Impact of E-Scooters on Pedestrian Safety: A Field Study Using Pedestrian Crowd-Sensing

Anindya Maiti[1*], Nisha Vinayaga-Sureshkanth[2*], Murtuza Jadliwala[2], Raveen Wijewickrama[2] and Greg Griffin[2]
[1]*University of Oklahoma (OU)*, [2]*University of Texas at San Antonio (UTSA)*, [*]*Equally Contributing Authors*
am@ou.edu, vsnisha@ieee.org, murtuza.jadliwala@utsa.edu, raveen.wijewick@ieee.org, greg.griffin@utsa.edu

***Abstract*—Micromobility solutions such as e-scooters are gaining popularity in urban communities. However, inadequate infrastructure (e.g., dedicated riding lanes), uncertain regulations, and lax enforcement have resulted in riders encroaching public spaces meant for pedestrians, causing significant safety concerns for both. It is now more critical than ever to understand factors that significantly impact pedestrian safety due to this upcoming micromobility paradigm, however there have been no realistic data-driven efforts in the community to address it. In this work, we fill this research gap by employing wrist-wearables (smart watches) to crowd-sense *encounter* data between e-scooters and pedestrians, and use that to investigate the pedestrian safety implications of unregulated micromobility.**

***Index Terms*—Micromobility, Wearables, Pedestrian Safety.**

I. Introduction

Micromobility, a transportation paradigm aimed at quickly moving people over relatively short distances, is gaining tremendous popularity in urban areas due to the introduction of battery-powered vehicles such as electric scooters (or e-scooters) [1]. Given their small physical footprint and ease of accessibility (through rental providers), they afford a convenient means to navigate urban areas with congested roads and sidewalks, making them a popular *last-mile* transportation solution [2].

As the popularity of micromobility vehicles and services has grown, new safety-related issues have emerged. Due to a lack of strong regulations (and enforcement) on how and where these vehicles should operate, riders often end up encroaching road infrastructure meant for pedestrians, causing significant safety concerns for both [3]. For instance, many recently reported micromobility vehicle related incidents involve some form of collision with pedestrians [4].

Despite this, micromobility research efforts so far have primarily focused only on the problem of rider safety, leaving out (either partially or wholly) the aspect of pedestrian safety [5], [4]. There have been no realistic, data-driven field studies conducted from a pedestrian perspective, which could empirically investigate and characterize new safety issues that arise due to micromobility services such as e-scooters. Such studies are needed to address the pedestrian safety challenge, however asking pedestrians to accurately collect and document information related to observed e-scooter movements and encounters, and their impact on their safety, is not only too cumbersome and error-prone, but also exposed to bias.

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This impediment to conducting a pedestrian-centered safety study can be overcome by taking advantage of a technical aspect of e-scooter vehicles belonging to most rental service providers. We observe that e-scooters operated by popular service providers (such as Bird [6], Lime [7] and Blue Duck [8]) are equipped with Bluetooth Low Energy (BLE) radios that constantly beacon messages to enable near-field operations with customers' mobile applications. Our main idea is to passively capture these beacons (emitted by e-scooters) using BLE receivers such as smartwatches carried by pedestrians. E-scooter BLE data crowd-sensed in this fashion can then be analyzed to extract fine-grained contextual (spatio-temporal) information about the mobility and proximity state(s) of the e-scooter riders and the (participating) pedestrians, which we hope will throw further light on the factors impacting pedestrian safety in such environments.

We leverage the above insight to conduct a large-scale field study to investigate how micromobility vehicles such as e-scooters impact pedestrian safety by recruiting participants from UTSA campuses. Urban university campuses have a high density of pedestrians (who are also often distracted [9]) and e-scooter riders, making them ideal environments for such studies. Our field study focuses on detecting and analyzing real-time e-scooter–pedestrian encounters over a three-month period by crowd-sensing BLE beacon packets emitted by e-scooters. This crowd-sensing of BLE packets is accomplished surreptitiously through customized BLE receivers such as smartwatches worn by participants during the study. Our analysis uncovers interesting encounter statistics and mobility trends, which could be used to identify potentially unsafe spatio-temporal zones and contexts for pedestrians. This information could be extremely useful in planning deployment and management of micromobility services such that it respects pedestrian safety.

