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

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The popularity and proliferation of micromobility vehicles, such as, electric- or e-scooters, as last-mile transportation solutions in our cities and urban communities has been rapidly rising. The growth of their popularity and numbers has been further accelerated due to the large number of service providers that offer these vehicles on a rent-by-the-minute scheme, which benefits riders with low trip costs without having to bear the upfront purchase and maintenance costs of owning such a vehicle. 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. Thus, it is critical to understand the current state of pedestrian safety in our urban communities vis-à-vis micromobility services such as e-scooters, identify factors that impact pedestrian safety due to such services, and determine how to enable pedestrian safety going forward. Unfortunately, till 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 pedestrians’ point-of-view. By crowd-sensing real-time encounter data between e-scooters and pedestrian participants on two distinct urban university campuses over a three-month period, we analyze specific spatio-temporal metrics which can be used as safety benchmarks to understand the impact on pedestrian safety from micromobility services operating on these campuses. Our analysis uncovers interesting encounter statistics and mobility trends which could be used to identify potentially unsafe spatio-temporal zones for pedestrians. This preliminary work also provides a blueprint on how crowd-sensed micromobility data can enable similar safety-related studies in other urban communities. The tools and (anonymized) encounter and other data from this study are publicly-available, and can be used as a resource to carry out additional investigations in this direction.

CCS Concepts:
• Human-centered computing → Ubiquitous and mobile devices;
• Applied computing → Sociology;
• Computer systems organization → Embedded and cyber-physical systems.

Additional Key Words and Phrases: Micromobility, Pedestrian, Safety, Electric Scooters, Wearables.

1 INTRODUCTION

One of the biggest challenges faced by cities due to an increasing population and population-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 [35], 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 [30], road rage, accidents [20] and economic waste [21, 22]. 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.

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Micromobility is an umbrella term used to describe a novel category of transportation using non-conventional battery-powered vehicles, such as, electric- or e-scooters and e-skateboards, which is 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. And due to their small physical footprint, such vehicles provide an easy way to navigate around a city with congested roads and sidewalks, making them a popular last-mile transportation solution in urban areas. 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 a rent-by-the-minute scheme, which benefit riders with low trip costs without having to bear the upfront purchase and maintenance costs of owning such a vehicle. Other aspects of such micromobility services that make them appealing to urban commuters include easy service accessibility by means of a smartphone app, 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.

However, as with any disruptive new technology, unforeseen problems have surfaced with or due to such micromobility services, and properly addressing these concerns will be pivotal to their future 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 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. 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 accidents involve some form of collision with pedestrians [2, 6, 14, 15, 17, 19, 33].

Thus, a key issue that administrators, policymakers and stakeholders in our cities and urban communities (e.g., school and university campuses) 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?”, “which factors impact pedestrian safety in such services?”, and “how to enable pedestrian safety going forward?” are urgently needed. Battery-powered and easily accessible micromobility vehicles and services is a great 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 [3, 8, 18, 29], while others have outright banned them [7, 10, 23, 31]) 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 need to be thoroughly studied in an empirical and data-driven manner.

Till 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 [1, 42]. 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 these micromobility vehicles (e.g., e-scooters), which come equipped with a constantly beaming Bluetooth Low Energy (BLE) radio, to act as signal emitters and pedestrians carrying some form of a BLE receiver (i.e., a smartphone or smartwatch) to act as signal capturers. Data crowd-sensed in such a fashion will have complete and fine-grained contextual (spatio-temporal) information about the mobility state(s) of the micromobility vehicles and physiological states of the (participating) pedestrians, and thus, will be able to provide a much more accurate analysis of the factors impacting pedestrian safety in such services.

Specifically, we conduct a field-study by recruiting participants (mostly, students) in two distinct urban university campuses (located within the same city) where micromobility vehicle services are extremely popular. University campuses have a large density of pedestrians (who are also often distracted [24]), 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 [34] and also on the said university campuses. We observed that BLE beacons transmitted by most service provider operated e-scooters, can be used to characterize encounters between these vehicles and pedestrians. Accordingly, we crowd-sense real-time encounter data and other participant-specific physiological data (such as heart-rate) on the two distinct urban university campuses over a three-month period, and utilize it to analyze specific spatio-temporal metrics which can be used as safety benchmarks to understand the impact on pedestrian safety from micromobility services operating on these campuses. 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.

