Impact of Urban Micromobility Technology on Pedestrian and Rider Safety: A Field Study Using Pedestrian Crowd-Sensing

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Abstract—The popularity and proliferation of micromobility vehicles, such as electric scooters or e-scooters, as last-mile transportation solutions in our cities and urban communities has been rapidly rising. Rent-by-the-minute pricing and a healthy competition of service providers is also benefiting riders with low trip costs. However, an unprepared and depleted urban infrastructure, combined with uncertain operation policies and poor regulation enforcement, has resulted in micromobility riders encroaching public spaces meant for pedestrians, thus causing significant safety concerns both for themselves and the pedestrians. As a consequence, it has become critical to understand the current state of pedestrian safety in our urban communities vis-à-vis micromobility services, identify factors that impact pedestrian safety due to such services, and determine how to enable pedestrian safety going forward. Unfortunately, to date there have been no realistic, data-driven efforts within the research community that address these issues. In this work, we attempt to fill this gap by conducting the first large-scale field-study to empirically investigate the safety issues due to micromobility services from the pedestrian’s perspective. By crowd-sensing real-time encounter data between e-scooters and pedestrian participants on two urban university campuses over a three-month period, we analyze the impact of these micromobility services on pedestrian safety and uncover encounter statistics and mobility trends that could identify potentially unsafe spatio-temporal zones for pedestrians. This first of its kind work also provides a blueprint on how crowd-sensed micromobility data can enable similar safety-related studies in other urban communities.

I. INTRODUCTION

One of the biggest challenges faced by cities due to population growth and density is the transportation of commuters and intra-city travelers, especially, over short non-walkable distances. A lack of adequate and/or frequent public-transportation infrastructure has partially catalyzed this situation [1], which has resulted in an increased use of personal vehicles, thus causing additional congestion on the roads. In addition to a sub-standard commute experience, this has also contributed to an increase in air pollution levels [2], road rage, accidents [3] and economic waste [4], [5]. Due to these escalating problems with intra-city transportation, and the resulting commuting woes, cities have been witnessing wide-spread deployment (and trials) of personal and service provider-owned electric or battery-powered micromobility vehicles.

Micromobility is an umbrella term used to describe a novel category of transportation using non-conventional battery-powered vehicles (standing scooters, also known as electric scooters or e-scooters [6]) aimed at shrinking the physical and environmental footprint required for quickly moving people over relatively short distances. Micromobility vehicles are suitable and designed for travel over distances that are too close to drive or utilize public transportation, yet too far to walk [7]. Moreover, due to their small physical footprint, such vehicles provide a convenient means to navigate around a city with congested roads and sidewalks, thus making them a popular last-mile transportation solution in urban areas [8].

Last-mile transportation bridges the gap between conventional transportation hubs (such as a bus stop, train station and parking lot) and final destinations (such as a work place, home, school and shopping center), which is especially appealing in cities where conventional transportation options are not abundantly distributed. The popularity of micromobility vehicles have been further accelerated due to a growing number of service providers that offer these vehicles on rent-by-the-minute schemes, which benefit riders with low trip costs without having to bear the upfront purchase and maintenance costs of owning such vehicles. Other aspects of such micromobility services that make them appealing to urban commuters include easy service accessibility by means of a smartphone application, flexibility in trip start and end points, ease of vehicle geo-location, flexibility of drop-off options with no parking fees, a simplified and intuitive riding process which requires no pre-training and license to operate, and negligible environmental impact compared to fossil-fuel powered vehicles [9].

However, as with any disruptive new technology, unforeseen problems have surfaced with or due to such micromobility services, and appropriately addressing these concerns will be pivotal to their success. For instance, city administrators and planners have been unable to cope with the sudden influx of micromobility vehicles, and as a result, most urban jurisdictions have very lenient or no regulations on how these vehicles should be operated. Even in cases where strict regulations are in place, often its enforcement is lacking primarily due to the scale and ubiquity of these services and

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the lack of human and infrastructure resources to oversee enforcement. As a result, micromobility riders often end up encroaching road infrastructure meant for pedestrians, thus causing significant safety concerns both for themselves and the pedestrians [10]. Given that pedestrians are faced with risks such as walking alongside riders traveling at high speeds and navigating around hazardously parked or standing vehicles on sidewalks, it is not surprising that a considerable number of reported micromobility vehicle incidents involve some form of collision with pedestrians [11], [12], [13], [14], [15].

Thus, a key issue that administrators, policymakers and stakeholders in our urban communities need to address in a timely fashion is: “how can pedestrians safely co-exist with micromobility vehicles and riders?” As part of this overarching question, answers to specific questions such as “what is the current state of pedestrian safety vis-à-vis micromobility services in urban communities?” “what factors impact pedestrian safety in such services?” and “how to support pedestrian safety going forward?” are urgently needed. Battery-powered and easily accessible micromobility vehicles and services provide a new transportation option for urban commuters if safely deployed around pedestrians, however, public opinion both for and against such services has been highly polarizing. This has resulted in abrupt responses from city administrators (e.g., some have welcomed e-scooters with open-arms [16], [17], [18], [19], while others have outright banned them [20], [21], [22], [23]) without clear justifications that are based on empirical data and analysis. Our position is that before making any policy decisions or implementing new regulations on micromobility vehicles and services, their impact on pedestrian safety needs to be thoroughly studied in an empirical and data-driven manner.

To date, there have been only a few research efforts that have attempted to empirically study the safety impacts of micromobility services in an urban environment [24], [25]. However, these efforts have primarily focused only on the problem of micromobility rider safety, either partially or completely leaving out the aspect of pedestrian safety impacted by these services. In this work, we attempt to fill this research gap by conducting a large-scale field-study to empirically investigate the safety issue in micromobility services from a pedestrian’s point-of-view and to procure some answers to the questions posed above. The biggest impediment in conducting such a field-study is enabling pedestrians to collect and document information related to micromobility vehicle movements and encounters, and its impact on their own safety. An approach of asking pedestrians to manually document each and every encounter will be too cumbersome, error-prone and exposed to bias. An alternative is to request service providers to share data corresponding to their vehicles and riders. Unfortunately, service providers are unwilling to share such data either due to corporate rules or customer privacy concerns. Moreover, as this data does not have any pedestrian information, it is not useful by itself to study pedestrian safety concerns. To overcome this challenge, we take advantage of the technical design of commercial micromobility vehicles such as e-scooters, specifically, the on-board hardware and communication interfaces. Current service-provider owned e-scooters come equipped with a constantly beaconing Bluetooth Low Energy (BLE) radio, typically employed for near-field operations such as vehicle unlocking and communication with customer’s mobile application. Our main idea is to passively capture the BLE signals/beacons continuously emitted by the BLE radios onboard these commercial e scooters by employing pedestrian participants who are carrying some form of a BLE receiver (i.e., a smartphone or smartwatch). BLE and other sensor data crowd-sensed in such a fashion can then be used to extract fine-grained contextual (spatio-temporal) information about the mobility state(s) of the e-scooters and physiological states of the (participating) pedestrians. By means of this information, and the resulting analysis, we will be able to better understand the various factors impacting pedestrian safety in such micromobility services.