II. Related Work

Prior research efforts by service providers and city administrators that have attempted to identify and address pedestrian and rider safety issues related to micromobility have not employed a holistic view of the underlying mobility patterns and context. For instance, reports from micromobility service providers [10], 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 have

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a business-related incentive to not highlight the significant negative impacts of their vehicles on pedestrian safety. Studies by some city governments and community administrators [5], [11] only employed subjective feedback and qualitative data (often, more from pedestrians than riders).

Initial studies took a broad approach to apply planning lessons from similar modes and identifying research needs [12], [13]. An observational study in west Los Angeles identified safety risks related to e-scooter driver behaviors, such as the ability to move between sidewalks and motor vehicle lanes, which may surprise motorists [14]. In Singapore, researchers measured rider predictability improvements after installation of directional arrows on paths, suggesting opportunities to improve safety through engineering for emerging modes [15]. An early field study in China observed e-scooter riders to more often ride against the flow of traffic and in motorized lanes [16].

Recent research efforts have attempted to connect safety research to mobility needs by leveraging e-scooter usage pattern data. For instance, McKenzie analyzed usage patterns of e-scooter and e-bikes in Washington, DC, using the city's publicly accessible API to micromobility data portals [2]. James et al. analyzed e-scooter safety perceptions and sidewalk blocking frequencies from survey data, and observed parking practices in different built environments [17]. Further, Gossling highlighted that the use of virtual reality would enable controlled experimentation of different e-scooter safety contexts without the risk of field interventions [18]. Initial empirical results in this direction support additional policy-focused work to integrate micromobility as part of a sustainable transportation system [19].

Although micromobility research in the literature has increasingly leveraged new data collection methods to address a wide range of issues, none so far have undertaken a real pedestrian-focused study to investigate interaction with mobile e-scooters. To address this gap, in this work we systematically analyze e-scooter and pedestrian encounters (a precondition to accidents involving e-scooters and pedestrians), and discern if or how pedestrians and such micromobility services can safely co-exist in urban environments.

III. Research Objectives

Our research plan comprises of three research objectives (RO1–RO3), where we analyze how certain *space* and *time* factors affect the safety state of pedestrians in the presence of e-scooters (and e-scooter riders) by means of empirically collected pedestrian-rider encounter data.

> RO1 *Correlating **space factors** with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.*

In RO1, 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 to understand their impact on pedestrian safety. We also relate this analysis to infrastructure-related shortcomings, such as missing bike lanes and sidewalk obstructions, to determine potentially unsafe encounters, if any.

> RO2 *Correlating **time factors** with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.*

In RO2, we analyze the temporal distribution of encounters, changes in encounter properties between time periods comprising of a large number of encounters versus the smaller number of encounters, and the effects of pedestrians' and riders' temporal diffusion on encounter rates and other encounter-related properties to understand their impact on pedestrian safety. We further relate this analysis to factors, such as unbalanced class schedules and common event times, to determine potentially unsafe encounters, if any.

> RO3 *Correlating a combination of **space** & **time factors** with empirical encounter and physiological data to identify potentially unsafe (to pedestrians) encounters and contexts.*

In RO3, we extend our previous analyses to study which combinations of space (e.g., poor shared space utilization) and time factors (e.g., event times) are the most significant enablers of unsafe encounters between pedestrians and riders.

