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E-Scooter safety: The riding risk analysis based on mobile sensing data

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ABSTRACT

The emergence of shared electric scooter (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 as compared to other travel modes such as cars and bicycles. The lack of crash records further prevents it from understanding the underlying mechanisms that drive the occurrences of E-Scooter crashes. The overarching goal of this paper 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 pavements was found to experience a multiple times higher frequency of vibration events when compared to riding on asphalt pavements 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.

1. Introduction

The growth of micro-mobility services in urban areas has been well evidenced over the last few years. Many service providers (e.g., Citi Bike) have emerged to offer travelers convenient options for first/last-mile transportation solutions through their docked or dockless mobility sharing systems (Yang et al., 2018). In particular, post the fast rise of global bike-sharing practices, the micro-mobility trend has been further re-energized with the emergence of the shared dockless electric scooters (E-Scooter). These E-Scooters rapidly found a very strong service-market fit that drives many companies (e.g., Lime and Bird) to reach billion-dollar valuations within a short period of their inception. The growing adoption of E-Scooters among different population groups, relatively low cost, and government support significantly stimulate the demand around the world. Similar to the shared bicycles, E-Scooters enable affordable first/last-mile transportation as compared to personal vehicles, other public transportation services, as well as on-demand transportation solutions. Equipped with lithium-ion battery, E-Scooters are often light-weight and have higher power efficiency to potentially curb the perils of air pollution (Hours, 2019). Besides, its flexibility, agility, and ease of operations in populated areas with heavy traffic provide additional advantages to fuel the user market growth. Therefore, the use of E-Scooters on public roadways is showing a fast-growing trend in many areas worldwide.

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Despite the popularity, the safety issues of E-Scooters have also drawn increasing attention to the public. Accompanying the fast-growing trips, there have been numerous E-scooters injuries as well as fatalities. According to the estimates of the Centers for Disease Control and Prevention (CDC), there are 20 crashes causing injury for every 100 K trips (APH, 2019). Likewise, many statistics from pilot programs in other local jurisdictions also evidence the alarming risk of E-Scooter riding. For example, the E-Scooter injury rate was 2.2 injuries per 10 K miles and 2.5 per 10 K trips during the pilot period in Multnomah County, Oregon (Multnomah County Health Department, 2019). As a disruptive transportation solution, there are many factors that drive the occurrences of these crashes. On the one hand, the policies, regulations, and laws still lag behind the technology advance and practices. 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-Scooter 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 of actions taken by local authorities. On the other hand, the factors associated with users are also an important aspect tied to the crashes. For example, the use of E-Scooters typically does not require a driver's license to operate. Whether a user has had enough training and obeyed the instructions to safely operate an E-Scooter is not well guaranteed. Perhaps this a key reason that about one-third of those injured were riding an E-Scooter for the first time (APH, 2019). In addition, 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 the 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 (Buckley, 2019; Rodriguez, 2019; TODAY, 2019) or in the entire jurisdictions (e.g., Alpharetta, GA and Elizabeth, NJ (Brasch, 2019; Meyer, 2019)).

The pressing safety risk of using E-Scooters warrants more in-depth investigations to understand the underlying crash mechanisms. Unfortunately, there were too scarce crash data to enable the probe of E-Scooter safety. Most of existing studies (APH, 2019; Mayhew and Bergin, 2019; Bekhit et al., 2020) 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 (Allem and Majmundar, 2019; Yang et al., 2020). To understand the riding risk, more data-driven studies are quite necessary to extend the spectrum of the safety assessment associated with E-Scooters. Motivated by the emerging safety issues and the significant research gaps, this paper intends to propose a data-driven analytical framework to quantitatively evaluate the riding risk of E-Scooters. Specifically, it aims to study the use of E-Scooters on different facilities (e.g., vehicle lanes, sidewalks), with a focus on the understanding of their interactions with the riding environments (such as surrounding objects and potholes). Taking advantages of the mobile sensing data, naturalistic riding experiments are conducted for various scenarios. Researchers can collect necessary data in an efficient manner. Such data are also helpful for further analyses of riding risk through the use of derived surrogate safety metrics.

2. Literature review

The emergency of E-Scooters has drawn growing attention to the research community. Table 1 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 have made some efforts in providing insights into different aspects of this emerging micro-mobility mode using different data sources. For example, origin-destination (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.) (Xin and MacEachren, 2020). By summarizing and analyzing such OD data, Liu et al. (2019) revealed travel patterns 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 emergency departments (ED). Due to the sample size issues, sometimes contradictory findings can be seen among different studies. For example, Beck et al. (2019) 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. (2019), the majority type of injuries (44 %) occurred on sidewalks and most victims were minor injured. Despite the efforts by Yang et al. (2020) that examined 169 E-Scooter crashes through the mining of multi-year news reports, more safety-related data are demanded to better depict various aspects on 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. (2019) 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 (2019) 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 on the pavement contributed to their injuries, 29 % were influenced by 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 (Reksten-Monsen and Han, 2019). Like other mobility modes (e.g., taxis, ride-hailing vehicles, shared bikes, etc.), such trajectory data can provide spatiotemporal records during each trip (Ma et al., 2019). Based on these data, advanced analysis can be conducted such as route selection, speeding detection, and so on (Hu et al., 2019; Xu et al., 2019; Yang et al., 2019). 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 the 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. (2017) 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. (2004) implies that older pavement is more likely to lead bicycle crashes with injuries. The mid-pilot report of 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

Table 1
Summary of the Major Studies on E-Scooter Systems.