Specifically, we conduct a large-scale field-study by recruiting participants (mostly students) in the main and downtown campuses of the University of Texas at San Antonio, where micromobility vehicle services are extremely popular. University campuses have a high density of pedestrians (who are also often distracted [26]), making it an ideal environment for a field-study such as this. We particularly focus on electric or e-scooters in this study as they are currently the most popular form of micromobility service, both globally [27] and also on the said university campuses. We observed that it is not only possible to uniquely identify BLE beacons transmitted by e-scooters operated by popular service providers (e.g., Lime and Bird) on the above two campuses, but it is also possible to characterize encounters between these vehicles and pedestrians who are passively capturing these BLE beacons by means of their smartphones or smartwatches.

Our field-study focuses on crowd-sensing real-time e-scooter-pedestrian encounters and other pedestrian physiological data (such as heart-rate) on the two campuses over a three-month period by recruiting pedestrian participants and equipping them with customized BLE receivers such as smartwatches. Well-defined spatio-temporal metrics are then computed from this crowd-sensed data and employed as safety benchmarks to further understand the impact that the micromobility services operating on these campuses have on pedestrian safety. Our analysis uncovers interesting encounter statistics and mobility trends which could be used to identify potentially unsafe spatio-temporal zones for pedestrians, especially in our target area(s). Although not generalizable to all possible urban environments and scenarios, our study makes a preliminary attempt to analyze the impact of upcoming micromobility transportation services on pedestrian safety, and provides a blueprint on how relevant data crowd-sensed by pedestrians can be employed to conduct similar studies in other urban environments and communities.

II. BACKGROUND AND RELATED WORK

Before outlining the research goals of this paper, we present a brief background on micromobility vehicles and services, and outline some relevant related literature.
A. Urban Micromobility Solutions and e-Scooters

Several different types and form-factors of urban micromobility vehicles are being offered, primarily on a rent-by-the-minute rental model, by a range of service providers. The more popular (and newer) battery-powered vehicles among them are e-scooters [28], [29], [30], [31], [32]. Depending on the vehicle form-factor and target market, service providers may offer their vehicles in either a docked or a dockless model. In the docked model, vehicles may only be picked up and dropped off at specific locations, commonly known as docking stations. This was a common model for manual (or automatic) bicycles which have a slightly larger form factor. The dockless model offers more flexibility to riders as they can pick up and drop off the vehicles at any location. This model is fairly common in small form-factor vehicles such as battery-powered e-scooters.

Vehicle rental (pick-up and drop-off), vehicle geo-location, service tracking and payments for both these models is facilitated by means of mobile apps implemented by the service provider. Although many of the vehicles discussed above are available for personal purchase, and many people also own them for last-mile commutes, it is the servitization of these vehicles that has resulted in the huge rise of their popularity, especially in the case of dockless vehicles. Servitization allows riders to use the nearest available vehicle, which in an urban setting should be easy to find due to a large density of vehicles, without having to securely store or carry along the vehicle when not in use. In other words, users receive all the convenience of using a last-mile commuting vehicle on-demand for a small fee without the liability or inconvenience of owning one. In addition to the on-demand nature of these micromobility services, the offered vehicles are environmentally friendly when micromobility trips replace personal automobile use [33].

In order to achieve focused and grounded results, in this work we study only dockless e-scooters and their impact on pedestrian safety. There are several reasons for focusing on dockless e-scooters. First, e-scooters are currently the fastest growing form factor throughout the micromobility industry [27]. Second, any middle or large-sized city in the US is currently served by a large number of local and national e-scooter service providers, offering ubiquitously available e-scooter vehicles and a range of different service options. Lastly, e-scooters are not only popular for short-distance/last-mile trips within the city, but also for commuting within larger self-administered communities inside cities such as universities, schools and company campuses and shopping malls. Dockless e-scooters are the most widely available and popular micromobility option in and around our university campus in which this study was conducted. See Table I for the range of service providers and e-scooter types (and their features) found on our university campuses.

Renting and operating these vehicles is fairly straightforward. By means of the service provider’s smartphone application, riders can activate any available e-scooter belonging to the provider that they find nearby and pay to ride it for as long as needed, or until the battery is drained. Riders can travel up to 28 miles per charge on certain e-scooter models, but most e-scooter trips are typically much shorter [9]. These vehicles fit the SAE “low-speed” category, with top speeds less than 20 mph [6]. Riders typically pay anywhere between 15 to 50 cents per minute to use the e-scooters, but some service providers also charge a small base fee to activate an e-scooter.

B. Prior Work on Safety Issues due to Micromobility Vehicles

Prior research efforts to identify and/or address issues related to micromobility, especially regarding safety of pedestrians and riders, did not have a holistic view of the underlying pedestrian and rider movement patterns. Analysis done by micromobility service providers [34], who can easily gather contextual data related to their vehicles (such as riding patterns and parking habits), did not have any quantitative information on fellow pedestrians and their movement patterns. Moreover, service providers would have a business incentive to not highlight the negative impacts (on pedestrian safety) due to their vehicles. Similarly, studies done by some city governments and community administrators [24], [35] only employed subjective feedback and qualitative data (often, more from pedestrians than riders).

Independent research efforts on micromobility related issues have thus far been very limited in scope. Researchers from medical institutions have analyzed micromobility related injuries of both riders and pedestrians [36], [37], [38], [39], and found that musculoskeletal fractures and head injuries were most common. While riders may be compelled to wear proper protection gear based on these findings (for example, mandatory use of helmets), the same cannot be enforced on fellow pedestrians. Sikka et al. [25] highlighted the health and financial impact for pedestrians involved in an e-scooter collision, using a case study. New approaches connect safety research to mobility needs, leveraging observational data. McKenzie [8] analyzed usage patterns of e-scooter and e-bikes in Washington, DC using the city’s publicly accessible API micromobility data portals. James et al. [40] analyze e-scooter safety perceptions and sidewalk blocking frequencies from survey data, and observed parking practices in different built environments.