IV. Research Methodology

A. Encounter Definition and Types

In our study, an *encounter* is as an event that occurs when an e-scooter and a pedestrian come in close (physical) proximity of each other regardless of their state of motion. Based on the data source used, specifically BLE and user feedback data collected during the study (refer to Section IV-D, and our extended technical report [20] for further details), encounters can be segregated into *predicted encounters* (E_P) and *observed encounters* (E_O). Predicted encounters are derived from the sensed BLE data after the study (Figure 3), whereas the observed encounters are voluntarily tagged by participants in real-time. While E_P is more deterministic, E_O has information about the direction, state of motion, and location of e-scooters detected in close proximity to the pedestrians, and can provide additional safety related insights (refer to Section IV-E). We analyze both moving (similar to Figure 4) and stationary scenarios for e-scooters and participants associated with E_P to accommodate the fact that an encounter (far away or stationary to the participant) may possibly affect nearby non-participant pedestrian(s).

B. Perceiving E-scooter Proximity

Received signal strength (RSS) from BLE data packets broadcast by e-scooters is a reliable means to determine source proximity due to its attenuation over distance. From our preliminary analysis to establish baseline RSS values for popular e-scooter providers such as Bird [6] and Lime [7], we observed that RSS of BLE packets captured from Bird brand e-scooters at a distance of one foot is approximately -60.5 dB, whereas RSS of packets from Lime brand e-scooters in the same setting is -46.25 dB. However, as a pedestrian moves away from an e-scooter, reception intervals of BLE packets transmitted from an e-scooter become inconsistent at the receiver (smartwatch), as shown in Figure 1, we observed irregular BLE reception intervals starting at a distance of 20-25 ft for e-scooters belonging to all targeted providers. Using these observations, we identify whether the e-scooter was proximate (within a foot or not) to the participant during the encounters (E_P) detected from the technique in Section IV-C.

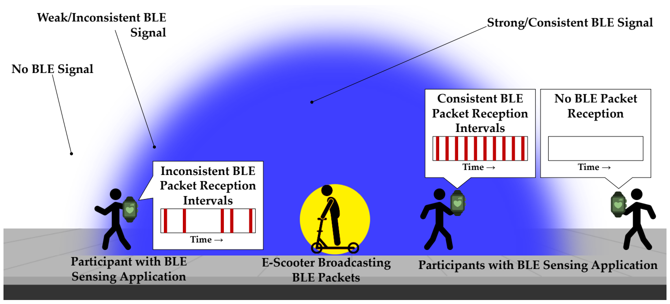

Fig. 1: BLE signal coverage around an e-scooter and how pedestrians at different distances from the e-scooter observe different reception intervals between BLE advertisements.

C. Encounter Detection

To detect encounters, we first identify e-scooter related packets in the sensed BLE packet/data stream. From a preliminary analysis on BLE packets advertised by different e-scooters from different providers at the study locations, we observed that the received BLE packets had easily distinguishable identifiers such as device names and HW MAC addresses (as shown in Figure 2). We use this property to filter out packets of a nearby e-scooter from the stream of BLE packets. This is accomplished directly on the smartwatch using our custom sensing application. Once BLE packets corresponding to an e-scooter are detected, we establish ground truth of this potential e-scooter encounter event by requesting participant feedback in real-time by soliciting participant response to the following three "Yes/No" questions:

- Is there a fast moving e-scooter in your vicinity?
- Was the scooter moving in your direction?
- Was the scooter in front of you?

Positive participant responses corresponding to potential encounters are used to tag them as observed encounters (E_O). To avoid participation fatigue, a minimum delay of 15 minutes is maintained between feedback notifications (to participants). As a result, not all potential encounters detected in our BLE data stream may have participant feedback (ground truth) associated with them.

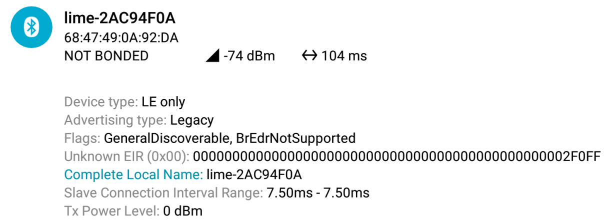

Fig. 2: A BLE advertising packet from a Lime e-scooter.

