defined by fan-shaped proximity grids to understand the instantaneous spatial proximity of E-Scooters to other objects. Using the longitudinal motion direction as a reference, a symmetric azimuth ranging from -105° to 105° is considered to be the hazard zone. The hazard zone is further evenly categorized using 30°-intervals, with $\theta_j$ defining the azimuth of each grid distributed from left to right on the map and $j=1,2,...,7$. Meanwhile, the distances ranging from 0 to 30 feet are also categorized by the arcs $d_i$ of the risk map assuming 5-ft intervals along the radius, where $i=1,2,...,6$. Depending on sensor capability and analysts' preference, both the angular and distance intervals are customizable. Thereafter, the risk map $g(d,\theta)$ is divided as $7\times 6=42$ proximity grids $g(d_i,\theta_j)$ in a polar coordinate system as shown in **Figure 26** (b). At each time step, if the sensed points are above a given threshold (e.g., five points) in a grid, this grid will be annotated with the presence of an object: $g(d_i,\theta_j)=1$; otherwise, the grid is marked as empty: $g(d_i,\theta_j)=0$. Multiple points are considered to be the threshold to exclude possible sparse and noisy measurements of the sensor. **Figure 26** (c) illustrates the proximity grids $g_t(d_i, \theta_j)$ and $g_{t+1}(d_i, \theta_j)$ for two consecutive timesteps $t$ and $t+1$, respectively, during a sample trip. With these instant risk maps, analysts will be able to trace the interaction between E-Scooters and their surrounding environments. Furthermore, these instant risk maps can be further aggregated to establish a trip-based risk map $G(d, \theta)$ for generalizing the proximity with encountered objects along the entire trip. The aggregation can be obtained based on the following equation:

$$G(d_i, \theta_j) = \sum_{t=1}^{T} g_t(d_i, \theta_j) \tag{11}$$

where, $g_t(d_i, \theta_j)$ denotes the presence of an object with the proximity grid of distance $d_i$ and angle $\theta_j$ at timestep $t$; and $T$ is the total number of timesteps analyzed. **Figure 26** (d) shows an example of the aggregated risk map of a trip. Different colors are used for describing the level of intensities (i.e., the value of $G(d_i, \theta_j)$). For example, a darker grid indicates that the rider has encountered more objects within a specific distance and direction. Apparently, more closer contacts toward the center of the risk map reflect a more impeded/restricted riding environment (e.g., a crowded sidewalk), which will be associated with higher riding risk in general as the likelihood of conflicts with others increases. Analysts can further define customized risk indicators by considering the weighted combination of distance and angle of each proximity grid $G(d_i, \theta_j)$. Certainly, $G(d_i, \theta_j)$ can be considered as the risk exposure and can be normalized based on length of each trip for comparison, if needed.

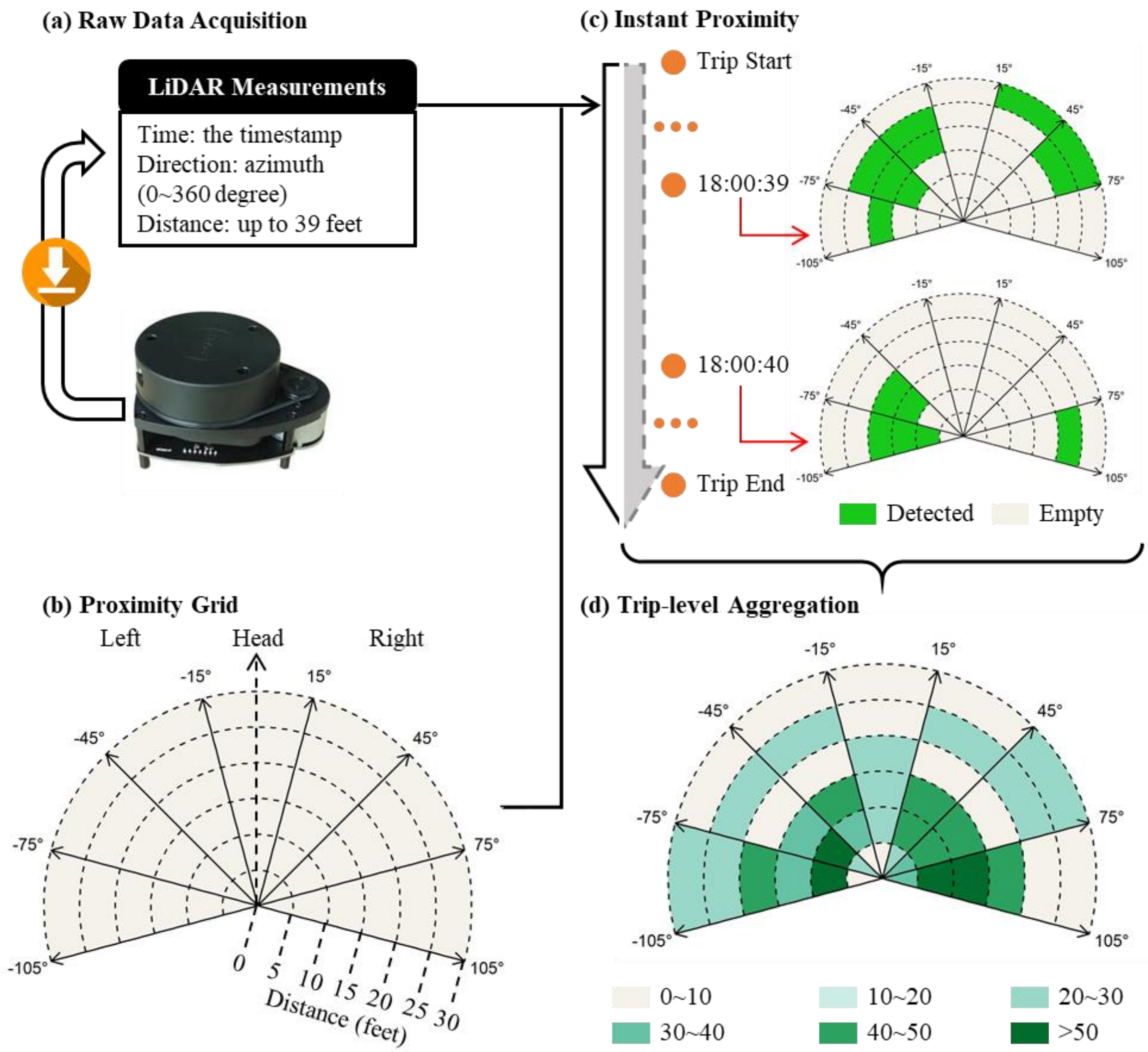



FIGURE 26. PROXIMITY ESTIMATION FRAMEWORK USING LIDAR MEASUREMENTS.

### 6.2.3 ASSESSING RIDING VIBRATION

Unlike bicycles, the relatively small wheels of E-Scooters may generate vibrations that influence comfort, human health, and safety [130]. To assess the real-world impact experienced by running E-Scooters on different facilities, vibration information needs to be collected and quantified. The motion detection sensor embedded in the mobile sensing system is used for such purposes. As shown in **Figure 27** (a), three-dimensional accelerometer data $X_t$, $Y_t$, and $Z_t$ are selected for evaluating vibrations encountered by E-Scooter riders. It should be noted that the +Y is identical to the E-Scooter's heading direction in the experimental settings. An example of the raw data collected by the IMU is shown in **Figure 27** (b), which is very sensitive with a minimum time resolution of 10ms. $N\,(N \in [50,100])$ observations can be included at the timestamp $t$. The frequency and amplitude are two important factors for such waveform data. The amplitude represents the vibration strength, and there are no unified ways of defining the vibration strength. For example, Fridman, et al. [131] analyzed accelerometer in Z dimension to evaluate vehicle vibrations. In terms of the E-Scooter device, vibrations in the X and Y dimensions are also considered in this study considering that E-Scooters may not just bounce in one direction when hitting potholes or cracks. Therefore, the accelerometer data $(X_{ti}, Y_{ti}, Z_{ti})\,(i \in 1, 2, ..., N)$ are converted to the vibration strength $S_t$ with the following equation.

$$S_t = \sqrt{(X_{t\max} - X_{t\min})^2 + (Y_{t\max} - Y_{t\min})^2 + (Z_{t\max} - Z_{t\min})^2} \tag{12}$$

where, the difference of maximum and minimum values in each dimension is calculated for the timestamp based on the collected data. **Figure 27** (c) shows the calculated results, which can be further mined to identify significant vibration events. There are two parameters to detect such events: (a) strength threshold $\theta$ and strength increment $\sigma$. The first parameter $\theta$ is used for controlling strength quantity. Only vibrations larger than $\theta$ will be defined as strong vibrations. $\sigma_t$ is calculated as the strength difference between two consecutive timesteps. If $\sigma_t$ is greater than a threshold $\sigma$, this fact will be collectively used as the second criterion to determine vibration events. **Figure 27** (d) shows the scatterplot with X axis indicating the strength $S_t$ and Y axis indicating the strength $S_{t+1}$. The selected points in the circle are the vibration events determined based on the parameters of $\theta = 2.5$ and $\sigma = 0.5$. For capturing more severe vibration events, larger values for these parameters can be considered.