In this work, we systematically analyze micromobility vehicle and pedestrian encounters (a precondition to micromobility accidents involving pedestrians), and discern if or how pedestrians and micromobility services can safely co-exist in urban environments.

III. RESEARCH OBJECTIVES

Disruptions to pedestrian movement due to micromobility vehicles such as e-scooters, and collisions between these vehicles and pedestrians, occur only when they closely (in some spatio-temporal sense) encounter each other on the streets. A more precise and empirically derived definition of an encounter is detailed later in Section V-A. Given the significant number of incidents involving pedestrians and micromobility vehicles reported in the last two years [12], [13], [14], [11], [15], we can postulate that every such close encounter between micromobility vehicles (moving or stationary) and pedestrians has some probability of resulting in a collision...
TABLE I: Micromobility service providers (in and around our university campus) and their vehicle features.

<table>
<thead>
<tr>
<th>Service Providers</th>
<th>Bird [28]</th>
<th>Lane [29]</th>
<th>Blue Duck [32]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xiaomi M365</td>
<td>Segway Ninebot ES2 (with extended battery)</td>
<td>Custom-made Ninebot</td>
<td>Segway Ninebot ES2 (with extended battery)</td>
</tr>
<tr>
<td>Headlights</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Tail/Brake Lights</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Bell/Horn</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Display</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Range (mi)</td>
<td>18.6</td>
<td>15.5 (28.0)</td>
<td>20-30</td>
</tr>
<tr>
<td>Top Speed (mph)</td>
<td>15.5</td>
<td>15.5 (18.6)</td>
<td>18.0</td>
</tr>
</tbody>
</table>

or a disruption to pedestrian movement. In other words, a higher density/concentration or frequency (or both) of such close vehicle-pedestrian encounters is indicative of a higher probability or potential for vehicle-pedestrian collisions, and is generally a good metric for benchmarking the state of pedestrians’ safety.

There are two critical factors that dictate the occurrence of close vehicle-pedestrian encounters, and their density and frequency. The first, also referred as space factors, are the spatial constraints imposed by the infrastructure (roads, sidewalks, etc.) shared by the micromobility vehicles and pedestrians. The second, also referred as time factors, are the temporal constraints that dictate the mobility (speed, direction, etc.) of the micromobility vehicles and pedestrians within a given shared space. A combination or co-existence of these space and time factors also impact the occurrence of encounters. In order to further clarify this, let us give some concrete examples of these factors as observed by us during our study. For instance, insufficient allocation of space for sidewalks and bike lanes can lead to unsafe encounters between micromobility vehicles and pedestrians. If a bike lane is not present, micromobility riders may feel compelled to use sidewalks meant for pedestrians. Similarly, if an improperly parked micromobility vehicle is blocking a sidewalk, pedestrians may be forced to use the main road to bypass the blockade (as shown in Figure 1a) which places them in great danger of getting hit by cars on the road. Other permanent obstructions, for example, trees, poles (as shown in Figure 1b), benches and fire hydrants, on spaces often shared between micromobility riders and pedestrians can also lead to unsafe encounters. Safe utilization of space allocated to riders and pedestrians also depends on proper planning of transportation hubs. For instance, if all commuters who just got off a bus, head in the same direction to their final destination, it may cause congestion among riders and pedestrians covering their last-mile. An optimally positioned bus stop, train station or parking lot should observe diffusion of commuters in all directions, thus minimizing chances of congestion and making safer utilization of the space allocated for riders and pedestrians.

Similarly, several time factors also play an important role in generating potentially unsafe micromobility vehicle-pedestrian encounters within a given space. For instance, if there is a spike in rider and pedestrian traffic due to multiple closely timed events (e.g., multiple classes scheduled in the same building and starting at the same time), it may cause congestion among riders and pedestrians en-route to these events. Another crucial time factor is the reaction time pedestrians get to navigate around micromobility riders traveling at different speeds and in different directions. Depending on whether a micromobility vehicle is moving towards or away from a pedestrian, and whether the vehicle is behind or in front of the pedestrian, the pedestrian may or may not get sufficient time to react appropriately.

Our research agenda, thus, is to first analyze by means of empirically collected encounter data how certain space and time factors affect the safety state of pedestrians when they are in co-existence with micromobility vehicles (and riders). Specifically, we seek to conduct the following three broad research analyses:

RA1 Correlating space factors with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.

Specifically, in RA1, we analyze the spatial distribution of encounters, changes in encounter properties between high and low encounter concentration or density areas, and the effects of pedestrians’ and riders’ spatial diffusion on encounter rates and other encounter-related properties in order to understand their impact on pedestrian safety. We will also correlate this analysis to infrastructure-related shortcomings (of our experimental environment), such as, missing bike lanes and sidewalk obstructions, in order to determine potentially unsafe encounters, if any.

RA2 Correlating time factors with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.

Specifically, in RA2, we analyze the temporal distribution of encounters, changes in encounter properties between time periods comprising of a large number of encounters versus smaller number of encounters, and the effects of pedestrians’
and riders’ temporal diffusion on encounter rates and other encounter-related properties in order to understand their impact on pedestrian safety. As before, we will correlate this analysis to the infrastructure-related shortcomings (of our experimental environment), such as, unbalanced class schedules and common event times, in order to determine potentially unsafe encounters, if any. Additionally, we will also analyze different encounter scenarios that gives varying levels of reaction time to pedestrian, and quantitatively measure pedestrians’ reaction to these different encounter scenarios.

RA3 Correlating a combination of space & time factors with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.

In RA3, we will extend our previous analysis to study which combinations of space factors (e.g., poor shared space utilization) and time factors (e.g., event times), as discussed earlier, are the most significant in enabling unsafe encounters between pedestrians and riders. In addition to the above quantitative analyses, which is primarily based on the crowd-sensed (BLE-based) encounter data and data from mobile sensors (e.g., heart-rate), we will also analyze pedestrians’ attitude and perception towards the impact that micromobility vehicles such as e-scooters have on pedestrian safety.