To identify other encounters not tagged by participants in real-time, we use a *sliding window* encounter detection approach on the stream of BLE packets captured by each participant, as shown in Figure 3. We chose a *window size* of 1 *second* with an 80% overlap (i.e., each window has an overlap of 80% with its previous window), and mark the windows that contain 4 or more BLE packets as *potential* encounter windows. Both the window length and threshold of 4 were empirically determined, based on the minimum time interval between the first and the last BLE advertisement packets and the maximum time interval between consecutive BLE advertisement packets across observed encounters, respectively. The potential encounter windows are then further refined as follows: If the time interval between two (or more) consecutive potential encounter windows (i.e., time interval between the last BLE packet in one window and the first BLE packet in the next window) is less than 300 *seconds*, the two windows together are considered as a single encounter, else they are considered as two separate encounters. Finally, to ensure that a single e-scooter or participant does not heavily bias our encounter data and the related analysis, we discard specific e-scooter encounters detected more than 4 times in one day by a single participant. This typically represents a situation where the participant is co-located near a parked e-scooter.

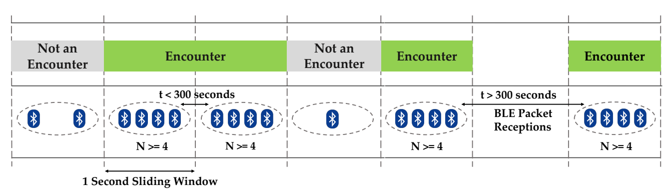

Fig. 3: Sliding window-based encounter detection.

D. Data Collection

The target area (field) of our study is the UTSA main and downtown campuses and neighboring points-of-interest (or POI), including off-campus student housing and transportation hubs. Among the 105 participants (aged between 18-54 years) who participated for at least 15 days (on average) for the 30-day study from April-June 2019, 77 participants completed all their assigned tasks, and thus only their data was used in our analysis presented later in Section V. Each participant completed a demographic survey, checked out a Mobvoi TicWatch E smartwatch running a custom data collection application, received a brief orientation on the operation of the installed application and their expected tasks during the study, and received instructions for providing voluntary real-time encounter feedback. The participants were expected to wear the loaned smartwatch during their entire stay on the university campuses. They also completed a pedestrian safety survey on the completion of their participation. The loaned smartwatch has a built-in GPS sensor, a heart rate sensor, and a BLE v4.1 radio, and is paired with the participant's smartphone for Internet connectivity (to upload the sensed BLE data to our back-end servers). Our custom data collection application detects when the participant is a pedestrian and if there is any e-scooter in their vicinity. When an e-scooter is detected (by our heuristic as described earlier), the application prompts the participant to answer up to three encounter-related questions (Section IV-C). The minimum interval between successive encounter-related questions was set to 15 minutes. Participants were also able to provide voluntary real-time encounter feedback via an online form.

E. Data Modalities

We record quantitative data such as the signal strength information from the BLE packets received from e-scooter(s), packet timestamp, GPS coordinates, participant heart rate, and all responses to encounter-related questions via the data collection application on the smartwatch. We also collect supplementary information such as the location and peak times of pedestrian and rider *attractors* and *generators*. These are POI where significant number of pedestrians and riders travel to (e.g., classrooms) or disperse from (e.g., bus stop or parking lot), respectively.

V. Empirical Findings

Next, we analyze the data collected during our field study based on the research goals outlined in Section III, and summarize key findings in this section. An in-depth perspective can be found in our technical report [20]).

A. Summary of Encounters

Overall, we noticed several e-scooter–pedestrian encounters $E_P = 1800$ and $E_O = 6482$ associated with 1058 of the 7919 uniquely observed e-scooters in our dataset over the entire study period. However, we will only consider encounters that occur between 06:00-23:00 (4993 feedbacks), because the earliest class (on either campus) started at 07:00 and the last class finished at 21:45. Therefore, the time period between 06:00-23:00 represents the most typical use of e-scooters as a last-mile transportation solution. Approximately 20% of the recorded observations in that period correspond to moving e-scooters, with at least 100 potentially hazardous observations where the e-scooter approached the participants from behind. A breakdown of the observed (E_O) encounters showing the different e-scooter moving directions and pedestrian line-of-sight combinations is depicted in Figure 4.