Index	Reference	Topic	Method	Data	Sample Size & Location
1	He and Shin (2020)	Usage	Spatial Analysis	8-month OD	2,430,806 trips (Austin, TX)
2	Zou et al. (2020)	Usage	Spatial Analysis	5-week OD	138,362 trips (Washington, D.C.)
3	Almannaa et al. (2020)	Usage	Descriptive Analysis	6-month OD	15,400 E-Scooters (Austin, TX)
4	Caspi et al. (2020)	Usage	Spatial Analysis (GWR)	1-year OD	11,358 trips per day (Austin, TX)
5	Jiao and Bai (2020)	Usage	Spatial Analysis (Moran's I)	11-month OD	158,208 trips per month (Austin, TX)
6	Liu et al. (2019)	Usage	Descriptive Analysis	3-month OD from two companies	425,000 trips (City of Indianapolis)
7	Smith and Schwieterman (2018)	Usage	Mode-Choice Analysis	Simulated OD	10,000 trips per study area (Chicago, IL)
8	James et al. (2019)	Behavior	Survey & Questionnaire	Survey responses	181 E-Scooter riders and non-riders (Washington, D.C.)
9	Todd et al. (2019)	Behavior	Descriptive Analysis	3-month videos	171 E-Scooters (Los Angeles & Santa Monica, CA)
10	Riggs and Kawashima (2020)	Policies	Mannual	Mannual collections	61 cities
11	de Bortoli and Christoforou (2020)	Policies	Survey & Questionnaire	Survey responses	445 responses (Paris, France)
12	Yang et al. (2020)	Safety	Descriptive Analysis	3-year news reports on crashes	169 news on E-Scooter-involved crashes
13	Bekhit et al. (2020)	Safety	Descriptive Analysis	7-month ED	770 patients (Auckland, New Zealand)
14	APH (2019)	Safety	Descriptive Analysis	3-month ED	271 E-Scooter-related injuries (Austin, TX)
15	Sikka et al. (2019)	Safety	Descriptive Analysis	ED based on literature	Synthesis of literature
16	Allem and Majmundar (2019)	Safety	Descriptive Analysis	414-day Bird's Instagram posts	324 posts
17	Mayhew and Bergin (2019)	Safety	Descriptive Analysis	4-month ED cases	63 patients (Auckland City, New Zealand)
18	Schlaff et al. (2019)	Safety	Descriptive Analysis	ED	5 patients (Washington, D.C.)
19	Badeau et al. (2019)	Safety	Descriptive Analysis	10-month ED	58 patients (Salt Lake City, UT)
20	Beck et al. (2019)	Safety	Descriptive Analysis	2-year ED	55 patients (Dunedin, New Zealand)

period and the top causes were speed, losing control, and hitting a pothole or a stationary object such as a pole (Basky, 2020). Similarly, ten percent injured E-Scooter riders reported uneven pavement as the reason of their falls (Bloom et al., 2020). These studies imply 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.

3. Methodology

The massive number of E-Scooters roaming streets can be disruptive and risky for both the riders and other road users. As discussed earlier, more explicit data are highly demanded 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 existed) in different municipalities that suggests where to use E-Scooters is usually lagged due to the inexperience of running the programs. It is highly likely that not all the facilities in their areas are appropriate for E-Scooters. For example, some sidewalks may be too narrow to ride, or their 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 (2019), 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 (Cano-Moreno et al., 2019). 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 the E-Scooter collisions. Thus, understanding the impact of different riding environments on E-Scooter riding experience and identifying hazard 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 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 more on providing surrogate measurements for depicting possible risky factors attributable to riding facilities.

3.1. 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. Fig. 1 (a) illustrates the architecture of the system design and Fig. 1 (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: (a) detailed trajectory logs with timestamp and coordination information acquired by the global positioning system (GPS); (b) 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; (c) 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 m, a typical scan frequency of 5.5 Hz, and a measurement frequency up to 8000 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 (d) real-time video recording through a portable camera for post review, if necessary.