IV. RESEARCH METHODOLOGY

We now describe the details of the field-study that we conducted for crowd-sensing the micromobility vehicle-pedestrian encounter and other pedestrian-specific data used for the safety analyses summarized earlier. As part of this description, we outline in detail the study environment, data collection process including participant recruitment and the type and granularity of the data that is collected.

A. Significance of Pedestrian’s Point of View

Let us first briefly describe why pedestrians are best suited for gathering (and crowd-sensing) detailed information on their encounters with micromobility vehicles. The vehicles may or may not have a rider at the time of an encounter (for example, a parked vehicle), which means we will fail to gather information on encounters between pedestrians and rider-less vehicles if we depend only on riders for data collection. The vehicles themselves feature several sensing options, but, (i) none of their sensors are suitable for detecting nearby pedestrians, and (ii) service providers operating these vehicles are not very willing to release their vehicles’ data due to potential misuse by competitors and customer/rider privacy concerns.

Pedestrians also carry a variety of sensors with them that are present on their mobile and/or wearable devices. While experimenting with different sensors that could be employed for detecting encounters, we determined that most micromobility vehicles such as e-scooters transmit BLE advertising packets at regular intervals which could be passively captured by the BLE receivers present on most smartphones or wearables carried by the pedestrians. These BLE packets also contain identifiers which can be used to distinguish them from other BLE devices. For example, they may contain the service provider’s name (as shown in Figure 2) or other unique naming conventions. And, due to the short range of BLE transmission, pedestrians may capture the BLE packets only when they encounter a micromobility vehicle in close proximity. This can minimize unwanted noise that could occur due to micromobility vehicles which are not close to the pedestrian which also reduces the task Section IV-B load for the participant. Further, it also obviates participants having to carry any specialized sensing hardware and it is reasonable to assume that most pedestrians are comfortable and used to carrying a smartphone or wearable such as a smartwatch.

B. Data Collection

In order to accomplish the research goals outlined earlier, we crowd-sensed real-life micromobility vehicle-pedestrian encounter data by capturing BLE packets emanating from e-scooters in two separate urban communities supplemented by physiological and contextual (location and time) information and real-time feedback from the participating pedestrians.

The Field. To have a controlled understanding of encounters, we limited the field of our study to the main and downtown campuses of the University of Texas at San Antonio and neighboring points-of-interest (such as off-campus student housings and transportation hubs). Both campuses are within the city perimeters and cover about 725 acres in total area. As an urban university with more than 35,000 students and more than 4,000 employees, our campuses observe significant foot traffic when classes are in session. Since their introduction in late 2018, micromobility vehicles, especially e-scooters, have gained significant popularity throughout the city, including our university campuses. Students and employees primarily use micromobility services as a last-mile solution on campus, e.g., to travel between parking lots, bus stops or student housings, and university buildings where classes are scheduled. Although the use of roller-skates, skateboard, and scooter is prohibited on university property as per regulations, its enforcement is mostly absent as multiple micromobility service providers operate their e-scooters in and around the university campuses.

Participants. We recruited 105 participants for our data collection program, out of which only 77 completed all their assigned tasks. The remaining 28 participants did not complete their tasks due to varying reasons, such as loss of interest, damaged sensing hardware, or other technical difficulties. Participants were recruited through advertisements made using IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, VOL. NN, NO. NN, JANUARY XXXX 5

Fig. 2: A BLE advertising packet from a Lime e-scooter.
email and fliers distributed around the university campuses. Out of the 77 participants who completed their tasks (and thus only their data was used in our analysis in Section V), 41 were female and 36 were males. Their age ranged between 18 and 54 years, and all of them were either students or employees at the university. 61 of the 77 participants primarily attended classes or worked on the main campus, while 16 attended the downtown campus for one or more classes or for work. Participants were remunerated with $25 for their participation in our data collection program. Our participant recruitment, data collection, and result dissemination procedures were reviewed and approved by the university’s Institutional Review Board (IRB).

Sensing Hardware and Application. In order to capture BLE packets broadcast by the e-scooters and at the same time collect additional physiological and contextual information related to each encounter, we loaned a smartwatch to each participant for the duration of their participation. The loaned watch came installed with a custom sensing and data collection application written by us, and was paired with the participant’s smartphone only for Internet connectivity (in order to upload the sensed data to our data servers). Only our loaned smartwatch hardware and the installed data collection application was used to sense and collect data. This was done to maintain data consistency (across participants), ease of application development (only application for one mobile OS and hardware was needed), to avoid liability due to damaging participants’ personal device, and for improving accessibility of carrying out some of the manual tasks (described below) during each encounter. We chose the state-of-the-art Mobvoi TicWatch E smartwatch as our data collection because of its built-in GPS and heart-rate sensors, modern BLE v4.1 radio, and IP67 rated water resistance. The TicWatch E also features a 1.4 inch round OLED display, and runs Wear OS based on Android 8.0.

Participant’s Tasks. Each participant was required to wear the loaned smartwatch, especially when present on any one of university campuses, for a total of at least 30 days. We initiated the data collection program in April 2019 and terminated it by the end of June 2019 (a total of 3 months). On the first day of participation, participants signed the IRB-approved consent form, completed a demographic survey, checked out their personal phones and received a brief orientation on the operation of the installed application and their expected tasks. Whenever our data collection application (running in the background) determines¹ that the participant is a pedestrian and if any e-scooter is detected in their vicinity (i.e., by sensing the BLE packets originating from the e-scooters) at that time, it prompts the participant to answer up to three Yes/No questions (Figure 3) related to the encounter. The goal of these questions is to collect some real-time ground truth related to the detected encounter. If the participant answered NO to the first question (“Is there a fast moving e-scooter in your vicinity?”), the remaining two questions related to the e-scooter mobility were not asked as they are not relevant anymore. If participants failed to answer the questions within a short period of time (say, within a minute) after the e-scooter detection, the interface displaying the question was no longer available to prevent false data entry. In order to prevent annoyance to participants, and to preserve participant engagement throughout the data collection period, the questions were asked only once every 15 minutes even if the participants encountered more than one e-scooter during that time period. Also, during the first day orientation participants were instructed that they can be as engaged in providing real-time feedback as they want, removing any pressure or coercion for providing feedback. On their last day of participation, participants returned the loaned smartwatch (and any other accessory), completed a post-study pedestrian safety survey and got remunerated. Details of the post-study survey instrument and its outcomes are presented later in Section VI-B.