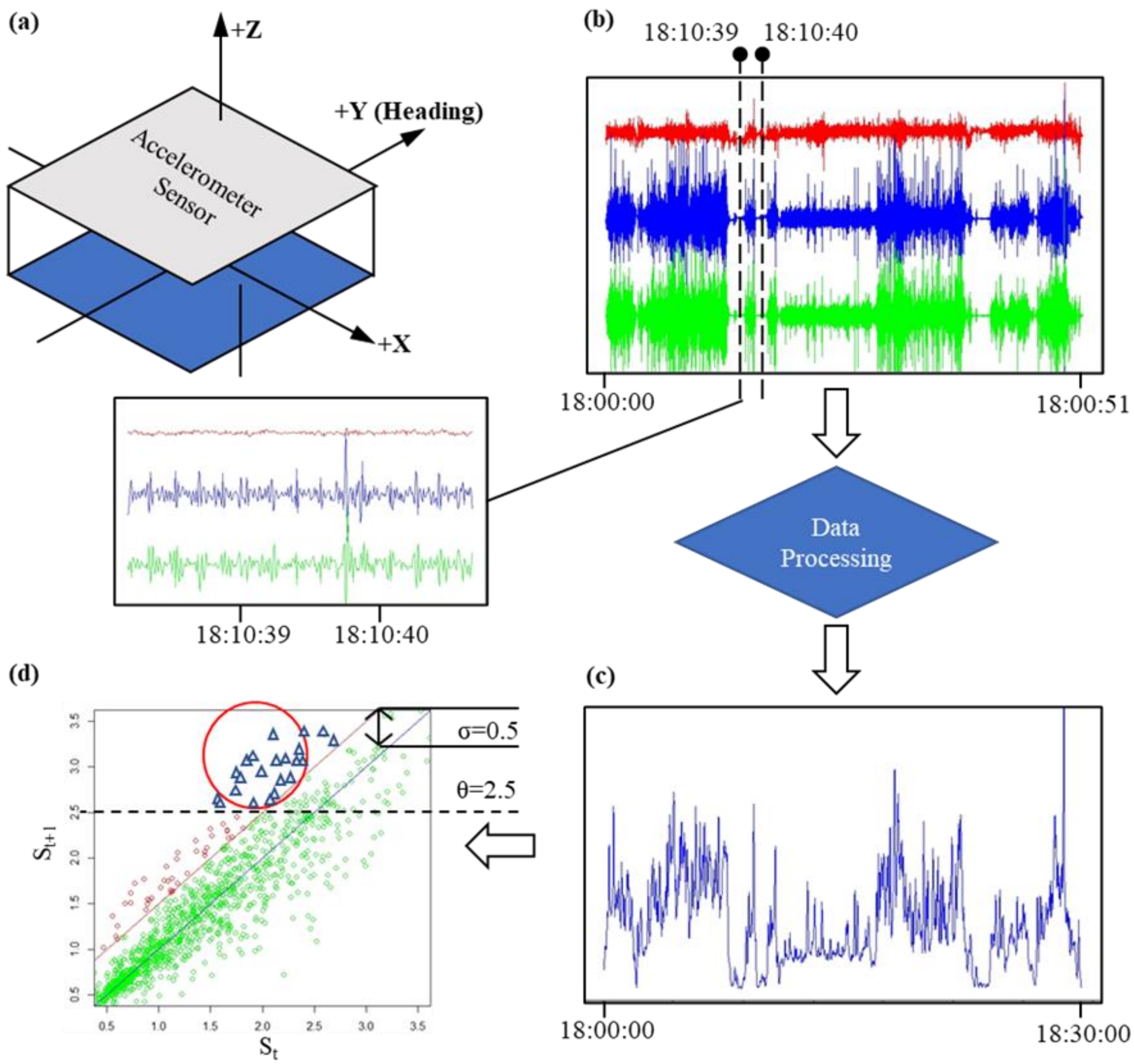



FIGURE 27. THE FRAMEWORK FOR QUANTIFYING VIBRATION BASED ON THE IMU SENSOR MEASUREMENTS.

### 6.2.4 MEASURING RIDING VELOCITY

Riding speed is a critical factor that can affect E-Scooter safety. As previously mentioned, scooters can easily reach a hazardous speed of 15 mph or more in a short period. The E-Scooter's velocity should be tracked and examined as a basic risk factor. In particular, the speed variation should be considered as frequent accelerating or decelerating actions may be taken by riders. In this study, velocity information will be extracted from the GPS device and hotspot maps will be applied in analysis. In addition, the correlation between velocity and vibration is also examined.

## 6.3 DESIGN OF EXPERIMENTS AND DATA COLLECTION

In general, there are three experimental scenarios included in this study. Firstly, the E-Scooter will be ridden back and forth on a selected road segment. The relevant parameters are tuned so that the detected vibration events match the sites with known issues (e.g., cracked surface) on that segment. Meanwhile, the velocity is also compared with the vibration to examine whether there was any correlation. The tuned parameters will be applied for vibration event detection tasks in later scenarios. In the second experiment, an E-Scooter is run on sidewalks and vehicle lanes sequentially to collect vibration data and nearby obstacles separately in each riding environment. Both types of facilities are adjacent to each other with the same circular alignments in a selected neighborhood. The collected data will be further analyzed using the tuned model in the first scenario, and explicit risk patterns will be extracted. The different risk patterns on sidewalks and vehicle lanes will be used to describe the performance of riding E-Scooters in each condition. Finally, the last experiment is designed to examine the magnitude of impact experienced by E-Scooters against bikes. It aims to illustrate how an E-S-scooter can experience increased vibrations on different types of pavements (e.g., concrete, asphalt) compared to other road users. This will provide surrogate evidence in highlighting the unique risk of E-Scooter riders under the same riding environment.

### 6.3.1 VIBRATION EVENT CALIBRATION

The vibration threshold in Section 3.3 should be calibrated and tuned so that correct vibration events can be detected appropriately. As shown in **Figure 28**, the research team rode roundtrips with an E-Scooter between A to B of a 165-ft roadway section with sidewalk following Route 1 on sidewalks and vehicle lanes along Route 2 shown in the figure. The E-Scooter was equipped with sensors to track vibrations. Meanwhile, GPS locations and speed measurements were also monitored for further analysis. During each trip, the rider was required to keep riding on either the sidewalks (in red) or the vehicle lanes (in blue). Each scenario was repeated 10 times. The collected vibration data were processed using the same method as depicted in Section 3.3. Then, the identified vibration events were mapped and compared with the sites of notable issues such as potholes or deep cracks. The vibration threshold can be adjusted accordingly to capture vibration events, which will be used as a standard configuration in later experiments.

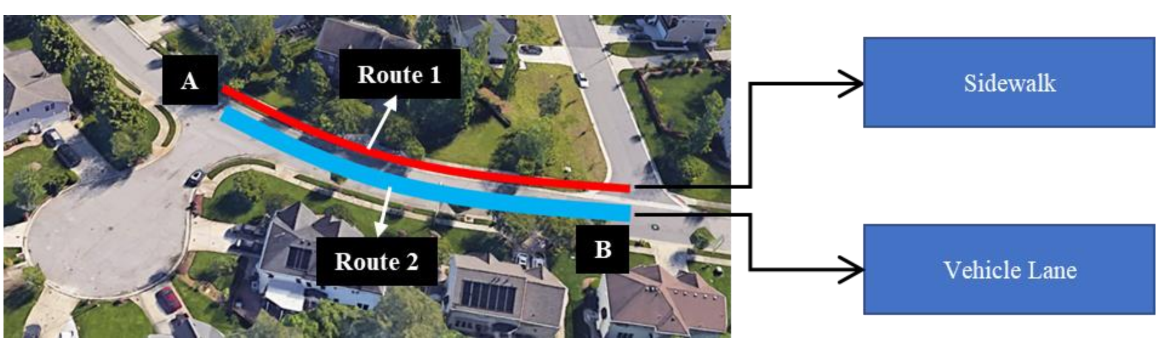



FIGURE 28. EXPERIMENTAL DESIGN FOR CALIBRATING VIBRATION THRESHOLD VALUES.

### 6.3.2 E-SCOOTER SAFETY ASSESSMENT: SIDEWALKS AND VEHICLE LANES

It has been widely argued whether E-Scooters should be ridden on sidewalks when they are accessible. On one hand, riders are more likely to be involved in crashes with vehicles on vehicle lanes; on the other hand, riders may also get injured by hitting pedestrians, trees, or curbs on sidewalks. Some cities (e.g., the City Council in Tempe, AZ) require E-Scooters to be used on sidewalks of roadways with high a speed limit [132]. However, many others are also concerned about safety when riding E-Scooters on sidewalks. For example, Badeau, et al. [10] indicated the majority of injuries (44%) occurred on sidewalks. Riding E-Scooters on sidewalks can be challenging with uneven pavement and relatively dense obstacles. To assess those impacts quantitatively, an experiment shown in **Figure 29** is designed. The study area is a residential neighborhood with both sidewalks and vehicle lanes available. The sidewalks have concrete pavement, and the vehicle lanes have asphalt pavement. This environment will allow the test to be performed without exposing riders to live vehicular traffic environment. On public streets, E-scooters are expected to experience additional risk when interacting with running vehicular traffic on shared lanes. In our experiment, a trip following the vehicle lane (as indicated by the thicker line) and another trip following the sidewalk (as indicated by the thinner line) are designed. Both trips are counterclockwise starting and ending at P1. Each route is about one mile. With LiDAR and IMU sensors, surrounding obstacles can be scanned and E-Scooter vibrations can be tracked. Taking advantage of the method introduced earlier, the aggregated proximity grid and vibration events will be derived and used as surrogate safety metrics for each trip. The sidewalk trip and vehicle-lane trip will be further analyzed based on such metrics.

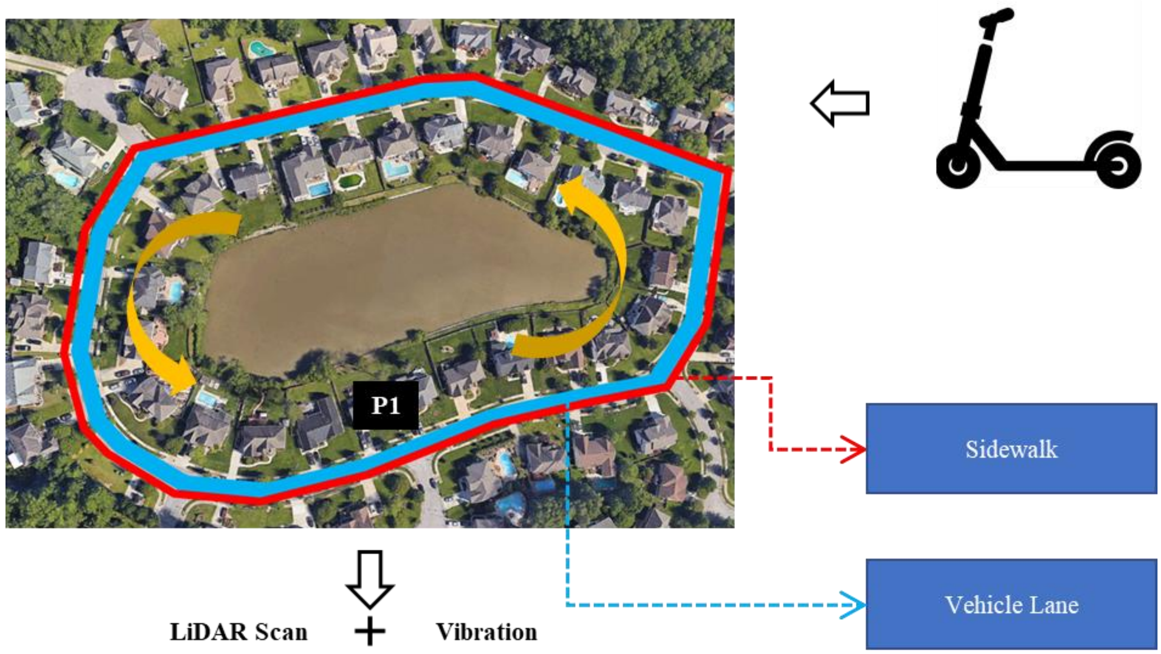



FIGURE 29. COMPARATIVE EXPERIMENTAL DESIGN FOR E-SCOOTER SAFETY ANALYSIS ON VEHICLE LANES AND SIDEWALKS.

### 6.3.3 ASSESSING THE MAGNITUDE OF IMPACT EXPERIENCED BY RIDERS ON DIFFERENT PAVEMENTS

Unlike bicycles with larger wheels that can be ridden smoothly on most types of pavements, E-Scooter riders may not feel comfortable when riding on facilities with uneven pavement. As the wheels of E-Scooters are typically very small, they are expected to be highly sensitive to roadway conditions. In this scenario, a scooter and a bike were installed with the mobile sensing system and conducted a trip on the sidewalk from A to B along a roadway section shown in **Figure 30**. The test route has consisted of multiple segments including two types of pavements: asphalt and concrete. Then the collected data for the E-Scooter and the bike were processed using the same workflow described in Section 3.3 so that vibration events were extracted and compared. In addition, speed heatmaps were produced for both the E-Scooter and the bike.