We also determined a personalized heart rate range threshold for each participant based on their overall heart rate data, and

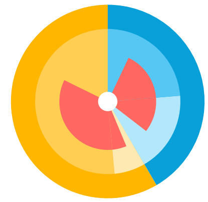

Fig. 4: Summary of observed (E_O) encounters for e-scooter moving direction and pedestrian line-of-sight combinations.

their most frequently occurring pulse rate(s) to check if an e-scooter encounter-related heart rate was within each participant's computed threshold (for most daily activities) or not. An increase in heart rate can occur when a pedestrian is startled by a fast-moving e-scooter, which in many scenarios implies that the pedestrian was faced with inadequate response time. Given most e-scooters emit minimal audible sound during their regular 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 reactions in a timely fashion. In roughly 60% of the moving e-scooter encounters seen in Figure 4, pedestrian participants had an elevated heart rate when e-scooters approached them from the front or behind and were *within one foot away*. Specifically, the mean of median heart rate for encounters where the e-scooter came from behind and went in the same direction was marginally higher (102.42 bpm) than for encounters where the e-scooter came from front and went in the opposite direction (100.95 bpm). This finding aligns with our intuition that pedestrians may have little time to respond to rapidly moving e-scooters and can be easily startled by them.

B. Outcomes of RO1

We first analyze how encounters are spatially distributed throughout the field of study based on *atomic segments* where encounters could potentially occur. An atomic segment is an edge in the graph of roads and walkways, where one can enter or exit only at its endpoints, and can connect with other atomic segments (such as at an intersection), or could end at a POI. An encounter map in Figure 5 shows the observed encounters concentrated across several atomic segments within the campus areas, with $E_P = 611$ and $E_O = 35$ being the highest (number of encounters) in the main campus and $E_P = 256$ and $E_O = 55$ in the downtown campus, respectively. Out of the 21447 atomic segments (combined for both the main and downtown campuses), at least twenty atomic segments in both campuses had a relatively high number of encounters: $E_P > 25$ and $E_O > 5$, with more than 95% of atomic segments having five or fewer E_P and E_O. This disproportionate number of encounters on both campuses implies that pedestrians in certain parts of the campuses are significantly more likely to encounter e-scooters than others.

As closer encounters are more likely to result in a pedestrian-related collision or disruption, analyzing spatial closeness of predicted e-scooter encounters becomes crucial.