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 (5 V) battery pack. As shown in Fig. 1 (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

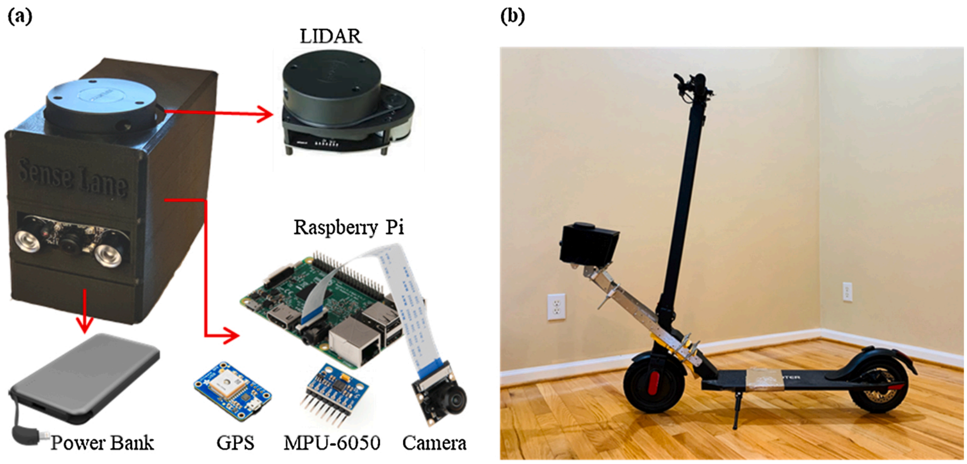

Fig. 1. E-Scooter Mobile Sensing System for Naturalistic Riding Data Collection.

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.

3.2. *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 will have chances to 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 up with severe injuries or fatalities (Basky, 2020; Yang et al., 2020). Also, because of the non-fixed riding paths and the changing built

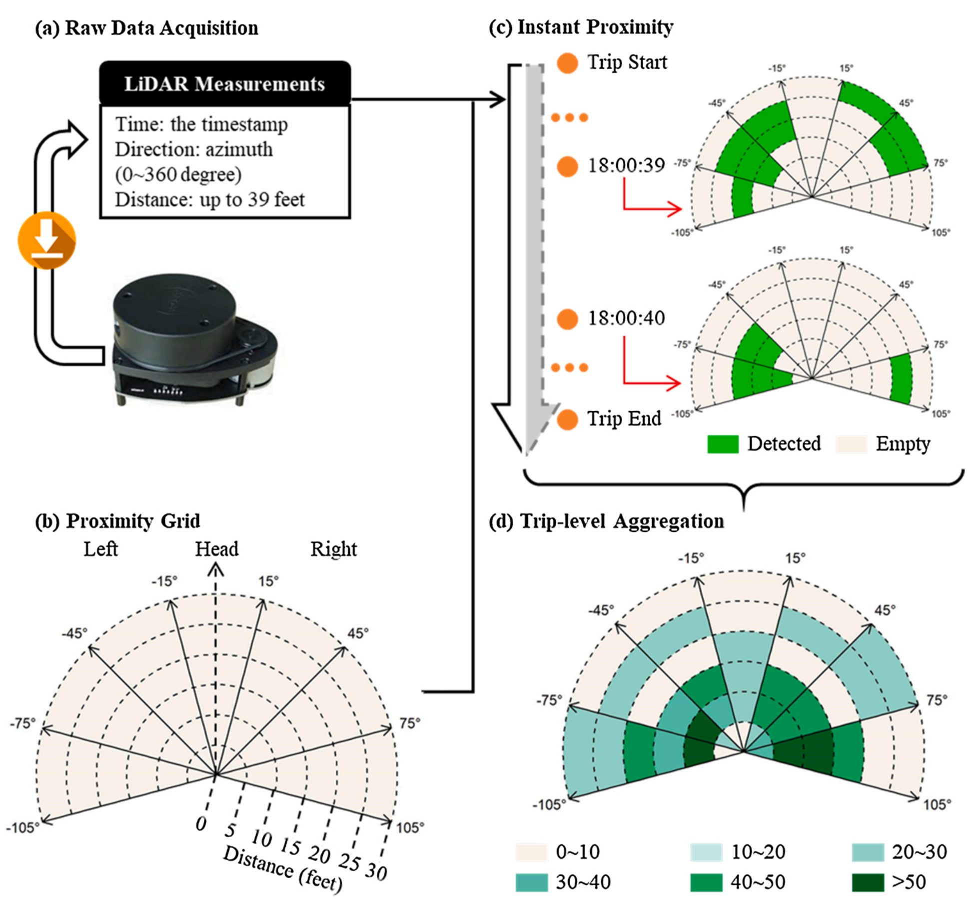

Fig. 2. Proximity Estimation Framework using LiDAR Measurements.

environments, the interference will drastically change as E-Scooter roam different urban streets and sidewalks. As a preventive risk assessment approach, the research team borrows some ideas of 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 measurement 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.

The following Fig. 2 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 paper introduces a risk map $g(d,\theta)$ as illustrated in Fig. 2 (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 ranges from -105° to 105° is considered as the hazard zone. The hazard zone is further evenly categorized using 30°-intervals, with θ_j defining the azimuth of each grid distributed from left to right on the map and $j = 1,2,\dots,7$. 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 $i = 1,2,\dots,6$. 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 Fig. 2 (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 object: $g(d_i,\theta_j) = 1$; otherwise, the grid is marked as empty: $g(d_i,\theta_j) = 0$. Multiple points are considered as the threshold to exclude possible sparse and noisy measurements of the sensor. Fig. 2 (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:

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

where, $g_t(d_i,\theta_j)$ denotes the presence of object with the proximity grid of distance d_i and angle θ_j at timestep t; and T is the total number of timesteps analyzed. Fig. 2 (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 comparisons, if needed.