C. Data Modalities

We collected real-time quantitative data related to the encounters between e-scooters and our participants by means of the data collection procedure and application described above. Table II summarizes all the information or data related to these encounters that were either directly sensed or indirectly inferred.

Quantitative Data. Our data collection application logged participants’ every encounter with e-scooters in their vicinity. Specifically, it recorded the signal strength information from the BLE packets received from the e-scooter(s), time, location (GPS coordinates), heart-rate, and participants’ responses to the three questions (Figure 3) if available. By conducting a comprehensive heuristic analysis of the BLE advertisement packets prior to the start of the study, we determined a technique for identifying the service provider corresponding to each received BLE packet. Using this information, our

<table>
<thead>
<tr>
<th>Quantitative</th>
<th>External</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>Pedestrian and Rider Attractors</td>
</tr>
<tr>
<td>Time</td>
<td>• Location</td>
</tr>
<tr>
<td>Heart-Rate</td>
<td>• Time</td>
</tr>
<tr>
<td>Bluetooth</td>
<td>Pedestrian and Rider Generators</td>
</tr>
<tr>
<td>• Signal Strength</td>
<td>• Location</td>
</tr>
<tr>
<td>• Service Provider</td>
<td>• Time</td>
</tr>
<tr>
<td>On-Spot Questions</td>
<td></td>
</tr>
<tr>
<td>• Stationary or Moving</td>
<td></td>
</tr>
<tr>
<td>• In Front or Behind</td>
<td></td>
</tr>
<tr>
<td>• Direction w.r.t. Pedestrian</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 3: Encounter questions.

TABLE II: List of all information from/about the encounters.

¹Accomplished using Android’s DetectedActivity API.
data collection application also recorded the service provider corresponding to each encountered e-scooter.

**External Data.** We also collected certain external information that can help us understand and/or support our findings from the quantitative data. Specifically, we gathered location and time information on pedestrian and rider *attractors and generators*. We refer to locations where a significant number of pedestrians and riders are headed, such as, a class starting at a particular time, as attractors. Similarly generators are locations where a significant number of pedestrians and riders are generated, such as, a bus stop or parking lot. Attractors and generators often play dual roles, for example when a class ends and another starts just afterwards. We collectively refer to such attractors and generators as *points of interest* (or POI).

V. **Empirical Findings**

In this section, we comprehensively analyze the data collected during our field-study by employing the criteria outlined in Section III.

A. **Encounters and Data Sources**

An *encounter*, as relevant to our analyses, occurs when an e-scooter and a pedestrian meet each other at close proximity. Detecting such encounters from our crowd-sensed data is important, and a prerequisite, before analyzing their spatio-temporal characteristics for safety. Thus, we first define the notion of an encounter based on available data (BLE and user feedback) as follows:

- **Predicted Encounters** ($E_P$): Derived from BLE data and tagged by the *algorithm* in Section V-A1 after the study.
- **Observed Encounters** ($E_O$): Derived from feedback data and tagged by the *participant* in real-time during the study.

While $E_P$ is more deterministic, $E_O$ has information about the direction and location of the scooter with respect to the pedestrian, and thus can provide safety insights on moving scooters based on user feedback (Table II). We provide details of both encounters in Sections V-A1 and V-A2, respectively.

1) $E_P$: BLE packets emitted by BLE radios on-board e-scooters is a reliable means to determine proximity between participants and scooters, however not all close-enough encounters may be relevant to our analysis. For example, our participant could have captured one or two BLE packets from inside their home when an e-scooter rode past their house, which should not be considered as a real encounter. Prior to our field-study, we empirically determined that as a pedestrian moves away from an e-scooter (i.e., distance between them increases), reception intervals of the BLE packets transmitted by the scooter becomes inconsistent at his/her smartwatch (as shown in Figure 4). For instance, we start observing inconsistent BLE reception intervals starting at a distance of 20-25 ft or more. This observation was consistently observed across most models of the e-scooters and providers targeted by us in this work. We used this observation to classify a sequence of BLE packets as an encounter and then outlined an efficient technique to detect such encounters within the BLE packet stream in our collected dataset.

2) $E_O$: The encounters are voluntarily tagged by the participant in real-time whenever an e-scooter is detected by the data collection application. In contrast to passively collecting the BLE data, which does not require active involvement of...

![Fig. 4: BLE signal coverage around an e-scooter and how pedestrians at different distances from the e-scooter observe different reception intervals between BLE advertisements.](image)

We use a sliding window approach to identify the encounters in a stream of fragmented BLE packets captured throughout the day by each participant. A window size of 1 second with a 80% overlap (i.e. each window has an overlap of 80% with its previous window) is used and the windows that contain 4 or more BLE packets are marked as potential encounter windows. Both the window length and threshold of 4 were empirically determined, based on the approximate minimum encounter duration and approximate maximum BLE advertisement interval, respectively. The potential encounter windows are then further refined as follows: if the time interval of BLE packets between two (or more) potential encounter windows is less than 300 seconds, the two windows are combined to form a single encounter. If the time interval is greater than 300 seconds, the two windows are considered as two separate encounters. Finally, if more than 4 encounters are detected for a specific e-scooter in one day by a single participant, the later encounters are discarded on the basis that the participant was spending abnormally long durations of time in close proximity of the same e-scooter (e.g., sitting at an outdoor restaurant where a scooter was parked nearby). This filtering step ensures that a single e-scooter or participant does not heavily bias our encounter data and its analysis. Figure 5 summarizes this encounter detection technique with different BLE packet reception examples. Using the above encounter detection technique, we classified pedestrian-scooter encounters with 1058 of the 7919 uniquely observed (by means of their unique id in the captured BLE packets) e-scooters in our dataset. Overall, we observed a total of 1800 encounters, including repeat encounters with previously encountered e-scooters.

![Fig. 5: The encounter detection algorithm applied on different BLE reception example cases.](image)
the participant, reliable feedback data is challenging to collect. This is because it not only requires reliance on the participants to actively provide feedback, but such data is also subjective in nature. This can be seen in the feedback dataset, which has 6482 participant feedbacks (among 10000+ observations) on both moving and stationary e-scooters in our dataset, that were provided by the participant during the entire study period. Out of the all feedback instances recorded, approximately 80% of the recorded observations were pertaining to stationary and out-of-sight scooters, while the remaining (1281) were related to sighted moving scooters. Of these 1281 feedbacks, 848 corresponded to the participant observing an e-scooter while being a pedestrian, and were used for our analysis. The pedestrian participants also observed 585 (approximately 59%) encounters, where the e-scooters were moving along with the participant in the same direction. And, they observed 218 encounters where the e-scooters were not in plain-sight and was behind the participants, a potentially hazardous scenario if the e-scooter was approaching them.