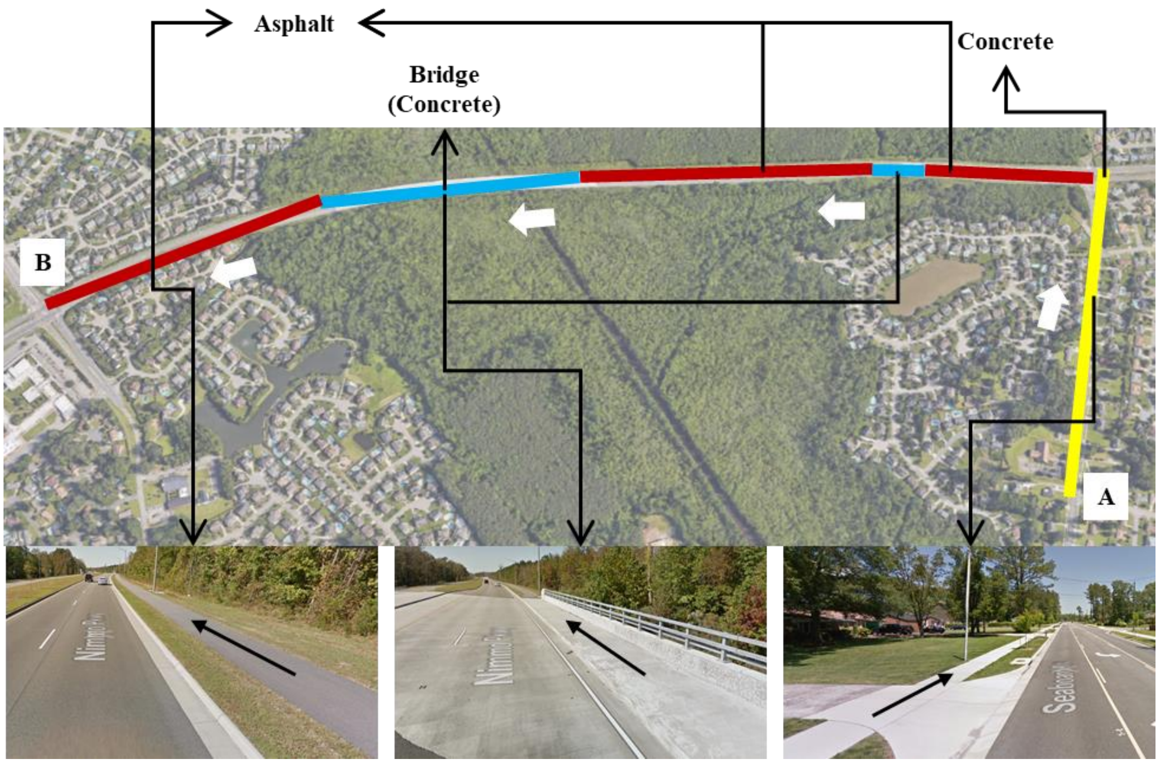



FIGURE 30. COMPARATIVE EXPERIMENTAL DESIGN FOR E-SCOOTER SAFETY ANALYSIS ON DIFFERENT SIDEWALKS.

## 6.4 EXPERIMENTAL RESULTS AND ANALYSIS

There are in total three experiments designed and conducted. The mobile sensing system was installed on an E-Scooter (i.e., MEGAWHEELS S5 Electric Scooter, 10-mile long-range battery, up to 15.5 mph, 8.5" pneumatic tires) and a bike (i.e., Roadmaster Granite Peak Men's Mountain Bike, 26" wheels) to collect real-time data including vibrations, locations, and LiDAR scans. As stated previously, this study focuses on applying mobile sensing to collect safety-related data instead of the characteristics of riders. All riding experiments were conducted by one of the researchers who is a male about 6 feet tall. The rider is an experienced E-Scooter rider and cyclist. Riding by the same rider helps reduce human behavioral impacts in the experiments and makes the results comparable. If human factors (e.g., weight of riders, age, etc.) and behavior are of interest, different sets of experiments can be designed by involving more riders, which is beyond the scope of this study.

### 6.4.1 VIBRATION EVENT DETECTION AND CALIBRATION RESULTS

As shown in **Figure 31**, the E-Scooter was ridden on the selected sidewalks (Route 1) and vehicle lanes (Route 2) 10 times separately. Vibration data were continuously collected during each trip. Typical examples of the results for Routes 1 and 2 are shown in **Figure 31** (a) and (b). Obviously, vibration events (the vibrations drastically change) can be observed on Route 1 while the vibration curve is smoother on Route 2. After applying the method described in Section 3.3, 25 vibration events associated with the 10 runs were detected on Route 1 under the parameters of $\theta = 2.5$ and $\sigma = 0.5$, but no vibration event was detected on Route 2. After mapping the detected events based on GPS information, it can be found that all of them are clustered near one site as shown in **Figure 31** (c). With the photo taken near that site (**Figure 31** (d)), the presence of the notable pavement crack should be attributed to the occurrence of the detected vibration events. Therefore, it has been demonstrated that the E-Scooter tracker is able to detect vibration events sensitively. The complex vibration raw data can be transformed into simple vibration events. An example of the vibration event output tables is shown in **Table** 12. Besides the spatiotemporal attributes, the vibration strength was also recorded for further analysis. This workflow of vibration detection was programmed in R Studio software.

**Figure 31** (c) and (d) are scatterplots between the vibration strength and the speed for each second during the test. Both of their correlation values were small, with values of 0.178 and

0.180, respectively. The weak correlation suggests that that speed and vibration variables are notably affecting each other. In particular, **Figure 31** (e) suggests that vibration events can be detected under both low-speed and high-speed situations on the same road.

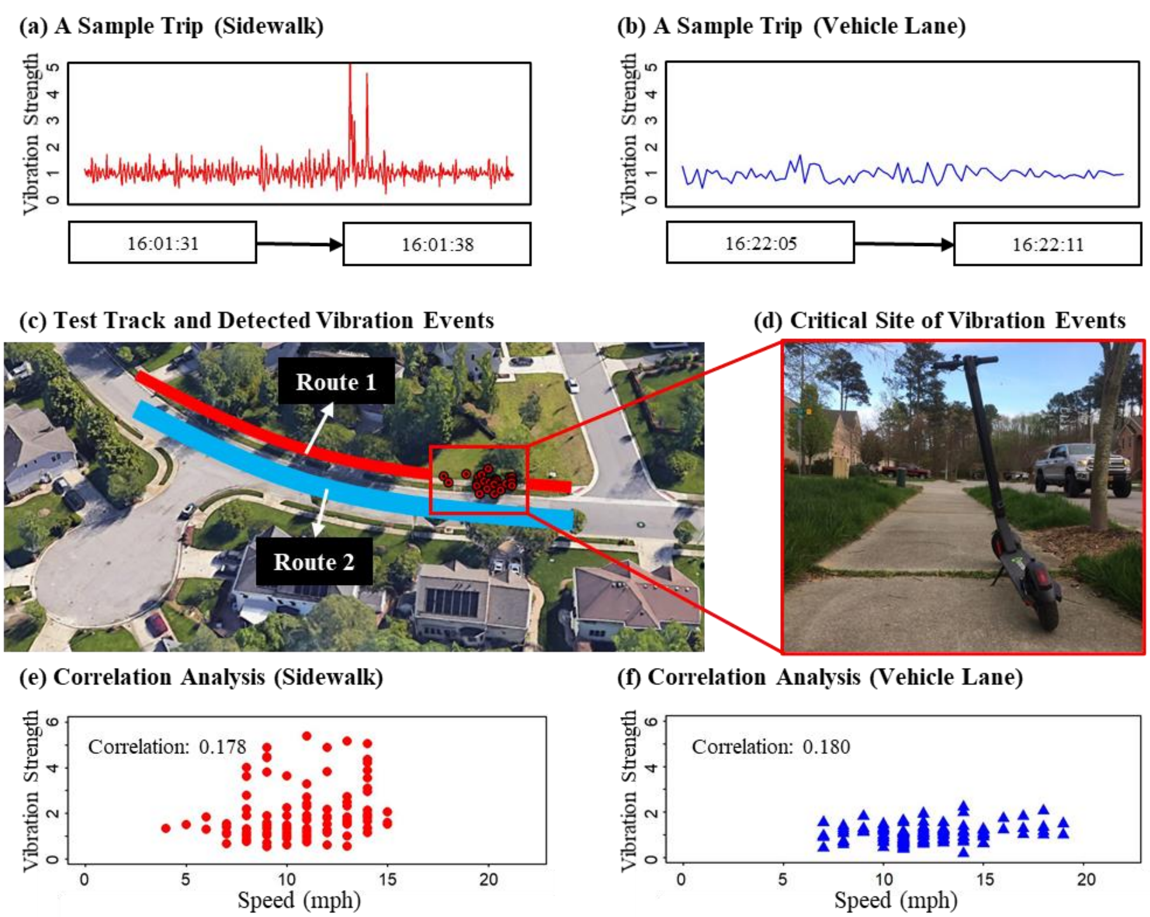



FIGURE 31. VIBRATION EVENT DETECTION MAP.

TABLE 12. EXAMPLE OF VIBRATION EVENT TABLE

| Event ID | Timestamp | Vibration Strength | Lat | Lon |
|---|---|---|---|---|
| 1 | 16:01:36 | 5.38 | 36.75774 | -76.03652 |
| 2 | 16:02:52 | 4.77 | 36.75775 | -76.03645 |

| | | | | |
|---|---|---|---|---|
| … | … | … | … | … |
| 25 | 16:21:02 | 2.86 | 36.75782 | -76.03642 |

### 6.4.2 E-SCOOTER SAFETY CHALLENGES: SIDEWALKS AND VEHICLE LANES RESULTS

The well-calibrated E-Scooter sensing system was used to collect safety data during a ride on concrete sidewalks and a ride on asphalt vehicle lanes in a neighborhood. The LiDAR scans, vibration events, and velocity maps constitute the surrogate safety metrics as illustrated in **Figure 32** where (a), (c), and (e) on the left side belong to the ride on sidewalks; while (b), (d), and (f) are for the ride on vehicle lanes. The proximity grids in **Figure 32** (a) and (b) are aggregated from the measurements of the LiDAR scans. Each grid represents the total frequency of object presence being detected in a relative position during a trip. The grids are organized in a polar coordinate system with a size of 30 degrees and 5 feet. Few obstacles can be detected along with the heading direction during a ride. Obstacles can present on either the left side or right side of the running E-Scooter and the grids closer to the center are riskier for the rider. The summarized proximity grids can always reflect obstacles in reality. According to the plots, obstacles detected when riding on sidewalks are clustered in inner circles between 0 to 15 feet. In reality, there are shrubs and trees along the ride on sidewalks, which lead to a narrow riding path. On the other hand, the detected obstacles on the tested vehicle lanes are mainly located in outer circles between 15 to 30 feet. The rider has a broader space compared to the sidewalks. Meanwhile, since the E-Scooter was ridden on the right side of vehicle lanes, very few obstacles were detected between 0 to 15 feet on the left side. There were several obstacles detected on the right side in the same range. They are mainly parked vehicles, trees, electicity poles, and mailboxes. **Figure 32** (c) and (d) show the detected vibration events. The rider experienced 149 vibrations when riding on the sidewalks, whereas the rider only experienced 38 vibration events while riding in the vehicle lane. The higher frequency of vibration events on the sidewalks is mainly attributed to uneven and/or damaged pavement conditions in the neighborhood. In contrast, the overall pavement surface quality of the vehicle lanes is better. The speed heatmaps are presented in **Figure 32** (e) and (f). As seen from the map, riding the E-Scooter in the tested vehicle lanes has a higher speed compared to running on the sidewalks. In summary, riding E-Scooters on the tested sidewalks can be more challenging compared to the tested vehicle lanes due to the narrower space and more vibrations. The riders operated their E-Scooters more cautiously by maintaining a lower average speed of 5.83 mph on the sidewalks compared to 9.87 mph in vehicle lanes.