3.3. Assessing riding vibration

Unlike bicycles, the relatively small wheels of E-Scooters may generate vibrations that influence comfort, human health, and safety (Cano-Moreno et al., 2019). To assess the real-world impact suffered 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 Fig. 3 (a), three-dimensional accelerometer data X_tY_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 Fig. 3 (b), which is very sensitive with a minimum time resolution of 10 ms. 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. (2016) analyzed accelerometer in Z dimension to evaluation vehicle vibrations. In terms of the E-Scooter device, vibrations in X and Y dimensions are also considered in this study considering that E-Scooters may not just bounce in one direction when hit potholes or cracks. Therefore, the accelerometer data (X_{ti}, Y_{ti}, Z_{ti}) ($i\in 1, 2, \dots, N$) are converted to the vibration strength S_t with the following equation.

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

where, the difference of maximum and minimum values in each dimension is calculated for the timestamp based on the collected data. Fig. 3 (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 θ and strength increment σ. The first parameter θ is used for controlling strength quantity. Only vibrations larger than θ will be defined as strong vibrations. σ_t is calculated as the strength difference between two consecutive timesteps. If σ_t is greater than a threshold σ, this fact will be collectively used as the second criterion to determine vibration events. Fig. 3 (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.

3.4. 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.

4. 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 if there was any correlation. The tuned parameters

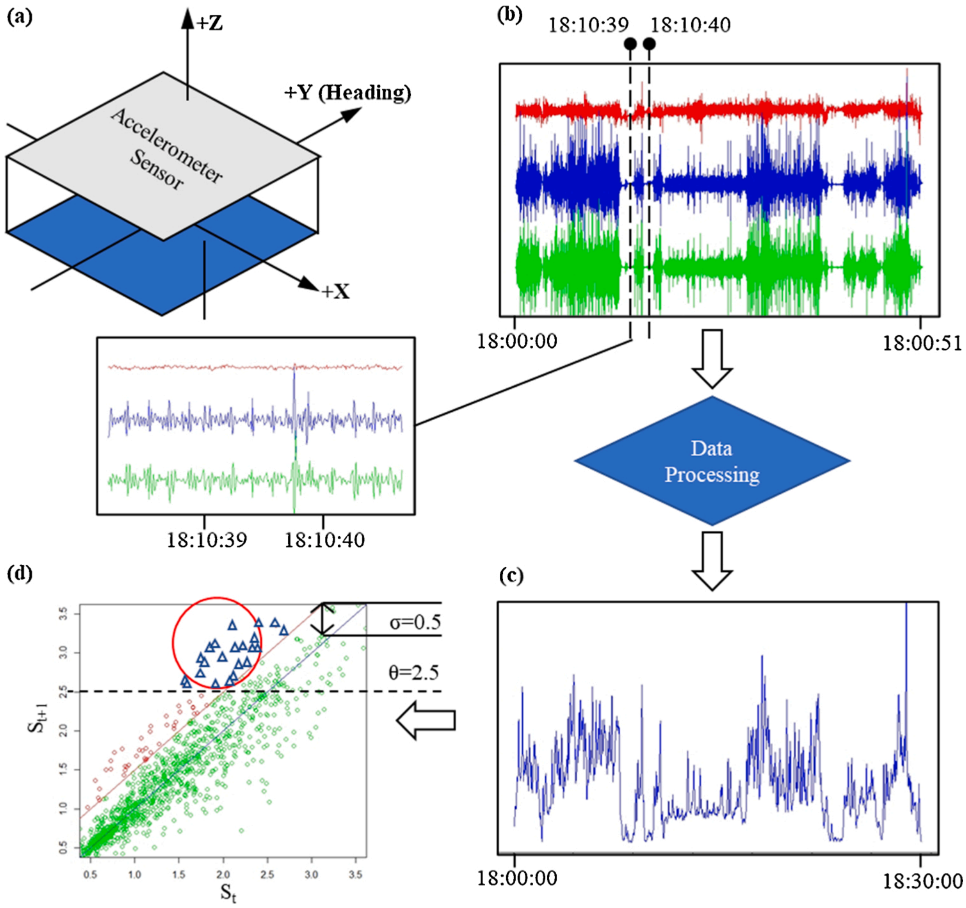

Fig. 3. The Framework for Quantifying Vibration based on the IMU Sensor Measurements.

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 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.

4.1. 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 Fig. 4, 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 color) or the vehicle lanes (in blue color). Each scenario was repeated for 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.