We also analyzed the sensed heart-rate of the participants to determine their reaction (as pedestrians) to moving e-scooters approaching them from the front and from the behind. We collected the heart-rate data from each participant whenever a feedback questionnaire is triggered. An increase in heart-rate can occur when a pedestrian is startled by a fast moving e-scooter, which in many scenarios imply that the pedestrian was faced with inadequate response time. Analyzing this parameter for our participants may validate if indeed our participants were startled by the observed e-scooter encounter. We first determine normal physiological information for each participant based on their overall heart-rate data, which can vary significantly from participant to participant. This calculation includes the heart-rate range from data related to both moving and stationary encounters. The threshold contains the most frequently occurring pulse rate, pertaining to the normal or resting rate for that person. We then identify if the encounter-related (moving) heart-rate was within the participant’s computed heart-rate range (for most daily activities) or not. In 554 of the 812 moving encounters, participants had a higher than usual heart-rate, where the e-scooter came from behind (144) and went in the same direction (based on 43 on-spot responses) and encounters where the e-scooter came from front and went in the opposite direction (based on 132 on-spot responses). This aligns with our intuition that pedestrians may have little time to respond to rapidly moving e-scooters and can be easily startled by them. Moreover, most e-scooters emit very little audible sound during their normal operation, and combined with their faster speed, they could present a significant safety risk to the pedestrians if they cannot observe them and take appropriate reaction in a timely fashion.

In both encounter types (E_P and E_Q), we observed that Blue Duck’s e-scooters, which constituted about 2% of all recorded e-scooters, were not encountered by our participants in either of the campuses. Therefore, all our further analysis will be based on encounters with the Bird and Lime brand of e-scooters only. Moreover, we will only count encounters that occur between 06:00-22:00. This is because the earliest class (on either campus) started at 07:00 and the last class finished at 21:45, and thus, the time period between 06:00-22:00 represents the most typical use of e-scooters as a last-mile transportation solution.

B. Outcomes of RA1

To analyze how the encounters are spatially distributed throughout our university campuses and their surroundings, we first build a set of atomic segments where encounters may occur. Each atomic segment is an edge in the graph of roads and walkways, and one can enter or exit an atomic segment only at its end. An atomic segment may connect with other atomic segments (such as at an intersection), or end at a POI. A frequency map can be seen in Figures 7a and 7b which shows the number of predicted encounters (E_P) that occurred in each of campus areas, during the entire study period. The main campus atomic segments have 611 E_P and 35 E_Q as the highest counts, whereas the downtown campus have 256 E_P and 55 E_Q as the highest counts.

At least twenty atomic segments in the main and the downtown campus observed relatively high number of predicted encounters (E_P) (25+) and observed encounter (E_Q) (5+). As seen in the frequency distribution charts in Figures 6a and 6d, out of the 21447 atomic segments (combined for both the main and downtown campuses), 21180 atomic segments did not have any predicted encounters and 20926 atomic segments did not have any observed encounters, with more than 95% of atomic segments having five or fewer predicted (E_P) and observed (E_Q) encounters. These results highlight the extremely disproportionate number of encounters in both the campuses, implying that pedestrians in certain parts of the campuses (and their surroundings) are significantly more likely to encounter e-scooters than the rest of the campuses.

From Figures 7a and 7b we observe that around on-campus residence halls and their parking lots, along with nearby off-campus apartment complexes, show the highest saturation of scooter encounters. Participants start from these residence areas and disperse into different directions to reach different academic buildings of the university, and later come back to their residence areas. Given that these areas are far from the buildings where the classes are held, pedestrians will either walk, take a shuttle or ride a scooter to their destination. In all these cases, they will walk for a short distance after leaving their residences, either till they reach a shuttle stop or a place where a scooter is parked. The resulting heavy pedestrian traffic along with targeted placement of scooters near the residence areas explains the high number of predicted and observed encounters observed in these areas. We also identified other POIs with high number of encounters (predicted and observed) near shuttle stops and outside staircases at the end of a long walking path. Scooter riders will have to park their scooters near these stairs, since carrying their scooters through top of the staircase is a strenuous task and not possible with shared scooters. This results in a high number of scooter encounters (predicted (E_P) and observed (E_Q)) near these places.

We also note the lack of sidewalks and bike lanes in the adjoining roads surrounding the parking and housing area in
the northwest side of the main campus, as seen in Figures 7a and 7c, that has high predicted \((E_P > 30)\) and observed \((E_O > 20)\) encounter counts, which may be a safety hazard for students who prefer to walk to a nearby buildings, and to riders who may be passing along to reach nearby parking lots or other destinations. In both cases, the pedestrian and rider is forced to use the roadway for vehicle traffic, which may lead to a dangerous situation. Coupled with the fact that more than 50% of the observed encounters startled our participants (based on heart-rate) demonstrates the need for caution when using roadways. To prevent mishaps, the usage guidelines (right-of-way, safety rules) on roadways with high pedestrian-scooter density and inadequate infrastructure could be revisited, and made aware to all road users via signboards, posters, etc.

We next focus on the spatial closeness of the predicted encounters because closer encounters have a higher likelihood of resulting in a pedestrian-related collision or disruption. Due to its attenuation over distance, BLE signal strength is a good indicator of the spatial closeness of encounters that occurred between our participants and e-scooters operating in our test deployment area. As seen in Figure 8, we discovered that predicted encounters in atomic segments with high encounter counts are on average closer (as the average BLE signal strength is relatively stronger) than predicted encounters in atomic segments with low encounter counts (as the average BLE signal strength is relatively weaker). Because of the different BLE transmission power used by different service providers, we conduct this analysis separately for Bird and Lime.