It should be mentioned that the results obtained in these experiments should not be extended as a conclusion that riding on sidewalks is more dangerous than vehicle lanes, or vice versa. Different facilities have different factors (e.g., vehicle volume, number of pedestrians, etc.) that were not able to be fully incorporated into the current experiments. Despite the analysis of proximity, vibration, and speed, the present study does not directly examine the impact in terms of conflicts or crashes due to those moving objects such as running vehicles.

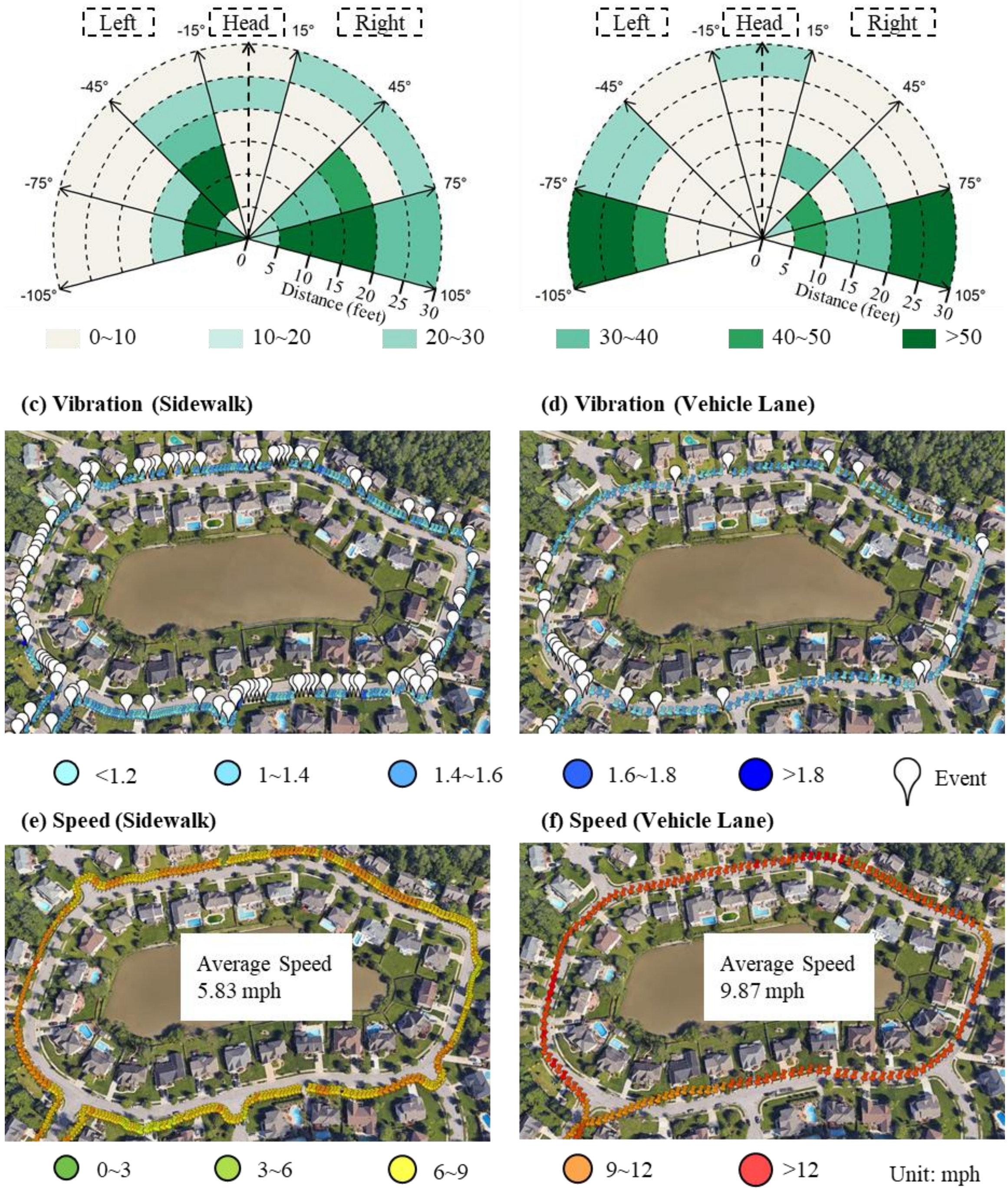



FIGURE 32. EXPERIENCED IMPACTS WHEN RIDING ON DIFFERENT FACILITIES.

### 6.4.3 THE MAGNITUDE OF FACILITY IMPACT ON E-SCOOTER RIDING

In order to provide a better understanding of the magnitude of the vibration impact encountered by E-Scooters, a comparative study was conducted between E-Scooters and bikes.

The scooter and the bike were ridden on the same test route separately by the same rider. The test route consisted of different types of sidewalks and was about 2 miles as shown in **Figure 30**. Vibration events and speed measurements were collected; the results are shown in **Figure 33**. In general, more vibrations are experienced on the concrete pavement than the asphalt pavement for both the E-Scooter and the bike. Fewer vibration events were observed during the bike trip compared to the E-Scooter trip (i.e., Bike: 8 vs. E-Scooter: 50). The bike with larger wheels provided a smoother riding experience for the rider. Thus, riding E-Scooters can be more challenging than riding bikes on the same pavement conditions, especially on concrete sections. In addition, according to the reported E-Scooter-related accidents collected by Yang, et al. [22], 30% of victims were injured by falling off E-Scooters. The method of riding E-Scooters by standing on the riding deck makes it prone for vulnerable riders to be thrown off the vehicle. Moreover, the average speed for the E-Scooter trip is similar to that of the bike trip ( E-Scooter: 8.07 mph and bike: 8.78 mph). Despite the similar average speed, more fluctuation in speed was observed for the E-Scooter trip. This can be evidenced by comparing the average absolute acceleration. The E-Scooter trip had a higher average absolute acceleration of 2.55 ft/($s^2$), whereas the bike trip only had 1.46 ft/($s^2$). The notable difference in the average absolute acceleration is largely attributed to the high sensitivity of the acceleration function of E-Scooters. Unlike most bikes that rely upon human power pushing the pedal, E-Scooters are typically accelerated by controlling the power device on the handlebars. Slightly pushing the device may quickly raise the power for motors to achieve higher speeds in a short amount of time. The forward force driven by the electric pulse is abrupt and difficult to control. This characteristic can cause difficulties in safely and smoothly controlling the speed when riding E-Scooters, especially for those with less experience in using E-Scooters.

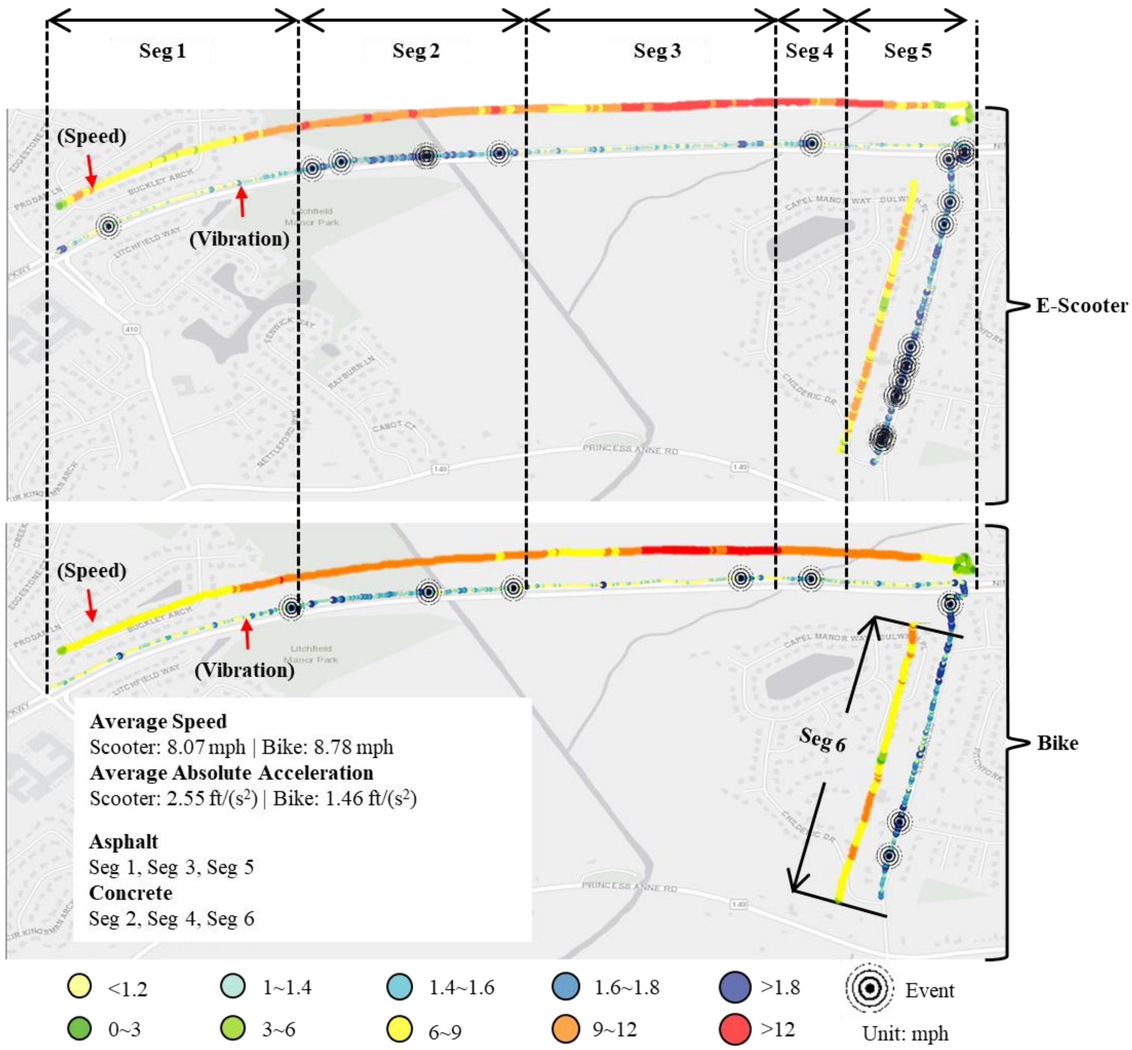



FIGURE 33. COMPARATIVE ANALYSIS OF VIBRATIONS AND SPEED CHANGES EXPERIENCED BY E-SCOOTERS AND BICYCLES.

In particular, the summarized vibration events on different facilities are shown in **Table 13**. Overall, the asphalt pavement is smoother, and riders experienced fewer vibrations when riding on it. For the test outside the neighborhood, the densities of vibration events for a 1-mile ride for E-Scooters and bikes are 5.6 and 1.1 for the asphalt pavement and concrete pavement, respectively. Comparatively, the density of vibration events on sections with concrete pavement is 7-9 times that on asphalt pavement. It should be noted that the E-Scooter rider experienced a high frequency of 49.2 vibration events per mile on the concrete pavement. Likewise, the vibration densities are 278 times per mile on sidewalks with concrete pavement and 70.1 times per mile in vehicle lanes with asphalt pavement in the neighborhood. Indeed, visually checking the pavement conditions suggests that the quality of the tested facilities outside the tested neighborhood indeed is better in terms of fewer cracks and potholes. Thus, according to the analysis results, the road facilities with the least vibrations should be considered as safer options if other conditions are similar.