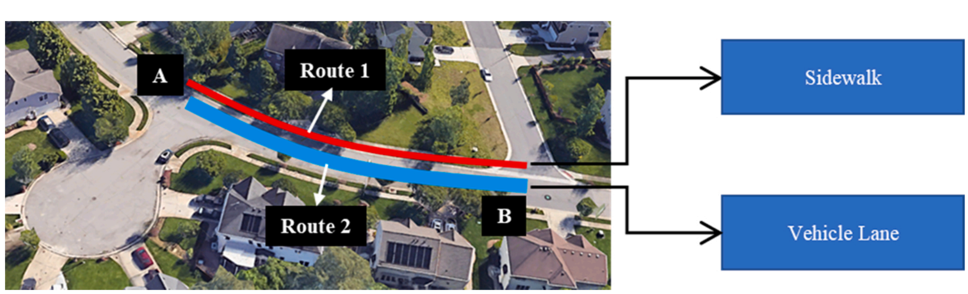

Fig. 4. Experimental Design for Calibrating Vibration Threshold Values.

4.2. 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. At 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 (City of Tempe, 2020). However, many others also concerned about safety when riding E-Scooters on sidewalks. For example, Badeau et al. (2019) indicated the majority of injuries (44 %) occurred on sidewalks. Riding E-Scooters on the sidewalks can be challenging with the uneven pavements and relatively dense obstacles. To assess those impacts quantitatively, an experiment shown in Fig. 5 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 a 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 from 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.

4.3. 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 pavements. As the wheels of E-Scooters are typically very small, they are expected to be highly sensitive to the 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 Fig. 6. 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 also produced for both the E-Scooter and the bike.

5. Experimental results and analysis

There are in total three experiments designed and conducted. The mobile sensing system was installed to 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 claimed previously that 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 of about 6-ft 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 experiment can be designed by involving more riders, which is beyond the scope of this study.

5.1. Vibration event detection and calibration results

As shown in Fig. 4, the instrumented E-Scooter was ridden on the selected sidewalks (Route 1) and vehicle lanes (Route 2) for 10 times separately. Vibration data are continuously collected during each trip. Typical examples of the results for Routes 1 and 2 are shown in Fig. 7(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 Fig. 7 (c). With the photo taken near that site (Fig. 7 (d)), it can be seen that 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 2. Besides the spatiotemporal attributes, the vibration strength was also recorded for further analysis. This workflow of vibration detection was programmed in R Studio

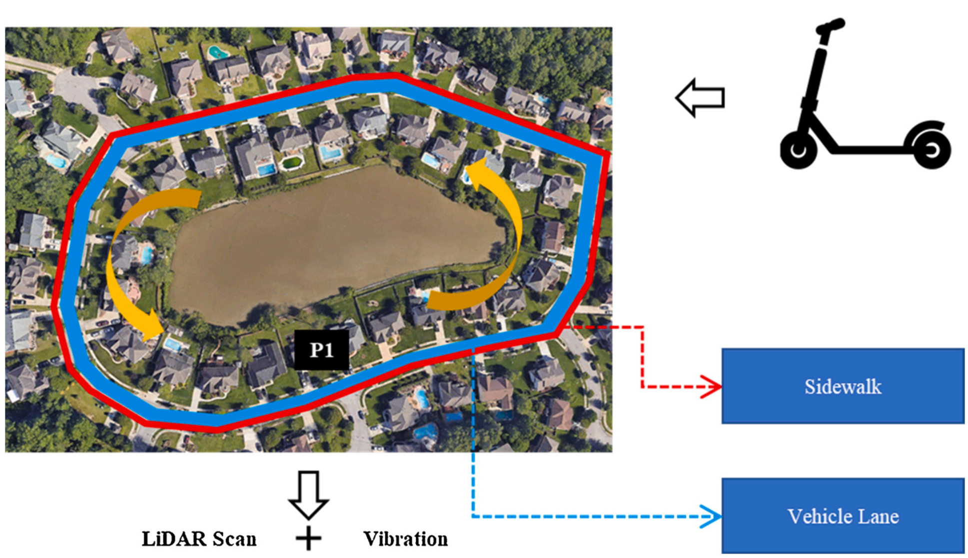

Fig. 5. Comparative Experimental Design for E-Scooter Safety Analysis on Vehicle Lanes and Sidewalks.