For reference, the signal strength of BLE packets captured (on the TicWatch E smartwatch) from Bird brand e-scooters within a feet away from their computer module (usually mounted on the stem of the scooter) is approximately -60.5 \(dB\), whereas for packets captured from Lime brand e-scooters in the same setting has an approximate signal strength of -46.25 \(dB\). In summary, this analysis tells us that encounters in high-encounter atomic segments are at a relatively closer range (distance between the participants and e-scooters) than encounters in low-encounter atomic segments, which indirectly suggests that collisions are more likely to occur in high-encounter atomic segments than in low-encounter atomic segments. As a result, scooter riders and pedestrians should be more cautious in high-encounter atomic segments,

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Fig. 6: Frequency distribution of predicted \((E_P)\), observed \((E_O)\) encounters between 06:00-23:00 among (a,d) 21447 atomic segments in main and downtown campuses combined, (b,e) 68 15-minute time periods in a day, and (c,f) all combinations of 21447 atomic segments and 68 15-minute time periods.

Fig. 7: Number of predicted and observed encounters respectively in and around (a,c) main campus, and (b,d) downtown campus.
and university administrators should focus on improving the infrastructure around such high-encounter atomic segments in order to alleviate the cause of such high number of encounters. **Generalized Implications.** We now generalize the implications of our findings both in and outside a campus setting. Service provider data can easily identify the scooter density and rider routes around a specific area at a given time. In contrast, our data allowed identifying pedestrian-scooter encounters and their density in specific areas, for instance, parking lots, recreation centers, etc. With this knowledge, planners can easily identify these hotspot areas, and remediate areas that lack adequate critical infrastructure through rules of co-existence (redirecting flow, rearranging) or additional structures (lanes, docking stations). For instance, safe walking space could be reclaimed in high-encounter areas by adding a bike lane alongside paths for micromobility and bicycle riding, or along nearby parallel routes [41], [42].

C. Outcomes of RA2

To analyze how the encounters are temporally distributed throughout the week, we partitioned the week into 476 15-minute time periods starting at 06:00 and ending at 23:00 each day. Although there were significantly fewer classes and events on campus during the weekends, we included them in our analysis for completeness. Figure 9 shows the number of encounters that occurred in each of the 476 time periods across both the campuses, during the entire study period. During two time periods, Wednesdays 12:45-13:00 and Thursdays 22:30-22:45, we observe the highest number of predicted encounters ($E_P$) (50+). At the same time, for twenty time periods on Wednesdays and Thursdays, we also see a relatively higher number (35+) of observed encounters ($E_O$). Also, we see several spikes and surges throughout Monday to Friday, and the number of encounters (both predicted ($E_P$) and observed ($E_O$)) on campus were significantly lower on Saturdays and Sundays. To understand the encounter frequency throughout the length of a day, we added the encounter counts observed during the 68 15-minute time periods each day (between 06:00-23:00). The results shown in Figure 6b demonstrates that pedestrians are significantly more likely to encounter e-scooters at certain times of the day, such as between 12:45-13:00 and between 14:45-15:00. During these time slots, our participants had a total of 28 encounters in observed encounters and 169 encounters in predicted encounters ($E_P$).

Similar to the spatial analysis, we again look into the spatial closeness of encounters that occurred during time periods with low encounter counts (1-84 for predicted ($E_P$), 1-83 for observed ($E_O$)), and compare them with encounters that occurred during time periods with high encounter counts (85-169 for predicted, 84-167 for observed); both intervals split equally into two halves based on the maximum encounter count for each encounter type. As shown in Figure 8, for both the Bird and Lime brand e-scooter encounters that occurred during time periods with high encounter counts are generally closer, as the observed average BLE signal strength is relatively stronger in these encounters. This is in contrast to encounters that occurred during time periods with low encounter counts, as the observed average BLE signal strength for encounters is relatively weaker in this case. This suggests that collisions are more likely to occur during time periods with high encounter counts than during time periods with low encounter counts. Similar patterns were observed in both predicted ($E_P$) and observed ($E_O$) encounters.

As students and some employees plan their arrival and departure to/from campus depending on class timings, it is intuitive that our encounter observations have some relation to the schedule of classes. We plot the hourly encounters recorded from April to early-May (when the classes ended at end of spring semester) alongside the number of classes scheduled per week in Figure 10. We observed that the highest number of classes occur on Tuesdays, Thursday and Wednesday in the week in Figure 10, and the average encounters on these
days are also higher than the rest of the week showing the occurrence of encounters follows closely with class schedules. Also, there are more predicted encounters \((E_P)\) at night than during the day, more likely due to late night study and exam preparations done by students. While we see a significant overlap in the afternoons, there are comparatively fewer encounters (predicted and observed) around the early morning periods. This could be due to a combination of multiple factors. First, the personnel who recharge the e-scooters (in return for a payment from the service provider) usually do so during the night, as certain e-scooter models can take up to 8 hours to fully recharge. These personnel generally collect drained e-scooters around late evenings or night, and are also responsible for distributing the recharged e-scooters around the city. We observed that the distribution of recharged e-scooters usually happen around the late morning periods, which aligns with our observation of negligible number of encounters around the early morning periods. Second, late spring-early summer mornings in our target field of study usually have a pleasant climate, which may prompt last-mile commuters to walk to their final destination instead of using micromobility vehicles. 

**Generalized Implications.** Scooters may be introduced or removed around the time periods with high encounters to provide reliable transportation options (to reach destinations in timely fashion without hindering other road users), and regulations set accordingly to improve the road user experience and provide a safer environment (for pedestrians) through better management of chaotic times. For an example, in a university setting, the shuttle buses can be made more frequent during the observed high encounter times, which could encourage students to use the shuttles instead of the scooters. Further, the shuttle stops could be placed in a such way that it would reduce the amount of walking a person is required to walk to reach a classroom after getting down from a shuttle. Similarly, in a crowded city setting, timing of frequent scooter encounters could be used in combination with other travel modes to compliment last-mile connections, and reduce conflicts.