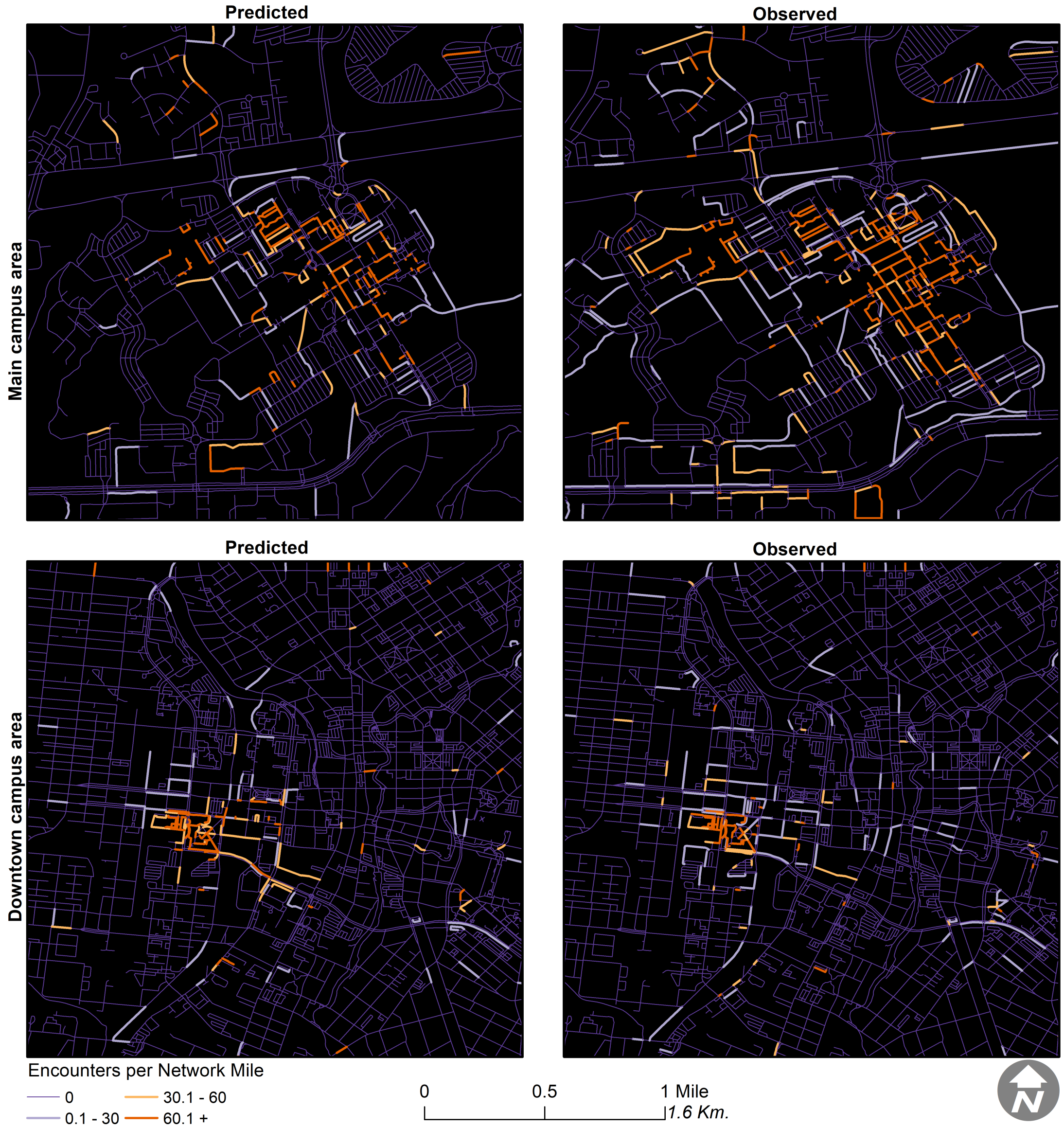

Fig. 5: Predicted (E_P) and observed (E_O) encounter density in and around main campus, and downtown campus.

Earlier in Section IV, we gauge e-scooter proximity using the signal strength of BLE packets emitted by e-scooters. Using the baseline RSS values observed in that preliminary analysis, we found that 0.43% of encounters (E_P) were less than one foot away from the participant.

As seen in Figure 6, we also 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). 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 suggests that collisions are more likely to occur in high-encounter atomic segments.

We also observed that a vast majority of close encounters between e-scooter riders and pedestrians happened on narrow pedestrian paths such as sidewalks (Table I). As there are very few bike lanes and shared-use paths (typically, at least 10 $feet$ wide) in the study area, this creates conflicts and potential for collision between pedestrians who prefer to walk to nearby buildings and riders attempting to reach adjacent parking lots.

C. Outcomes of RO2

We next analyze how encounters are temporally distributed throughout the week by partitioning into 15-minute and 1-hour periods. We initially computed the number of encounters across both campuses in each of the 476 15-minute time periods in a $week$ that included Sunday. We observed that

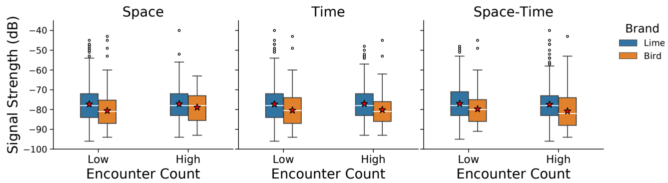

Fig. 6: Comparison of maximum BLE signal strength of predicted encounters (E_P) belonging to (a) atomic segments, (b) 15-minute time periods, and (c) their spatio-temporal combinations with High (85-169) and Low (1-84) encounter counts, respectively. Star sign denotes the mean BLE signal strength across encounters in each group.