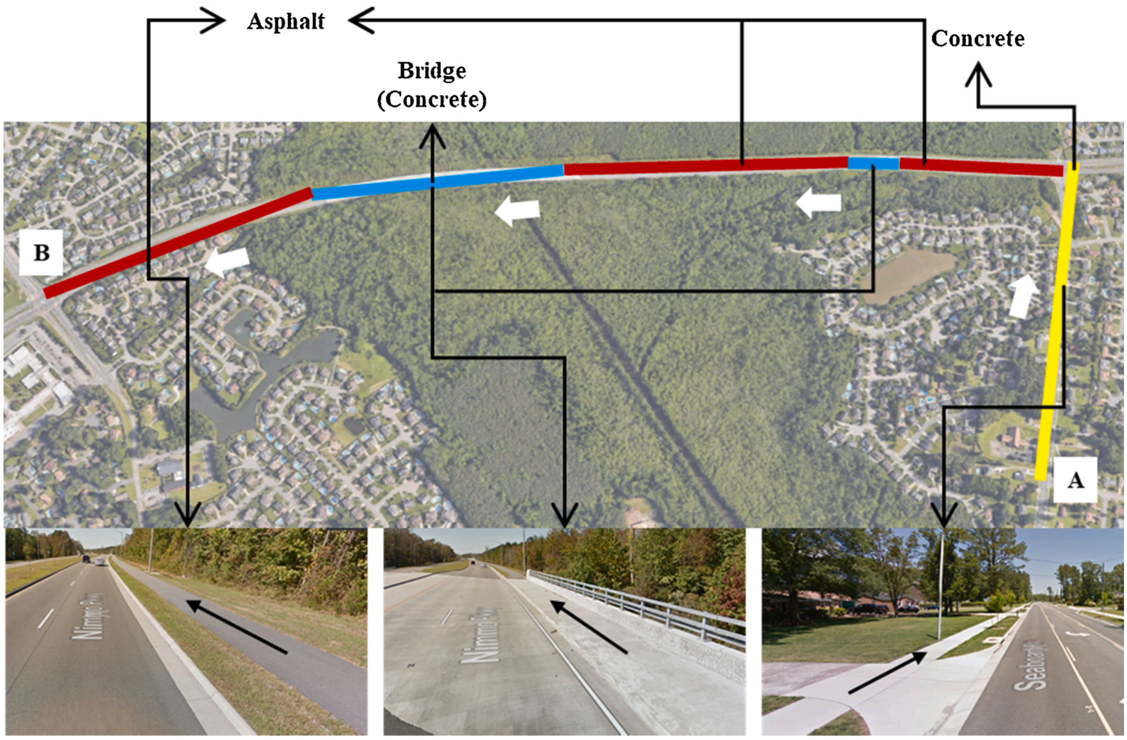

Fig. 6. Comparative Experimental Design for E-Scooter Safety Analysis on Different Sidewalks.

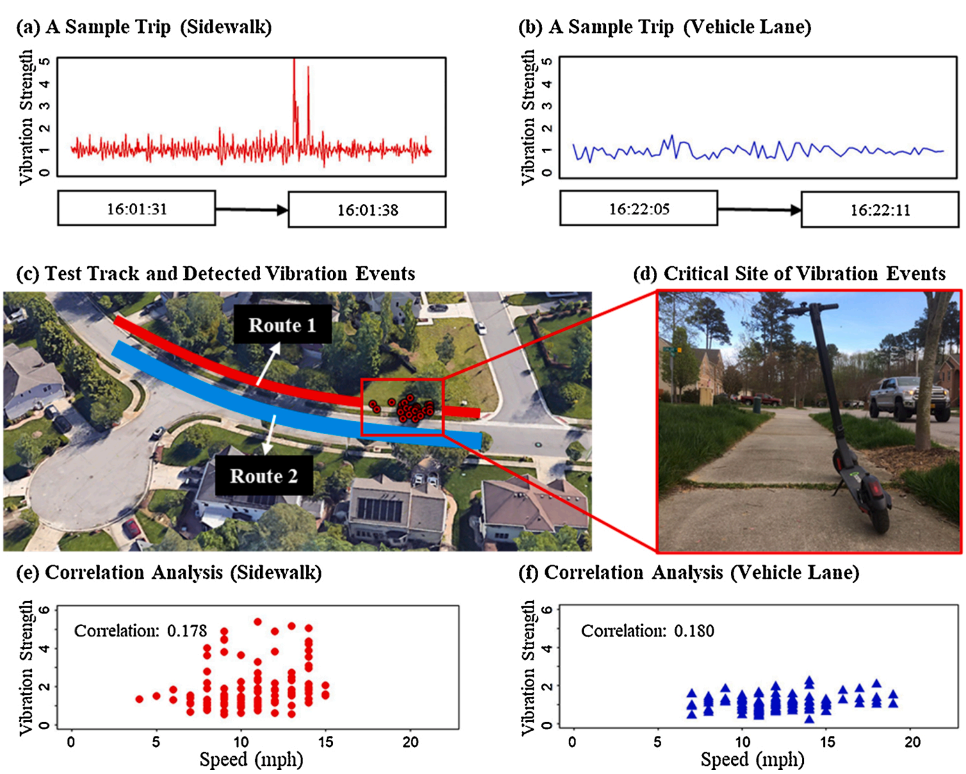

Fig. 7. Vibration Event Detection on a Selected Test Track.

software.

Fig. 7 (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, Fig. 7 (e) suggests that vibration events can be detected under both low-speed and high-speed situations on the same road.

5.2. E-Scooter safety challenges: sidewalks and vehicle lanes results

The well-calibrated E-Scooter sensing system was used to collect

Table 2
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

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 constitue the surrogate safety metrics as illustrated in Fig. 8 where Fig. 8 (a), (c), and (e) on the left side belong to the ride on sidewalks; while Fig. 8 (b), (d), and (f) are for the ride on vehicle lanes. The proximity grids in Fig. 8 (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 toward 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 0–15 feet. In reality, there are shrubs and trees asides during 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 15–30 feet. The rider has a broader space comparing to the sidewalks. Meanwhile, since the E-Scooter was ridden on the right side of vehicle lanes, very few obstacles were detected between 0–15 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 mail-boxes. Fig. 8 (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 running in the vehicle lane. The higher frequency of vibration events on the sidewalks is mainly attributed to its uneven and/or damaged pavement conditions in the neighborhood. In contrast, the overall pavement surface quality of the vehicle lanes is relatively better. The speed heatmaps are presented in Fig. 8 (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 comparing to the tested vehicle lanes due to the narrower space and more vibrations. The riders operated