2 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.

2.1 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 vehicles comprise of the more popular (and newer) battery-powered vehicles such as e-scooters [4, 13, 16, 25, 27, 36] and e-skateboards [11, 12, 28] or the more traditional manual bicycles [26, 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. 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 a using a last-mile commuting vehicle on-demand for a small fee without the liability or inconvenience of owning on. In addition to the on-demand nature of these micromobility services, the offered vehicles are environmentally friendly (due to their electric-powered nature) and easily navigable on urban roads, thus making them an excellent choice for last-mile transportation.

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 [34]. Secondly, 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 popular for commute within larger self-administered communities inside cities such as university, school and company campuses and shopping malls. As a matter of fact, 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 1 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 stray e-scooter 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 [39]. Top speed that riders can travel at on a flat pavement depends on the e-scooter model, with 18.6 miles per hour (30 km/h) being the top speed among commonly found e-scooters. 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 a stray e-scooter.

### 2.2 Prior Work on Safety Issues due to Micromobility Vehicles

Prior research efforts to identify and/or address problems 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 [5], 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 an incentive to not highlight the negative impacts (on pedestrian safety) due to their vehicles. Similarly, studies done by some city governments

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**Table 1. Micromobility service providers (in and around our university campus) and their vehicle features.**

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and community administrators [1, 9] were also biased as they only employed subjective feedback and qualitative data (often, more from pedestrians than riders). Such studies, and the resulting policy making, could have also been influenced by the prospect of negative economic impact of micromobility services on other government-run or private transportation services and entities. For instance, popularity of micromobility services would possibly mean lower utilization of existing public and private transportation infrastructure, which could result in loss of revenue from ticket and fossil-fuel sales and loss of employment for workers in those industries.

Independent research efforts related to micromobility problems have thus far been very limited in scope. Researchers from medical institutions have analyzed micromobility related injuries of both riders and pedestrians [37, 38, 43, 44], 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. [42] highlighted the health and financial impact for pedestrians involved in an e-scooter accident, using a case study. However, analysis of the consequences does help in prevention of such accidents. 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.

3 RESEARCH OBJECTIVES

Disruptions to pedestrian movement due to micromobility vehicles such as e-scooters, and accidents 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 in our setting appears later in Section 5.1. Given the significant number of accidents involving pedestrians and micromobility vehicles reported in the last two years [2, 6, 14, 15, 17, 19, 33], we can postulate that every such close encounter between micromobility vehicles (moving or static) and pedestrians has some probability of resulting in an accident 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 accidents, 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 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 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 1) 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 2), 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. Moreover, 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 get insufficient 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.

Here 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.

Here 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-sourced (BLE-based) encounter data and data from mobile sensors (e.g., heart rate), we will also throw light on pedestrians’ attitude and perception towards the impact that micromobility vehicles such as e-scooters have on their (and their fellow pedestrians’) safety.

4 RESEARCH METHODOLOGY

Next, we describe details of the field-study that we conduct for crowd-sourcing 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.

4.1 Significance of Pedestrian’s Point of View

Let us first briefly describe why pedestrians are best suited for gathering (and crowd-sourcing) detailed information on their encounters with micromobility vehicles. Micromobility 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 riderless vehicles if we depend on riders for data collection. Micromobility 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 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 5) 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 prevent unwanted noise in our data by micromobility vehicles not near the pedestrian, which can in turn help minimize the task load on the participants of our field-study (more details on participants and their tasks in Section 4.2). An added advantage of such an approach is that the pedestrians would not have to carry any specialized sensing hardware for participating in the crowd-sourcing process - it is reasonable to assume that most pedestrians are comfortable or used to carrying a smartphone or wearable such as a smartwatch.
4.2 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. We further supplemented this data with physiological and contextual (location and time) information and real-time feedback from the participating pedestrians. The details and scope of our data collection procedure are further described below.

The Field. To have a controlled understanding of encounters, we limited the field of our study to two of our distinct university campuses and neighboring points-of-interest (such as off-campus student housings and transportation hubs). The university has one main campus (Figure 3) and a satellite downtown campus (Figure 4), both of which 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 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 5), 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 Institutional Review Board (IRB) at our university.