**D. Outcomes of RA3**

To analyze how the observed encounters \((E_O)\) are spatio-temporally distributed, we study all combinations of the 21,447 atomic segments in both campus and 68 15-minute time periods in one day (between 06:00-23:00), for a total of 1,458,396 spatio-temporal zones in each campus. More than 90% of the spatio-temporal zones in both the main and the downtown campus did not have any predicted encounters \((E_P)\) or observed encounters \((E_O)\), as seen in the frequency distribution charts in Figures 6c and 6f. This indicates that pedestrians are significantly more likely to encounter e-scooters in certain parts of the campuses (and their surroundings) than the rest of the campus areas, and only at certain time periods. For instance, there were lesser or no predicted encounters \((E_P)\) on the Main campus from 06:00-23:00 on Tuesdays, compared to the latter part of the day as seen in Figure 11. We also identified that the residential areas outside the campuses had lesser or no encounters in the early morning Figure 11a more likely due to e-scooter recharges schedules, lack of classes and availability of bus shuttles. We noticed predicted encounters \((E_P)\) inside the campus mostly between 12:00-15:00. These high encounter counts, both predicted \((E_P)\) and observed \((E_O)\), could be explained by the following factors. Firstly, people usually start going out of the university for lunch around this period of time. Also, students who only have morning classes for the day start leaving the campus and on the other hand students who only has afternoon classes start coming on to campus around this time period. Since there are more classes (150+) from mid-day to early-evening (12:00-16:00) on most weekdays except Fridays, depicted in Figure 10, this could also how show scooter usage also increases around that time, with the highest encounters occurring in 14:45-15:00.

Similar to the individual spatial and temporal analyses outlined earlier, we discovered from Figure 8 that predicted encounters in atomic segments with high encounter counts are on average closer in range (as the observed average signal strength of the BLE packets in the encounters is relatively stronger) than predicted encounters in atomic segments with low encounter counts (as the observed average signal strength of the BLE packets in the encounters is relatively weaker) for Lime and Bird brand scooters. This suggests that e-scooter related pedestrian collisions are more likely to occur in spatio-temporal zones with high encounter counts than in the ones with low encounter counts. 

**Generalized Implications.** The spatio-temporal analysis provides insights on multiple location-time combinations, providing alternative options to help planners easily identify a suitable location and time period to host events accommodating a crowd, thus leading to optimized planning and scheduling around these time periods to avoid traffic congestion (foot or auto) and reduce conflicts.

**VI. Discussion**

**A. Limitations and Broader Impact**

One main limitation of our field-study was that its scope was restricted to the two suburban and urban campuses and surrounding neighborhoods of one university. Subsequently, some of the results and insights gained from the study may be more directly applicable to our university’s infrastructure and regulations, locally-available micromobility vehicles, and student riders and pedestrians. That being said, our first-of-a-kind study’s methodology and analyses (including the employed statistics and benchmarks) can serve as a blueprint on how crowd-sensed micromobility data can be used to enable similar safety-related studies in other urban communities. Due to the privacy sensitive nature of the location data collected in this study, our dataset will be made available only to researchers up on their request.

An important aspect of our study is that it only relies on the participating pedestrians to passively crowd-sense the micromobility encounters and other sensor data on-board their mobile devices. Although such an approach has its advantages (e.g., relatively low study deployment cost), if this data is supplemented with sensor data collected from the micromobility vehicles themselves, for example, video feed from a camera...
mounted on the vehicles or packets received by the vehicles’ BLE receivers, it could result in an even better analysis. However, employing commercially-owned micromobility vehicles to collect data is not easy due to restrictions put in place by the service providers owning these vehicles. One could deploy their own micromobility vehicle or e-scooter testbed for this purpose which could enable a much easier data collection process, but deployment and maintenance of such a testbed could be very expensive.

B. Participants’ Perception about Safety

Our study ended by participants completing a post-study survey (outlined in Appendix A). In contrast to the quantitative encounter data which helped us gain useful insight on how riders’ mobility patterns and infrastructure-related constraints within shared spatio-temporal zones or spaces could impact pedestrians’ safety, the post-study survey response data from participants will shed light on their subjective perception of this issue. This survey comprised of two parts: a set of questions to measure how well our data collection application (specifically, the notifications and the manual feedback interface) performed, and another set of questions to capture participants’ interests and preferences vis-à-vis pedestrian safety and mobile device based safety applications.

One highlight of responses to the first set of questions is that despite having a minimum 15-minute interval between sending e-scooter detection notifications, one-third of all participants found these notifications annoying. This is not surprising as there are many HCI studies [43], [44] that show that notifications have a very high chance of causing annoyance if they are not well-designed, and could eventually disengage users. Fortunately, as our application was passively collecting encounter data irrespective of whether participants responded to or ignored our notifications, it did not impact our data collection process significantly. Another highlight is in the responses received to our second set of questions where 58% of the participants expressed interest in a mobile application that would alert them about potential encounters with electric or e-scooters. Although this shows that there is significant interest among users to protect their safety from upcoming micromobility transportation vehicles, it also shows that a significant number of users (42%) are either not interested in such an application or are indifferent to the problem of pedestrian safety from such vehicles. Given the number of participants who were annoyed at the frequency of notifications (from our application), our hypothesis is that these 42% of the participants who did not express interest in a micromobility vehicle alerting application responded that way because of their displeasure with the high number of notifications in our data collection application. Although our data collection application was not a pedestrian safety application (because it notified users of all encounters and not only the hazardous ones), the above results highlight an important property that any safety application should possess—a good balance between useful functionality and user engagement through carefully designed notifications.

VII. Conclusion

We conducted a large-scale field-study to understand the current state of pedestrian safety in our urban community, in relation to micromobility services (such as e-scooters). In the field-study, we crowd-sensed real-time encounter data between e-scooters and pedestrian participants on two distinct urban university campuses over a three-month period. We analyzed specific spatio-temporal metrics and used them as benchmarks to understand the impact on pedestrian safety from micromobility services. Our analysis uncovered encounter statistics and mobility trends which could be used to identify potentially unsafe spatio-temporal zones for pedestrians. Our work also provides a blueprint on how crowd-sensed micromobility data can enable similar safety-related studies in other urban communities.

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APPENDIX A – POST-STUDY SURVEY

Study Application Usage

1) How often did you receive the feedback notifications from the study application? 

- Rarely 
- 1 
- 2 
- 3 
- 4 
- 5 Very often

2) Did you at any point find the feedback alert notifications to be annoying? 

Yes No

3) If yes, did you turn the notifications off? 

Yes No

4) How effective was the notification mechanism? 

Not effective at all 
- 1 
- 2 
- 3 
- 4 
- 5 Very effective

General Pedestrian Safety

6) Have you ever used any wearable technology that provides pedestrian safety? 

Yes No

7) If yes, please specify some.

8) Would you be interested in a smartwatch application that alerts you about electric scooters in the vicinity? 

Yes No

9) If yes, what type of alert would you suggest for this scenario? Select all that apply.

Audio (e.g. beep) 
Visual (e.g. flashing LED light) 
Tactile (e.g. vibration) 
A combination of the above
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