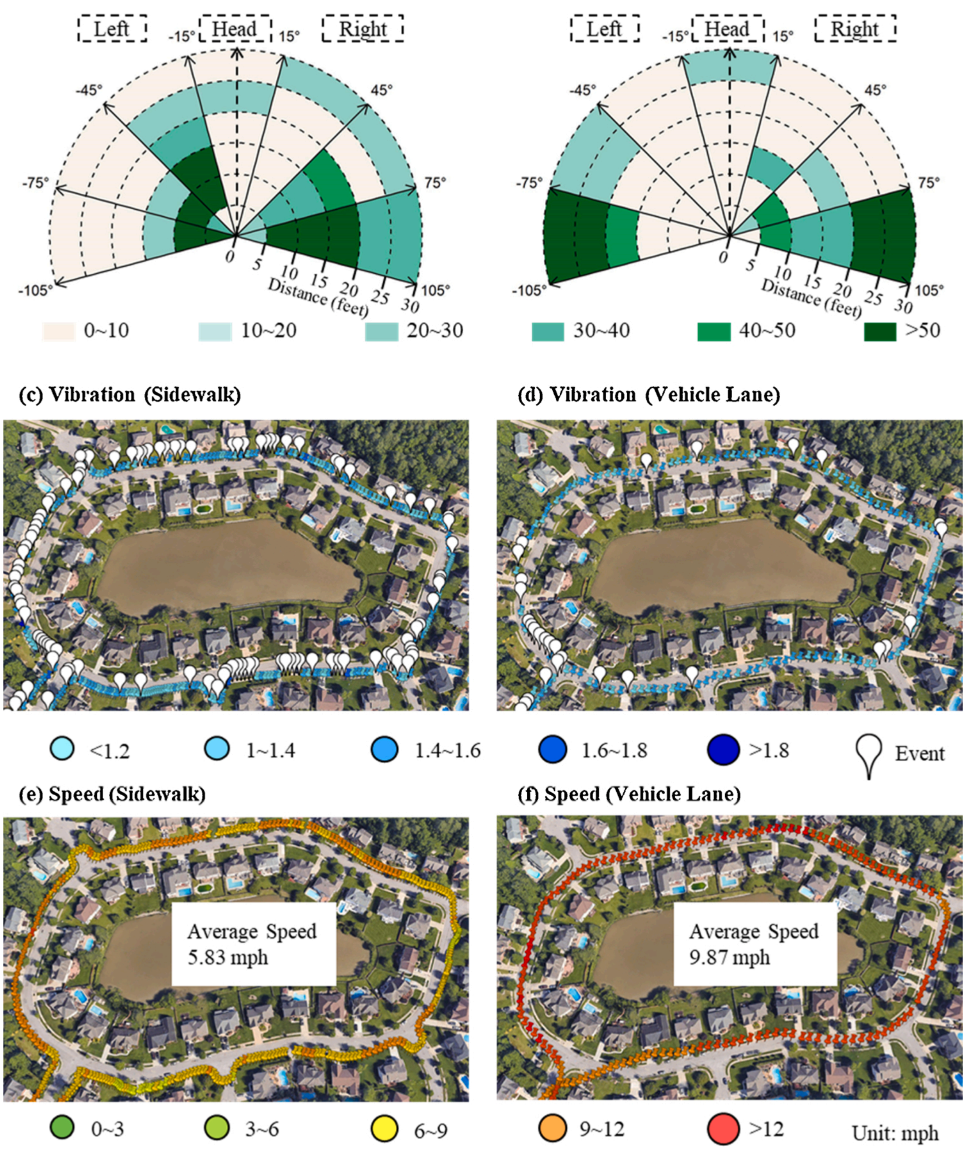

Fig. 8. Experienced Impacts When Riding on Different Facilites.

more cautiously by maintaining a lower average speed of 5.83 mph on the sidewalks compared to that of 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 sidewalk is more dangerous than on 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 experimented in 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.

5.3. 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 is about 2 miles as shown in Fig. 6. Vibration events and speed measurements were collected; and the final results are shown in Fig. 9. In general, more vibrations are experienced on the concrete pavements than the asphalt pavements for both the E-Scooter and the bike. Fewer vibration events were observed during the bike trip comparing 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 crashes collected by Yang et al. (2020), 30 % of victims got injured by falling off from E-Scooters. The way of riding E-Scooters by standing on the riding deck makes it prone for the 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 relies upon human power pushing the pedal, E-Scooters are typically accelerated by controlling the power device on the handlebars. Slight 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 having less experience in using E-Scooters.