**Sensing Hardware and Application.** In order to sense BLE packets 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 Bluetooth (LE) 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 at 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 the smartwatch with the installed data collection application, received assistance in pairing the loaned smartwatch with 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) determines that the participant is a pedestrian and if an e-scooter is detected in his/her 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 6) 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 6.2.

### 4.3 Data Modalities

We collected real-time quantitative data related to the encounters between micromobility vehicles such as e-scooters and our participants by means of our data collection procedure and application, as described above. Table 2 lists all the information/data related to these encounters that we either sensed or 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 participant’s response to the three quantitative questions (Figure 6) if available. By conducting a comprehensive heuristic analysis of the BLE advertisement

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1Accomplished using Android’s DetectedActivity API.
Fig. 5. A BLE advertising packet transmitted from a Lime e-scooter.

Table 2. List of all information that we learned from/about the encounters.

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packets prior to the start of the study, we found a way to identify the service provider corresponding to each received BLE packet. Using this information, our 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).

5 EMPIRICAL FINDINGS

In this section, we thoroughly analyze the quantitative and external data collected during our field-study by employing the benchmarks and criteria outlined in RA1 to RA3 earlier.
5.1 Encounters
Detecting relevant encounters (between e-scooters and our pedestrian participants) from the collected data is important, and somewhat of a prerequisite, before analyzing their spatio-temporal characteristics for safeness. As discussed earlier, BLE signals or packets emitted by these e-scooters is a reliable means to determine proximity between participants and e-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. Thus, we first need to more precisely define the notion of an encounter and then outline an efficient technique to detect such encounters within the BLE packet stream in our collected dataset.

Encounter Definition and Detection. An encounter in our setting occurs and is relevant when an e-scooter and a pedestrian meet each other on the streets at close proximity. 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 e-scooter become inconsistent at his/her smartwatch (as shown in Figure 7). 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

Fig. 7. BLE signal coverage around an e-scooter and how pedestrians at different distances away from the e-scooter observe different reception intervals between BLE advertisement packets.

<table>
<thead>
<tr>
<th>BLE Packet Receptions</th>
<th>Not an Encounter</th>
<th>Encounter</th>
<th>Not an Encounter</th>
<th>Encounter</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 &lt; 300 seconds</td>
<td>N=4</td>
<td>N=4</td>
<td>N=4</td>
<td>N=4</td>
</tr>
<tr>
<td>t &gt; 300 seconds</td>
<td>N=4</td>
<td>N=4</td>
<td>N=4</td>
<td>N=4</td>
</tr>
</tbody>
</table>

Fig. 8. The encounter detection algorithm applied on different BLE reception example cases.
We used this observation to classify a sequence of BLE packets as an encounter. Below we give details of our BLE-based encounter detection technique.

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 is used and the windows that contain 4 or more BLE packets are marked as potential encounter windows. Both the window length and the threshold 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 8 summarizes this encounter detection technique with different BLE packet reception examples.

We observed a total of 7919 unique e-scooters in our dataset, identified by their unique BLE packets, during the entire study period. Using the above encounter detection technique, we classified encounters with 1058 of them. Overall, we observed a total of 1800 encounters, including repeat encounters with previously encountered e-scooters. Figure 9 shows the observed and encountered e-scooters during our study, broken down based on the service providers. Blue Duck’s e-scooters, which constituted about 2% of all observed e-scooters, were not encountered even once by our participants in either of the campuses. Therefore, all our analysis that follows will be based on encounters with the Bird and Lime brand of e-scooters only. Moreover, we only count encounters that occur between 6:00 AM and 11:00 PM. This is because the earliest class (on either campus) started at 7 AM and the last class finished at 9:45 PM, and thus, the time period between 6:00 AM to 11:00 PM represents the most popular use of e-scooters as a last-mile transportation solution.