TABLE 13. SUMMARIZED VIBRATION EVENTS ON DIFFERENT TESTED FACILITIES

| **Mode** | **Facility** | **Vibration Event** | **Length (mile)** | **Vibration Density** |
|---|---|---|---|---|
| E-Scooter | Asphalt Sidewalk | 5 | 0.898 | 5.6 events/mile |
| | Concrete Sidewalk | 45 | 0.914 | 49.2 events /mile |
| Bike | Asphalt Sidewalk | 1 | 0.898 | 1.1 events /mile |
| | Concrete Sidewalk | 7 | 0.914 | 7.7 events /mile |
| E-Scooter | Concrete Sidewalk (in Neighborhood) | 149 | 0.536 | 278.0 events /mile |
| E-Scooter | Asphalt Vehicle Lane (in Neighborhood) | 38 | 0.536 | 70.1 events /mile |

## 6.5 SUMMARY AND DISCUSSION

The rapid expansion of E-Scooter programs in many urban areas has sparked discussion concerning issues related to their operation and usage, riding behavior, policy, and safety. Other than sharing facilities with other mobility modes, typically no dedicated roadway resources have been allocated to E-Scooters. Consequently, E-Scooters in many cities have significantly disrupted the use of sidewalks and other facilities without sufficient regulations, guidance, and enforcement. Urgent efforts are necessary to support safer operations for E-Scooters by understanding riding behavior and how they interact with the riding environment. However, no relevant data have been publicly available for supporting such understanding. To fill this gap, the current study adds to the existing literature by developing and deploying a mobile sensing system that facilitated data collection efforts for advancing our understanding of riding risk associated with E-Scooters on different facilities. The developed system has integrated a set of sensing devices including GPS, IMU, and LiDAR to collect real-time information on geospatial coordinates, vibrations, and surrounding obstacles of an instrumented E-Scooter. With both descriptive analysis and in-depth data mining, the proposed E-Scooter safety metrics can be used as surrogates, rather than estimations of crashes to support the examination of potential riding risk associated with each trip. The introduced safety metrics contain three main components: (a) summarized proximity grids showing the accumulated frequencies of riders who encountered close contact with obstacles along each riding path; (b) vibration events that significantly affect riding experience as standing on the deck while riding is liable to lead to falling on uneven pavement; and (c) speed variations that affect riding volatility during each ride.

The developed approach for detecting vibration events can facilitate capturing the risky metrics on different types of facilities. Repeated experiments were conducted following a 165-ft road section with a known crack on its sidewalk with no notable physical deficiencies in its vehicle lanes. With the tuned parameters, 25 vibration events were correctly identified at the cracked site, whereas no such event occurred in vehicle lanes. Besides, the detected vibrations were found to be independent of the riding speed as a low correlation presented between the two variables. Then the derived safety metrics were applied to assess the riding processes on different facilities. The comparative experimental results highlight the riding challenges on different road facilities. It can be concluded that riding on both sidewalks and vehicle lanes are highly likely to encounter many close interactions with obstacles, and riders are likely to experience different frequencies of vibration events due to the differences in materials and physical conditions of these facilities. Riding on designed sidewalks with concrete pavement is likely to encounter higher frequencies of vibration events than those with asphalt pavement. Also, it is safe to conclude that E-Scooter riders will experience more severe vibration impacts than cyclists if they were riding on the same facilities. Compared to the cyclists' smooth accelerations, E-Scooters' quick changes in acceleration are risky because they prevent riders from stably controlling the vehicles under varying forward forces.

The safety metrics in terms of vibration, speed variation, and LiDAR-based proximity focus on the relationship between E-Scooter riders and the facilities in the riding environment (e.g., trees, buildings, curbs, pavement, and potholes). These metrics do not provide a direct approximation to crash risk of E-Scooters. Instead, it offers some possible surrogates to help explore part of the riding risk associated with E-Scooters. In addition to those explored factors, more safety surrogate measures such as modified time to collision [133, 134] can be derived to enrich the description of E-Scooter safety. For example, Maiti, et al. [135] analyzed the relationship between E-Scooters with pedestrians using recorded videos. Pedestrians can be recognized using computer vision methods, and their distances towards E-Scooters can be measured by matching the data with LiDAR measurements. If this technique is deployed, it will enrich the information that can be captured in denser areas with high pedestrian volumes. In addition, the developed systems and metrics can also be used to provide some concrete facts in supporting the observational studies on riders' risky behavior.

# CHAPTER 7 – E-SCOOTER SAFETY: THE COUPLING OF E-SCOOTER VEHICLE FEATURES AND ROAD INFRASTRUCTURE

## 7.1 INTRODUCTION

With more travelers selecting shared E-Scooters for short-distance trips, their safety issues have caught the attention of researchers. E-Scooter riders feel more vibrations compared to bicycles with traditionally larger wheels. Such riding experience may lead to discomfort and impact riders' health. Theoretically, increasing E-Scooters' wheel sizes can be a good strategy for improving the riding experience. However, this assumption has not yet been demonstrated. The main objective of this chapter is to develop a mobile sensing platform for collecting vibration data. This platform will be distributed to E-Scooters with small wheels and big wheels. Then, the testing E-Scooters will be ridden on selected routes with different road infrastructures. The collected data will be further processed for evaluating various riding behaviors in each scenario. The results suggest that E-Scooters with big wheels can efficiently alleviate vibrations during a ride compared to those with small wheels. Therefore, E-Scooter vendors are encouraged to replace small-wheel E-Scooters with big-wheel ones.

## 7.2 PAVEMENT SUITABILITY EVALUATION FOR RIDING E-SCOOTERS

The relatively small wheel size of E-Scooters may lead to stronger feeling for vibrations compared to riding bicycles. Meanwhile, there can be different patterns of vibrations when riding on sidewalks with different pavements. As there is no detailed guidance on suitable sidewalks for riding, such road quality deficiencies will raise more challenges for E-Scooter riders. According to the 125 E-Scooter riders surveyed by [136], 50% believe pavement conditions like potholes or cracks contributed to their injuries. On the other hand, when riding across such potholes or cracks, E-Scooter riders are more likely to feel uncomfortable with strong-strength vibrations [130]. Thus, understanding the impact of vibrations on E-Scooter riding experience and identifying hazard potholes or cracks are helpful in mitigating potential crashes. The present study developed a systematic framework to collect data and evaluate riding vibrations. It should be noted that this framework is not aimed at providing direct quantitative assessment of E-Scooter riding safety in the light of crashes or riders' risky behavior. Instead, it emphasizes depicting possible risky factors attributable to riding vibrations.

### 7.2.1 ACCESSING RIDING VIBRATION

The research team adopted a mobile sensing application to record naturalistic riding data for each E-Scooter trip. As shown in **Figure 34** (a), the mobile phone was attached to the E-Scooter's decker using tape. Three-dimensional accelerometer data $X_t$, $Y_t$, and $Z_t$ are selected for evaluating vibrations for the timestamp $t$. It should be noted that $+X$ is identical to the E-Scooter's heading direction. The data collected by these settings are very sensitive with a minimum time resolution of 10ms. **Figure 34** (b) shows raw vibration data for an exemplar trip. The major vibrations can be observed in $X$ and $Y$ dimensions. Then the vibration magnitude $M_t$ is calculated using the following equation.

$$M_t = \sqrt{{X_t}^2 + Y_t^2 + {Z_t}^2} \tag{13}$$

Then, maximum value $M_{\max}$ and standard deviation $M_{sd}$ are calculated for each second during the trip. The calculated $M_{\max}$ is taken as the vibration magnitude for each second, which can be further mined to identify significant vibration events as shown in **Figure 34** (e). $M_{\max,i-1}$ and $M_{\max,i}$ are the X axis and Y axis of the scatterplot where, $M_{\max,i}$ represents the vibration magnitude for the $i^{th}$ second and $M_{\max,i-1}$ indicates the vibration magnitude for its previous second. The blue triangle points indicate timestamps with vibrations larger than $\theta$. On the other hand, another parameter $\sigma$ shown in **Figure 34** (d) will be used for as the threshold for $M_{sd}$. The two parameters $\theta$ and $\sigma$ will be used for determining vibration events based on the following rules: (1) $M_{\max,i} > \theta$; (2) $M_{sd,i} > \sigma$.

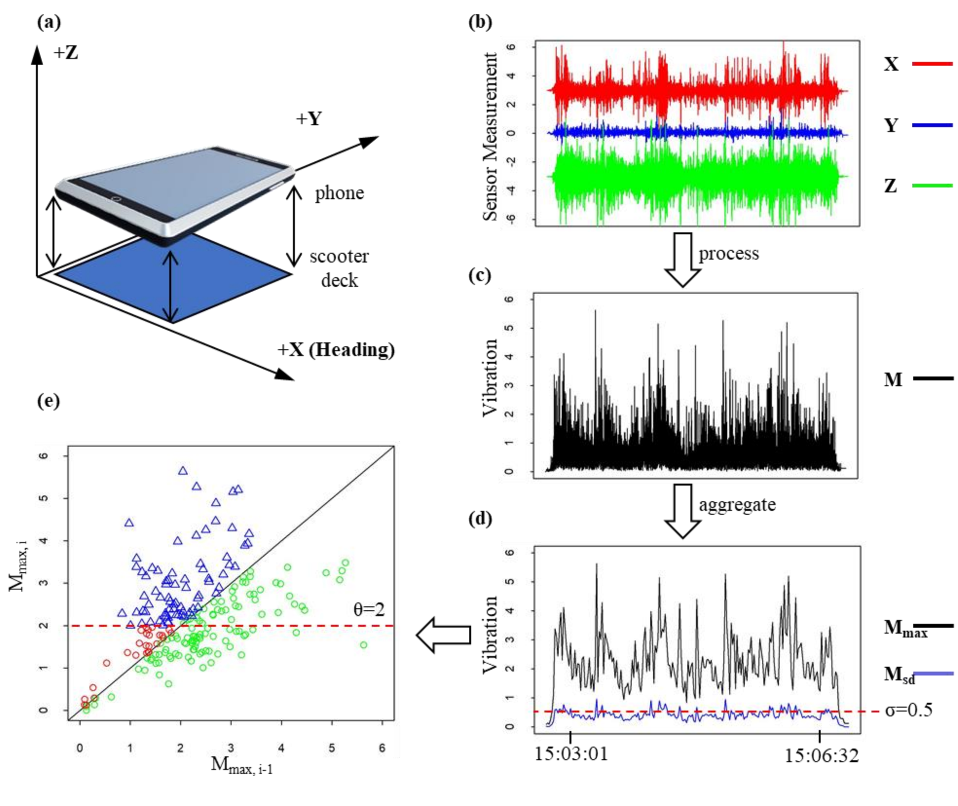



FIGURE 34. CALIBRATING VIBRATION EVENTS WITH SMALL- & BIG-WHEEL E-SCOOTERS.