In particular, the summarized vibration events on different facilities are shown in Table 3. Overall, the asphalt pavements are smoother, and riders experienced fewer vibrations when riding on them. 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 pavements is 7–9 times as that on asphalt pavements. It should be noticed that the E-Scooter rider experienced a high frequency of 49.2 vibration events per mile on the concrete pavements. Likewise, the vibration densities are 278 times per mile on sidewalks with concrete pavements and 70.1 times per mile in vehicle lanes with asphalt pavements 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

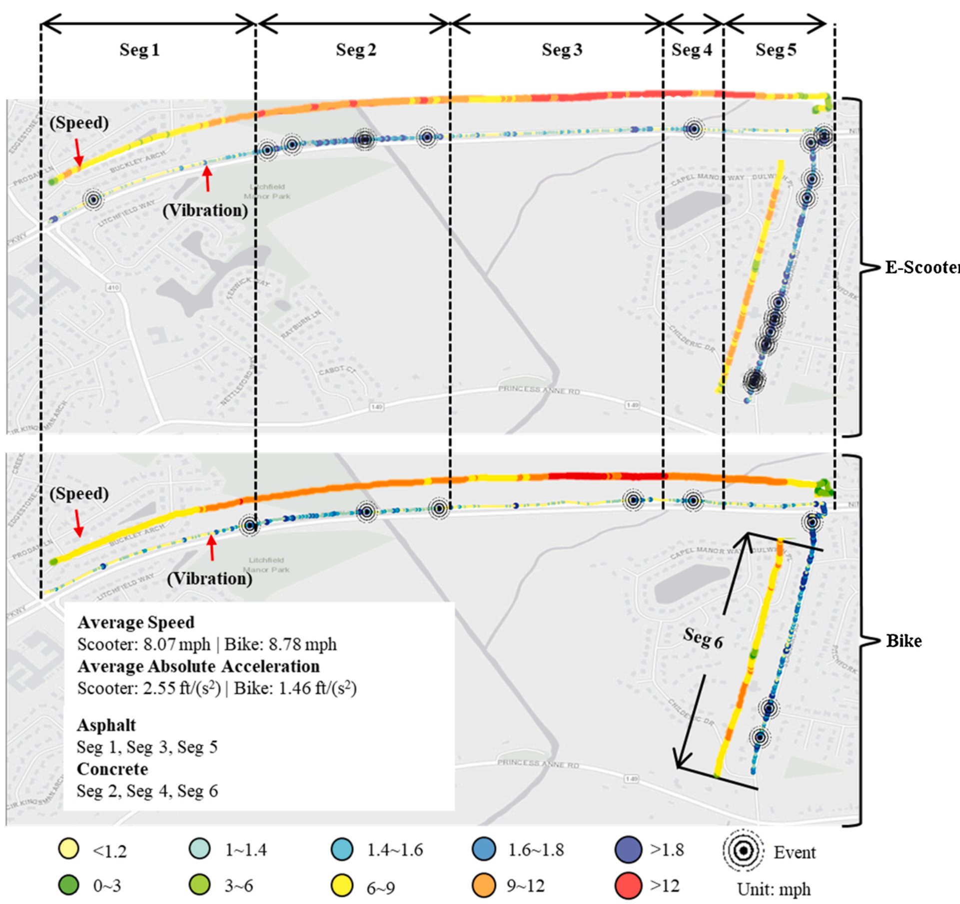

Fig. 9. Comparative Analyses of Virbrations and Speed Changes Experienced by E-Scooters and Bicycles.

Table 3
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

safer options if other conditions were similar.

6. Conclusions and discussion

The rapid expansion of E-Scooter programs in many urban areas has sparked wide discussion concerning issues related to their operations 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 demanded to support safer operations for E-Scooters by understanding their 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 existing literature by developing and deploying a mobile sensing system that facilitated the 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 rider encountered close contacts with obstacles along each riding path; (b) vibration events that significantly affect riding experience as standing on the deck while riding is prone 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 sensitivity. Repeated experiments were conducted following a 165-ft road section with a known crack on its sidewalk while 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 the 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 pavements is likely to encounter higher frequencies of vibration events than those with asphalt pavements. Also, it is safe to conclude that E-Scooter riders will experience more severe vibration impact than cyclists if they were running on the same facilities. Comparing to the cyclists' smooth accelerations, E-Scooters' quick changes in accelerations are risky by preventing 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, pavements, 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 (Ozbay et al., 2008; Yang, 2012) can be derived to enrich the description of E-Scooter safety. For example, Maiti et al. (2019) 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.

Authorship contribution statement

The authors confirm contribution to the paper as follows: study conception and design: H. Yang, Q. Ma; system development and test: H. Yang, Q. Ma, A. Mayhue, R. Sun; data collection: Q. Ma, H. Yang, Y. Ma; analysis and interpretation of experimental results: Q. Ma, H. Yang, A. Mayhue, Y. Sun, Z. Huang, Y. Ma; visualization: Q. Ma, H. Yang, Y. Ma; draft manuscript preparation: Q. Ma, H. Yang, A. Mayhue, Y. Sun, Z. Huang, Y. Ma; manuscript revision: Q. Ma, H. Yang, and Y. Ma.

Declaration of Competing Interest

The authors report no declarations of interest.

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