Fig. 9. Brand share of (a) unique e-scooters observed, (b) unique e-scooters encountered, and (c) all e-scooter encounters (including repeat encounters with previously encountered e-scooters). Calculated using the captured BLE advertisement packets.
5.2 Outcomes of RA1

To analyze how the encounters are spatially distributed throughout our university campuses and their surroundings, we partitioned each campus into 1600 smaller subareas of equal size. Figures 3 and 4 show the $40 \times 40$ grids that were used to determine the subareas in the main and satellite campuses, respectively. Each subarea in the main campus is roughly $9639 \text{ ft}^2$, and each subarea in the satellite campus is about $3463 \text{ ft}^2$. Figures 10a and 10b show the number of encounters that occurred in each of the 1600 subareas per campus, during the entire study period. Two subareas in the main campus observed relatively very high number of encounters ($175+ \text{})$ and one subarea in the satellite campus observed relatively high number of encounters ($60+ \text{)$. As seen in the frequency distribution chart in Figure 11a, out of the 3200 subareas (combined for both the main and satellite campuses), 2933 subareas did not observe any encounters and more than 97% of subareas had five or fewer 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.

Upon in-field inspection of the two subareas in the main campus that observed $175+ \text{ encounters, we found out that neither of the subareas had dedicated bike lanes that e-scooters could utilize. Very recently, after our field-study was completed, the university started constructing new bike lanes around one of the subareas that observed $175+ \text{ encounters (Figure 18 in Appendix B). However, our study results were not directly responsible for this new development.}

We next look in to the finer characteristics of encounters that occurred in subareas with high encounter counts (105-209 encounters), and compare them with encounters that occurred in subareas with lower encounter counts (1-104 encounters). Specifically, we focus on the spatial closeness of the encounters because closer encounters have a higher likelihood of resulting in an accident or a 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. As seen in Figure 12, we discovered that encounters in subareas with high encounter counts are on average closer (as the average BLE signal strength is relatively stronger) than encounters in subareas 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 the e-scooters’ computer module (usually mounted on the stem of the e-scooter) is approximately $-60.5 \text{ dB}$, whereas for packets captured from Lime brand e-scooters in the same setting has an approximate signal strength of $-46.25 \text{ dB}$. In summary, this analysis tells us that encounters in high-encounter subareas are at a relatively closer range (distance between the participants and e-scooters) than

Fig. 10. Number of encounters observed in each of the 1600 subareas in and around (a) main campus, and (b) satellite campus.
Fig. 11. Frequency distribution of encounters among (a) 3200 subareas in main and satellite campuses, (b) 68 15-minute time periods in a day, and (c) all combinations of 3200 subareas and 68 15-minute time periods.

encounters in low-encounter subareas, which indirectly suggests that accidents are more likely to occur in high-encounter subareas than in low-encounter subareas. As a result, pedestrians should be more cautious in high-encounter subareas, and university administrators should focus on improving the infrastructure around such high-encounter subareas in order to alleviate the cause of such high number of encounters.

Figures 13a and 13b show examples of how different POIs diffuse the number of encounters in to neighboring subareas. Figure 13a is an example of a student housing with only one entrance/exit. As a result, the high encounter count propagates across multiple consecutive subareas, extending the spatial region where pedestrians are relatively more unsafe. In contrast, Figure 13b is an example of a satellite campus building (that hosts a significant number of classes) with several entry/exit points. Moreover, other neighboring POIs (such as transportation hubs, housing, and shopping centers) were distributed in all directions around this building. As a result, the high encounter count in the center diffuses evenly around this building or POI. These examples show
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5.3 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 6:00 AM and ending at 11:00 PM each day. Although there were significantly fewer classes and events on campus during the weekends, we included them in our analysis for completeness. Figure 14 shows the number of encounters that occurred in each of the 476 time periods across both the campuses, during the entire study period. Three of the time periods observed relatively high number of encounters (25+), which were on Monday, Tuesday and Thursday. Overall, we observe several spikes and surges throughout Monday to Friday. As expected, the number of encounters 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 6:00 AM and 11:00 PM). The results shown in Figure 11b...
Fig. 14. Number of encounters observed in each of the 476 15-minute time periods (sorted chronologically), starting at 6:00 AM and ending at 11:00 PM for seven days of a week.

demonstrate that pedestrians are significantly more likely to encounter e-scooters at certain times of the day, such as between 12:45 PM and 1 PM during which our participants had a total of 100 encounters.

Similar to the spatial analysis, we again look into the spatial closeness of encounters that occurred during time periods with high encounter counts (51-100), and compare them with encounters that occurred during time periods with low encounter counts (1-50). As shown in Figure 12, 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 accidents are more likely to occur during time periods with high encounter counts than during time periods with low encounter counts.