### 7.2.2 CALIBRATING VIBRATION EVENTS

The vibration parameters should be calibrated and tuned to ensure that correct vibration events can be detected. **Figure 35** shows three typical vibration events at selected locations. Event A is a typical pothole, while B and C are two types of slopes. E-Scooter riders will feel remarkable vibrations when crossing those locations compared to their flat riding experiences. Both small-wheel and big-wheel E-Scooters will be ridden multiple times between P1 and P2. Meanwhile, a mobile device will be attached to the testing scooter and vibration data will be collected. Then, vibration events can be identified following the workflow as described previously. The vibration parameters will be tuned so that the detected vibration events are consistent with the potholes and slopes.

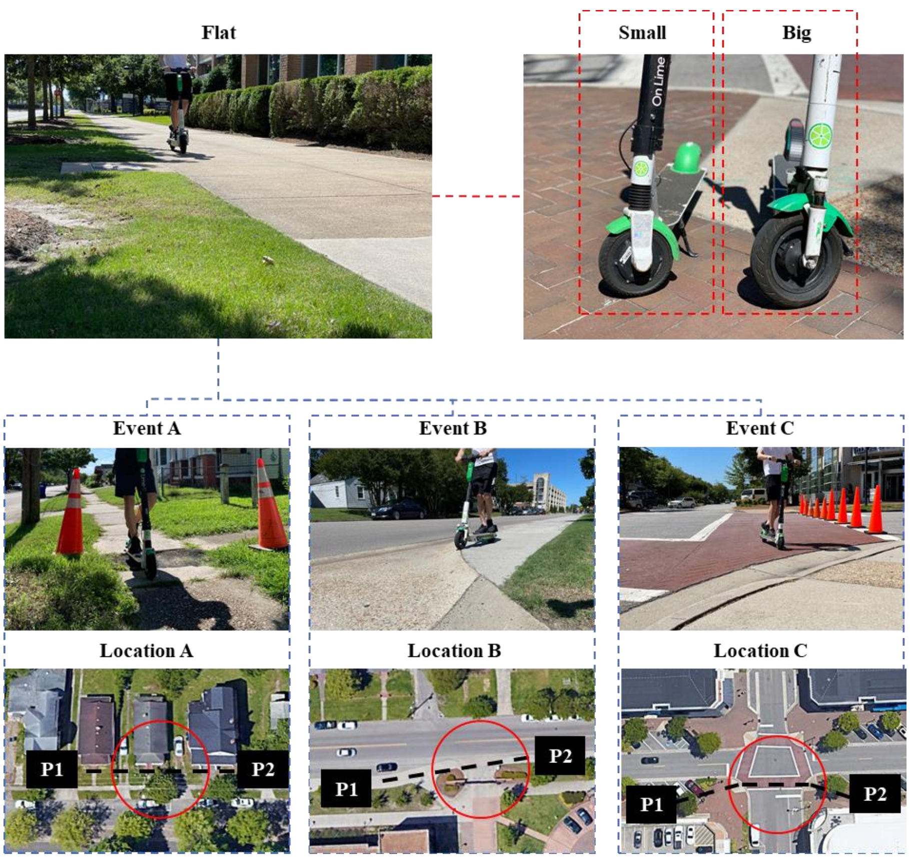



FIGURE 35. TYPICAL VIBRATION EVENTS TO BE TESTED AT SEVERAL SELECTED SITES.

### 7.2.3 MEASURING RIDING VELOCITY

Riding speed is a critical factor for E-Scooter safety. When riding in regions without a speed limit, the E-Scooters can easily reach a hazardous speed of 15 mph in a short time. The E-Scooter's velocity should be tracked and calculated during a trip. In this study, the velocity for the second can be calculated using the follow equation.

$$V_i = \frac{Dist(i-1,i) + Dist(i,i+1)}{2} \tag{14}$$

where, $Dist(i-1,i)$ indicates the distance between the locations of the $(i-1)^{th}$ and the $i^{th}$ second.

## 7.3 DESIGN OF EXPERIMENTS

### 7.3.1 EXPERIENTAL ROUTES

According to the work published by Jiao and Bai (2020), land use is one of the primary factors affecting the demand for E-Scooters. This study will focus on the sidewalks near three typical land use categories: (1) sidewalks in neighborhoods; (2) sidewalks near campus; and (3) sidewalks on commercial streets. The three sidewalk routes are shown in **Figure 36** (a), and **Figure 36** (b) contains the photos of their pavements. It can be observed that neighborhood sidewalks have comparably narrow lanes, where large cracks with weeds can be frequently observed. On the contrary, campus sidewalks are wider and smoother compared to the neighborhood sidewalks. Both have concrete pavement. The pavement of the commercial streets primarily consists of bricks, where different vibration patterns are expected.


FIGURE 36. PROTOTYPE IMPLEMENTATION IN DESIGNED SCENARIOS.

### 7.3.2 SCENARIO DESIGN

There are two researchers conducting the relevant experiments. It should be noted that this study does not focus on human factors. Instead, it focuses on quantifying vibrations during E-Scooter trips. Theoretically, the vibration patterns should be similar between the two under each scenario. This assumption will be tested with statistical methods in later sections. As previously mentioned, there are two types of E-Scooters distributed by Lime: (1) type A has small wheels (diameter: 8 inch); (2) type B has big wheels (diameter: 10 inch). Both types of E-

Scooters will be ridden on the three designed routes. Meanwhile, the distributions of detected vibration events will be compared between the two types of E-Scooters using statistical methods.

### 7.3.3 CALCULATING VIBRATION INDEXES

After applying the calibrated model, vibration events will be identified in each scenario. Then, a set of vibration indexes will be calculated: (1) number of events; (2) E-Scooter trip length; and (3) vibration density. The vibration density equals the number of events divided by the trip length, which describes the density of encountered vibration events during an E-Scooter ride. The higher the vibration density, the less suitable for riding E-Scooters on that particular type of facility.

### 7.3.4 MANN WHITNEY WILCOXON RANK SUM TEST

The Mann Whitney Wilcoxon (MWW) rank sum test has been widely used for comparing whether two sample values are from the same population [137]. The MWW test is given by

$$U_t = \frac{1}{n_1}\frac{1}{n_0}\sum_{i_1=1}^{n_1}\sum_{i_0=1}^{n_0} I\{y_{i_1 1} \leq y_{i_0 0}\} \tag{15}$$

where, $y_{i_l k}$ denotes the observed version of the potential outcome corresponding to the treatment received ($k = 0,1$). $I(A)$ is an indicator with $I(A) = 1$ if $A$ is true and 0 otherwise.

In this study, the detected vibration events will be aggregated every 0.1 miles along the route. Then, the MWW rank sum test will be applied for testing whether the performances between two riders are similar with the same experimental configuration; and if the performances between the two types of E-Scooters are similar to each other.

## 7.4 EXPERIMENTAL RESULTS AND ANALYSIS

### 7.4.1 VIBRATION EVENT CALIBRATION RESULTS

As illustrated in **Figure 35**, a big-wheel E-Scooter and a small-wheel E-Scooter were ridden back and forth 10 times at selected locations. After collecting and processing vibration data, the maximum value and standard deviation of vibration magnitude are shown in **Figure 37**. Then, the parameters for identifying vibration events were calibrated. As a result, $\theta = 3$ and $\sigma = 0.6$ were derived based on the following two rules: (1) no vibration event can be detected on “Flat” scenarios; (2) significant vibration events can be observed at typical potholes or slopes. There are several significant patterns that can be observed from **Figure 37**. First, at the location for Event A, the frequencies of the detected vibration events are similar between the E-Scooters with two types of wheels. On the other hand, intensive vibration events were detected for the E-Scooter with small wheels while fewer vibration events can be detected for the big-wheel E-Scooter at locations for Events B and C. Therefore, both small-wheel and big-wheel E-Scooters are sensitive to vibration events at potholes like Event A. Meanwhile, only small-wheel E-Scooters are sensitive to vibration events at slopes like Events B and C. The big-wheel E-Scooter performed better when riding across slopes with fewer experiences of vibrations.

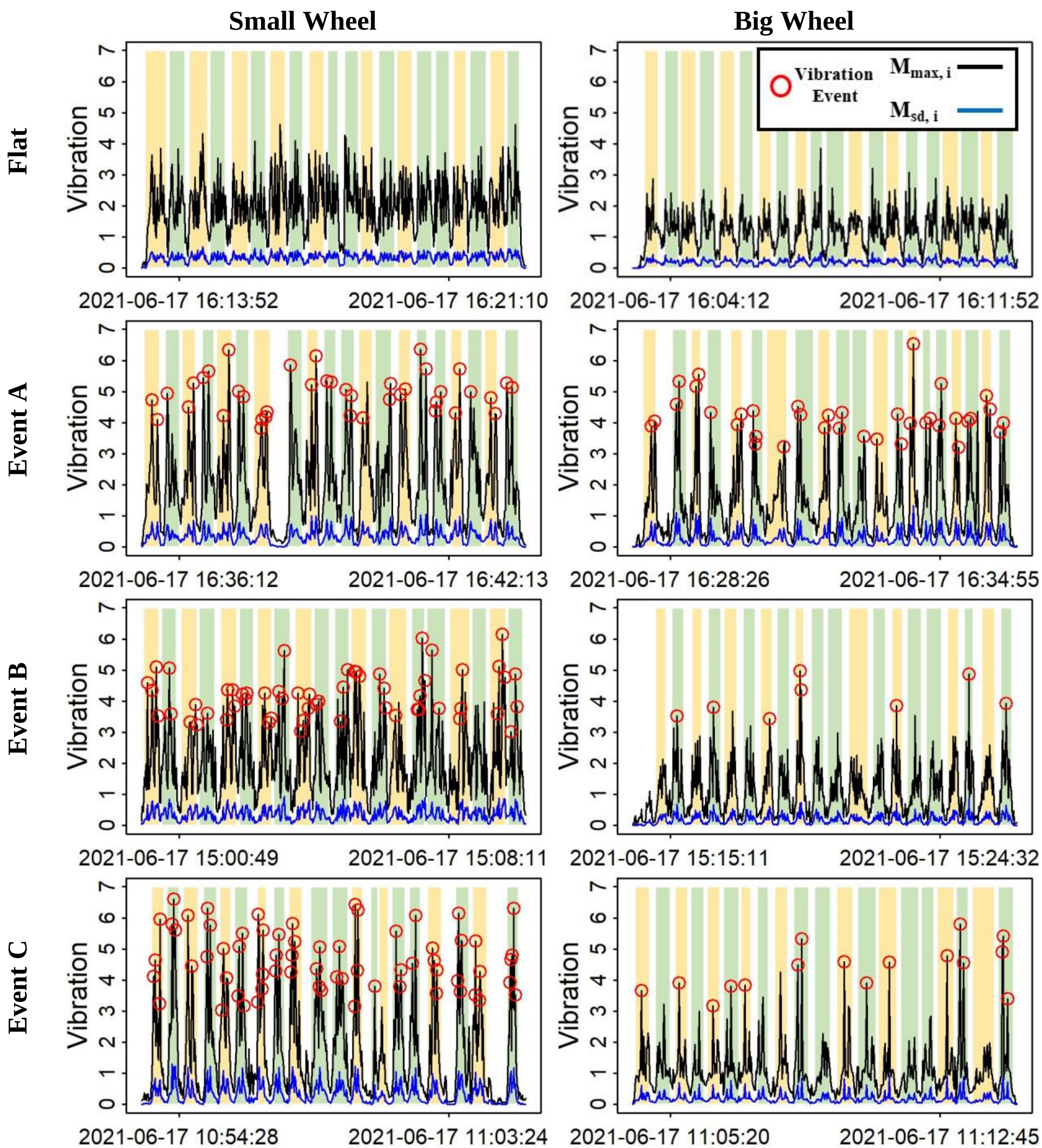



FIGURE 37. VIBRATION CALIBRATION FOR TYPICAL EVENTS.