We also conducted an analysis of the sensed heart-rate to determine participants’ reaction to moving e-scooters coming from front and going in the opposite direction vs. e-scooters coming from behind and going in the same direction (as the pedestrian). 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. The median heart-rate for encounters where the e-scooter came from behind and went in the same direction (based on 61 on-spot responses) was marginally higher than for encounters where the e-scooter came from front and went in the opposite direction (based on 187 on-spot responses): 102.42 bpm and 100.95 bpm, respectively. The marginal difference in heart-rate could be because our participants were undertaking pedestrian activities during these encounters, which already elevated their heart-rate above their resting heart-rates. While it is hard to derive conclusions based on this marginal increase in heart-rate, it aligns with our intuition that pedestrians are more likely to be startled by e-scooters that appear from behind. 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.

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) alongside the number of classes scheduled per week in Figure 15. While we see significant overlap in the afternoons, we observe negligible number of encounters around the early morning periods. This could be due to a combination of multiple factors. First,
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Fig. 15. Number of encounters observed in each of the 102 1-hour time periods (sorted chronologically), starting at 6:00 AM and ending at 11:00 PM for six days of a week, plotted along with the number of classes scheduled in the corresponding time periods. No regular classes were scheduled on Sundays.

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. Secondly, 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.

Fig. 16. Heatmap of number of encounters observed in each of the 108,800 spatio-temporal zones (sorted west to east) in main campus.

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vehicles. In conclusion, university administrators can potentially regulate the number of encounters if they plan class schedules around these factors that affect temporal diffusion of encounters.

5.4 Outcomes of RA3

To analyze how the observed encounters are spatio-temporally distributed, we study all combinations of the 1600 subareas in each campus and 68 15-minute time periods in one day (between 6:00 AM and 11:00 PM), for a total of 108,800 spatio-temporal zones in each campus. Figures 16 and 17 show the distribution of encounters across the spatio-temporal zones for the main and satellite campuses, respectively, in form of heatmaps. The spatio-temporal zone with the highest number of encounters contained 14 of them, whereas more than 99.62% of the 217,600 spatio-temporal zones did not observe any encounters (Figure 11c). These results once again demonstrate that pedestrians are significantly more likely to encounter e-scooters at certain locations during certain times of the day.

Similar to the individual spatial and temporal analyses outlined earlier, we look in to the spatial closeness of encounters that occurred in spatio-temporal zones with high encounter counts (18-34), and compare them with encounters that occurred in spatio-temporal zones with low encounter counts (1-17). As shown in Figure 12, for both the Bird and Lime brand e-scooter encounters that occurred in spatio-temporal zones with high encounter counts are generally closer in range (as the observed average signal strength of the BLE packets in the encounters is relatively stronger) than encounters that occurred in spatio-temporal zones with low encounter counts (as the observed average signal strength of the BLE packets in the encounters is relatively weaker). This suggests that e-scooter related pedestrian accidents are more likely to occur in spatio-temporal zones with high encounter counts than in the ones with low encounter counts.

6 DISCUSSION

6.1 Limitations and Broader Impact

One main limitation of our field-study was that its scope was restricted to our university, and its associated campuses, on which the study was completed. Thus, the results and some of the insights and recommendations
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. Although these results may also offer insights to other universities on how develop or adapt infrastructure around POIs (attractors and generators) to offer a safe environment to student pedestrians (against micromobility riders), we understand that it may not generalize well to other types of urban communities. 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. 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. The developed software tools and (anonymized) encounter and other data from this study will be made publicly-available, and can be used as a resource by the community to carry out additional investigations in this direction.

6.2 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 [40, 41] 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 result highlights an important property that any safety application should possess - a good balance between useful functionality and user engagement through carefully designed notifications.
7 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 interesting 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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REFERENCES

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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?

<table>
<thead>
<tr>
<th>Rarely</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Very often</th>
</tr>
</thead>
</table>

(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?

<table>
<thead>
<tr>
<th>Not effective at all</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>Very effective</th>
</tr>
</thead>
</table>

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

APPENDIX B – POST-STUDY DEVELOPMENTS

Fig. 18. New bike lanes being constructed inside one of the main campus subareas where 194 encounters took place between our participants and e-scooters.

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