**Figure 38** shows the maps for detected vibration events on selected testing routes. Due to the disturbance of GPS signals, the events are located within a 10-meter range of the potholes/slopes. For each testing scenario, a scatter plot is drawn with the x axis indicating event speed and y axis indicating calculated vibration. The correlation values between the x and y axes are close to zero for all testing scenarios. The weak correlation suggests that the speed and vibration variables are not affecting each other.

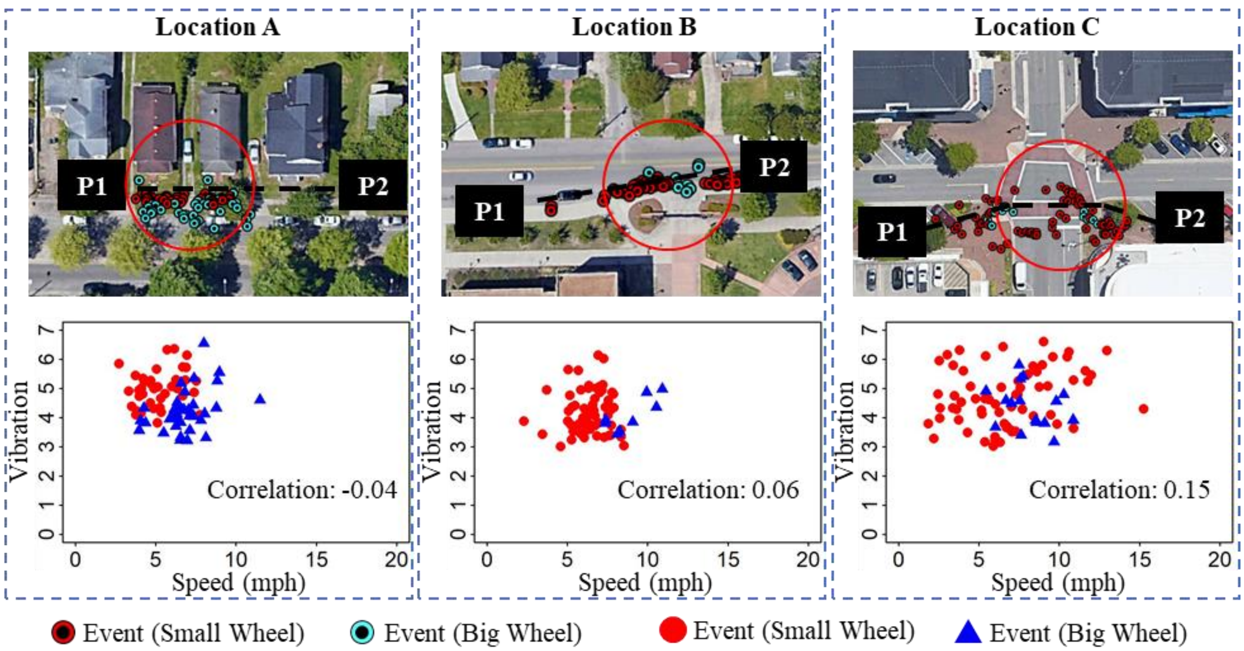



FIGURE 38. VIBRATION EVENTS ON SELECTED TEST ROUTES.

### 7.4.2 COMPARATIVE ANALYSIS FOR E-SCOOTERS WITH DIFFERENT WHEEL SIZES

After applying the calibrated model with $\theta = 3$ and $\sigma = 0.6$, vibration events were detected, and the corresponding indexes are shown in **Table 14**. In general, riders with big-wheel E-Scooters feel fewer vibrations compared to those with small-wheel E-Scooters. Big-wheel E-Scooters have smaller vibration densities on all three selected routes. Specifically, campus sidewalks are most comfortable for riding small-wheel E-Scooters; riders with big-wheel E-

Scooters feel most comfortable on commercial street sidewalks. One interesting observation is that the two types of E-Scooters have distinguished performances when riding on the commercial street where bricks are the primary pavement. It can be inferred that small-wheel E-Scooters are sensitive to the bricks by generating strong vibration patterns, while big-wheel E-Scooters are not affected. This observation will be further explored in later sections.

TABLE 14. VIBRATION INDEXES FOR SMALL-WHEEL AND BIG-WHEEL SCENARIOS

| E-Scooter Type | Facility | Vibration Event | Length (mile) | Vibration Density |
|---|---|---|---|---|
| Small Wheel | Neighborhood Sidewalk | 44 | 0.48 | 91.7 events/mile |
| Small Wheel | Campus Sidewalk | 64 | 1.68 | 38.1 events/mile |
| Small Wheel | Commercial Street Sidewalk | 43 | 0.57 | 75.4 events/mile |
| Big Wheel | Neighborhood Sidewalk | 27 | 0.48 | 56.3 events/mile |
| Big Wheel | Campus Sidewalk | 22 | 1.68 | 13.1 events/mile |
| Big Wheel | Commercial Street Sidewalk | 3 | 0.57 | 5.3 events/mile |

**Figure 39** visualizes the vibrations in each second and the detected vibration events. It provides a straightforward overview of the distributions of the events. Moreover, those spatial data can be used for developing an alerting system for E-Scooter riders. Determined by the type of E-Scooters, the riders will be notified when vibration events are near their riding paths.

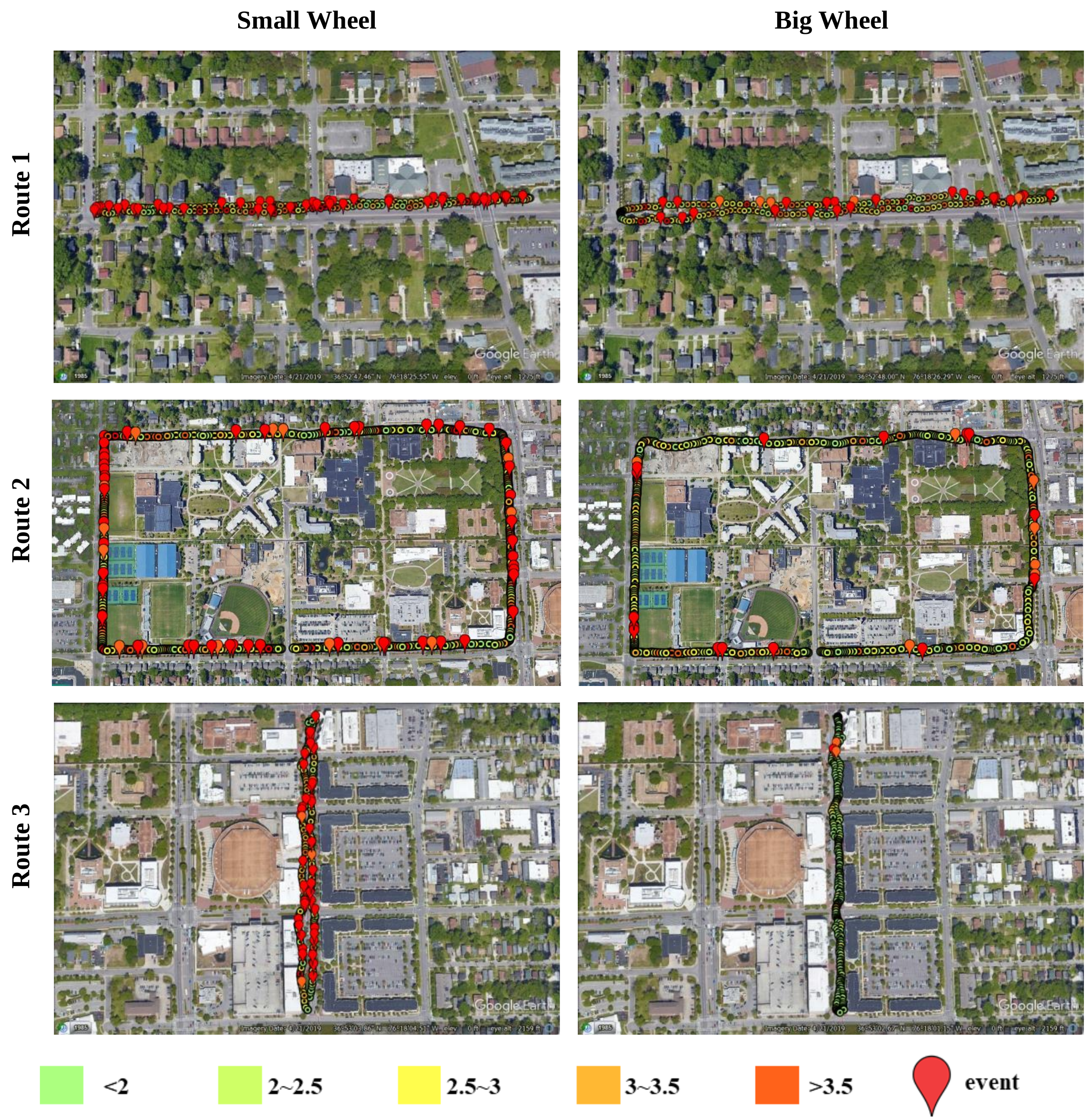



FIGURE 39. COMPARATIVE ANALYSES FOR E-SCOOTERS WITH SMALL- AND BIG-WHEELS.

### 7.4.3 MANN WHITNEY WILCOXON RANK SUM TESTING RESULTS

Two-Rider Comparison

**Table 15** shows the results of MWW tests by pairing two E-Scooter riders in the six designed scenarios (3 routes by 2 E-Scooter types). All p-values presented are larger than 0.1. Therefore, the null hypothesis failed to be rejected. The testing results indicate that the differences between the two E-Scooter riders can be ignored. There is no statistical difference in the analytic results by different riders.

TABLE 15. MANN WHITNEY WILCOXON RANK SUM TEST BETWEEN TWO RIDERS

| Wheel Size | Route | p-value |
|---|---|---|
| Small Wheel | 1 | 0.7827 |
| Big Wheel | 1 | 0.1666 |
| Small Wheel | 2 | 0.6874 |
| Big Wheel | 2 | 0.8858 |
| Small Wheel | 3 | 0.8079 |
| Big Wheel | 3 | 0.6733 |

Big-Wheel and Small-Wheel Comparison

Similarly, the MWW tests were applied to compare whether there is a statistical difference during the E-Scooter trips with small wheels and big wheels. The p-values on the three selected routes are 0.0439, 0.0008, and 0.0043 respectively. The small p-values indicate that there is significant difference in detected vibration events between E-Scooter trips with small wheels and big wheels.

### 7.5 SUMMARY AND DISCUSSION

The rapid rise of E-Scooter programs provides riders a new option for short-distance traveling. By sharing facilities with other transport modes, no dedicated road resources have been allocated to E-Scooters. Consequently, many cities do not have clear guidance on where and how to ride E-Scooters safely. Besides the complex naturalistic environments, E-Scooter riders can feel strong vibrations on sidewalks with bad pavement conditions. Urgent efforts are necessary to support safer E-Scooter operations by understanding riding behaviors. As emphasized by [138], E-Scooter riders encounter strong vibrations due to the small wheel size compared to bicycles with relatively larger wheels. Meanwhile, the vibration patterns vary across different types of pavements (e.g., concrete or asphalt). However, no sufficient work has been explored on the vibrations of E-Scooters with different wheel sizes. To fill this gap, this study adopted mobile sensing technology to collect vibration data for three designed routes. With both statistical analysis and in-depth data mining, it was found that E-Scooters with big wheels have significantly improved comfort over those with small wheels. On the other hand, campus sidewalks have the best pavement conditions for small-wheel E-Scooters, while commercial streets with brick pavement are best for big-wheel E-Scooters.

This study has developed procedures and systematically examined the performances of E-Scooters with different wheel sizes. The experiments were conducted on typical routes with large demand for E-Scooters. It has derived a clear conclusion that E-Scooters with big wheels can better alleviate vibrations than previous small-wheel E-Scooters. The vibration detection workflow with mobile-sensing technologies is also portable and extendable. For example, E-Scooters with vibration sensors installed can be used for evaluating pavement conditions. The vibration event density (VED) can be calculated as an important indicator. If the evaluation process is conducted once per year, VED values are expected to increase due to emerging potholes or cracks. The lower VED values, the better road conditions. When the VED values reach a pre-defined threshold, the corresponding roads should be maintained. Besides the contributions and possible future applications, this study is also limited in the following two aspects. First, besides the wheel size, the two types of E-Scooters involved in this study also have different structures in damping springs. Therefore, the wheel size may not be the only reason for the experiment results. Further experiments are necessary that select E-Scooters with the same damping spring structure. Second, the proposed vibration evaluation method requires researchers to attach mobile phones to E-Scooters' dockers. This method can hardly be scaled and distributed to multiple E-Scooters at the same time. Thus, E-Scooter vendors are encouraged to deploy vibration sensors on E-Scooters to have a broader understanding of riding behavior.

# CHAPTER 8 – CONTRIBUTIONS AND FUTURE WORKS

## 8.1 SUMMARY OF CONTRIBUTIONS

This dissertation provides a comprehensive study of E-Scooters by covering topics including usage, policy, and safety. Specifically, it contributes to the academic field in studying micro-mobility in following aspects. First, Chapter 3 is the first mode choice analysis on how E-Scooters have been integrated as one of the first-/last-mile solutions. The analysis implications are consistent with previous literature that E-Scooters have been mainly used near campus and used for recreational purposes. Distinctively, ranks of mode preferences have been summarized and interpreted, which allows researchers to have a thorough understanding of how E-Scooters are advantaged / disadvantaged over bikes and taxis. Second, in Chapter 4, this study examined E-Scooter policies for all municipal cities in the United States. This pioneering exploration provides other researchers with a basic understanding on existing E-Scooter policies as a reference. The scoring methodology provides researchers with a way of evaluating E-Scooter policies considering aspects of thoroughness and similarities. Then, in Chapter 5, this study is the first to utilize news reports as the data source for identifying E-Scooter-involved crashes. The successful implementation of the data mining methods has revealed multiple key factors on E-Scooter safety issues. The news report data source can be referred to by other safety research when no crash data is available. Furthermore, in Chapter 6 we developed a patentable platform for collecting E-Scooter riding risk data. The platform includes portable devices and sensors that can be easily attached to any E-Scooter/bike/vehicle. With these mobile sensing technologies, real-time riding data such as GPS, vibrations, and LiDAR scans can be collected for evaluating riding risks for E-Scooter riders. This work has become the paradigm among other researchers who intend to conduct similar research. For example, Chapter 7 adopted mobile sensing technologies for collecting vibration data of E-Scooter trips. The performances between big-wheel and small-wheel E-Scooters were systematically tested and compared on multiple road infrastructures. No quantitative study was found to assess the impacts of wheel sizes during E-Scooter trips, and this research work has shortened that gap in the literature.

## 8.2 LIMITATIONS

It should be noticed that there are still some limitations in this study. For example, in Chapter 3, other transport modes such as Uber or Lift were not specifically considered in the models due to limited data accessibility. If such data are available, the mode choice models can be improved and extended by considering more travel options. In Chapter 4, the summarized policies may change in different years. Thus, the analyses only captured the E-Scooter policies up to 2020. In Chapter 5, the sample size of collected news reports are fewer than 200, which restricts further statistical analysis. These analyzed data tend to be major crashes and the interpretation of the findings should be limited to these data only. Last but not least, in Chapters 6 and 7, the methodology of extracting vibration events can be further tested in other locations. At the current stage, the models were only tested at a limited number of sites with asphalt, concrete, and brick pavements.

## 8.3 FUTURE WORKS

There are multiple components in this research that can be extended in future studies. First, the choice of models developed in Chapter 3 can be extended for weekday/weekend comparisons to better understand how E-Scooters are used at different times. Second, an evaluation procedure can be developed by taking advantage of the summarized policies in Chapter 4, which provides government agencies a surrogate approach to track the effectiveness of the policies. On the other hand, the crash data derived from news reports in Chapter 5 can be expanded and shared with the research community as an important safety data source for E-Scooters. Furthermore, the frameworks proposed in Chapters 6 and 7 can be extended to other safety-related studies. For example, vibrations and mobility data were collected previously, which can be summarized as E-Scooter riding patterns on different pavements (e.g., brick roads, concrete roads, and asphalt roads). Understanding various riding behaviors is helpful in developing simulation models involving E-Scooters as a transport mode and integrating such a new mode into existing simulation platforms such as SUMO and Carla to support simulation-based studies. In addition, the developed mobile sensing framework can be used for evaluating and mapping facility conditions on the go.

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## APPENDIX A – RELEVANT PUBLICATIONS OF EACH CHAPTER

Chapter 3 is based on a co-authored paper led by Qingyu Ma that has been accepted by Transportation Research Board Annual Meeting 2022. Qingyu Ma conceptualized the research, processed and analyzed the data, interpreted results, and led the writing.

Chapter 4 is a co-authored paper led by Qingyu Ma that has been published by Transportation Research Part D: Transport and Environment.

Chapter 5 is a co-authored paper led by Qingyu Ma that has been published by Accident Analysis & Prevention. Qingyu Ma conceptualized research approaches, collected, processed, and mined the data, interpreted results, and contributed to the writing.

Chapter 6 is a co-authored paper led by Qingyu Ma that has been published by Accident Analysis & Prevention.

## APPENDIX B – PUBLICATIONS FROM THIS DISSERTATION

1. **Ma, Q.**, Xin, Y., Yang, H., and Xie, K., 2022. Connecting Urban Metro Systems with Shared E-Scooters: A Comparative Study with Shared Bikes and Taxis. *Accepted by Transportation Research Board 100th Annual Meeting, Washington D.C*.
2. **Ma, Q**., Yang, H., Ma, Y., Yang, D., Hu, X., and Xie, K. 2021. Examining Municipal Guidelines for Users of Shared E-Scooters in the United States. *Transportation Research Part D: Transportation and Environment, Volume 92, 102710*.
3. **Ma, Q.**, Yang, H., Mayhue, A., Sun, Y., Huang, Z., and Ma Y., 2020. E-Scooters Safety: the Riding Risk Analysis based on Mobile Sensing Data. *Accident Analysis & Prevention, 151, p.105954*.
4. Yang, H., **Ma, Q**., Wang, Z., Cai Q., Xie, K. and Yang, D., 2020. Safety of Micro-Mobility: Analysis of E-Scooter Crashes by Mining News Reports. *Accident Analysis & Prevention, 143, p.105608.*

# VITA

## EDUCATION

**Ph.D. Candidate in Engineer** 01/2018 - 12/2021
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- School of Design, University of Pennsylvania, Philadelphia, PA

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- School of Geodesy and Geomatics, Tongji University, Shanghai

## AREA OF SPECIALIZATION

Modeling and Simulation; Spatial-Temporal Data Analytics; Mobility Analysis and Modeling; Data Mining; Spatial Statistics; Geovisual Analytics; Remote Sensing

## PUBLICATIONS

1. **Ma, Q.**, Xin, Y., Yang, H., and Xie, K., 2022. Connecting Urban Metro Systems with Shared E-Scooters: A Comparative Study with Shared Bikes and Taxis. *Accepted by Transportation Research Board 101st Annual Meeting, Washington D.C.*

2. Yan, Z., **Ma, Q.**, Yang, H., Huang, Z., Shen, Y., and Li, Y., 2022. Development of a Human-in-the-Loop Simulation Framework for Supporting Autonomous Vehicle-Pedestrian Interaction Testing. *Accepted by Transportation Research Board 101st Annual Meeting, Washington D.C.*

3. Zuo, F., Gao, J., Kurkcu, A., Yang, H., Ozbay, K., and **Ma, Q.** 2021. Reference-free Video-to-real Distance Approximation-based Urban Social Distancing Analytics amid COVID-19 Pandemic. *Journal of Transportation & Health, Volume 21, 101032.*

4. **Ma, Q**., Yang, H., Ma, Y., Yang, D., Hu, X., and Xie, K. 2021. Examining Municipal Guidelines for Users of Shared E-Scooters in the United States. *Transportation Research Part D: Transportation and Environment, Volume 92, 102710*.

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6. **Ma, Q**., Yang, H., Wang, Z., Xie, K. and Yang, D., 2020. Modeling Crash Risk of Horizontal Curves Using Large-Scale Auto-extracted Roadway Geometry Data. *Accident Analysis & Prevention, 144, p.105669*.

7. Yang, H., **Ma, Q**., Wang, Z., Cai Q., Xie, K. and Yang, D., 2020. Safety of Micro-Mobility: Analysis of E-Scooter Crashes by Mining News Reports. *Accident Analysis & Prevention, 143, p.105608.*

8. **Ma, Q**., Yang, H., Wang, Z., Xie, K., and Zuo, F., 2019. Modeling Crash Frequencies at Horizontal Curves on Low-volume Highways. *In RSS 2019: Road Safety and Simulation 2019 Conference*.

9. **Ma, Q**., Yang, H., Xie, K., Wang, Z. and Hu, X., 2019. Taxicab Crashes Modeling with Informative Spatial Autocorrelation. *Accident Analysis & Prevention, 131, pp.297-307*.

10. **Ma, Q**., Yang, H., Zhang H., Xie, K., and Wang Z., 2019. Modeling and Analysis of the Daily Driving Patterns of Taxis in a Reshuffled Ride-hailing Service Market. *Journal of Transportation Engineering. Part A: Systems, 145(10), p.04019045.*

11. **Ma, Q**., Yang, H., Xie K., and Wang Z., 2019. Characterizing the Evolution of Taxi Driving Patterns in a Mega City Before and After the Booming of Ridesourcing. *Transportation Research Board 98th Annual Meeting, Washington D.C., January 13-17, 2019*. <TRB Standing Committee on Urban Transportation Data and Information Systems (ABJ30)>

12. Zhang, S., Yu, S., **Ma, Q**., Shang, P., Gui, P., Wang, J. and Feng, T., 2013, December. Pedestrian Counting for a Large Scene Using a GigaPan Panorama and Exemplar-SVMs. In *2013 Ninth International Conference on Computational Intelligence and Security* (pp. 229-235). IEEE.