TABLE I: Space: Encounters by functional classification.

	TES[a]		MEM[b]		PEM[c]	
Functional Class[d]	E_P	E_O	E_P	E_O	E_P	E_O
Arterial Streets	998	709	146.1	60.7	6.9	2.3
Collector Streets	269	336	68.4	55.2	3.2	2.1
Local Streets	1285	2255	176.0	171.8	8.3	6.6
Shared-use Paths	102	119	306.0	432.6	14.5	16.6
Sidewalks	994	1163	617.8	470.7	29.2	18.1
Other/Unclassified	154	411	799.1	1410.0	37.8	54.2
Total	3802	4993	352.2	433.5	100.0	100.0

[a] Total Encounters per Segment (TES) is the sum of all detected proximal pedestrian-scooter encounters in a network segment.
[b] Mean Encounters per Mile (MEM) is the average number of encounters per segment divided by the length of the segment in miles.
[c] Percent Encounters per Mile (PEM) refers to the percentage of TES w.r.t sum total of all encounters over all segments.
[d] Arterial streets include OpenStreetMap (OSM) API tags "primary" and "secondary". Collector streets include OSM tags "tertiary". Local streets include OSM tags "residential" and "service". Shared-use paths include OSM tags "path" and "cycleway". Sidewalks include OSM tags "footway" and "pedestrian". Other/unclassified uses all other OSM tags.

most predicted encounters ($E_P > 50$) occurred during two time periods: Wednesdays 12:45-13:00 and Thursdays 22:30-22:45, while most pedestrian-observed encounters ($E_O > 35$) occurred in twenty time periods on Wednesdays and Thursdays. Also, we noticed several spikes and surges throughout Monday to Friday, and both E_P and E_O were significantly lower on Saturdays and Sundays. Additionally, we analyzed the encounter counts observed during 68 15-minute periods in a day between 06:00 and 23:00. We found 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 the most encounter encounters: $E_P = 169$ and $E_O = 28$.

From Figure 6, we observe that encounters that occurred during periods with high encounter counts are generally closer, for both the Bird and Lime brand e-scooters, as the observed average BLE signal strength is relatively stronger in these encounters. This finding is in contrast to encounters that occurred during 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.

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. To verify, we analyze the hourly encounters from April to early May alongside the number of classes scheduled per week (Figure 7). We observe that the average number of encounters across atomic segments was higher on days with the highest number of classes (Tuesdays, Thursdays, and Wednesdays) than the rest of the week. This observation supports the intuition that 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 by students. While we see significant overlap in the afternoons, there are comparatively fewer encounters (predicted and observed) around the early morning periods. This overlap could be due to factors including, but not limited to, personnel who recharge drained e-scooters (in return for a payment from the service provider) during late-night or early-morning hours, and a pleasant climate which may prompt last-mile commuters to walk rather than take scooters.

D. Outcomes of RO3

To analyze how the observed encounters (E_O) are spatio-temporally distributed, we study all combinations of the 21,447 atomic segments in both campuses and 68 15-minute 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 campuses did not have any predicted (E_P) or observed encounters (E_O). This asymmetry 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 specific times. For instance, there were lesser or no predicted encounters (E_P) on the Main campus from 06:00-11:00 on Tuesdays, compared to the latter half of the day.

We also observed that the residential areas outside the campuses had fewer or no encounters in the early morning, more likely due to e-scooter recharges schedules, lack of classes, and availability of bus shuttles. Inside the campuses, we noticed high predicted encounters (E_P), mostly between mid-day to early-evening (12:00-16:00) on most weekdays (except Fridays) when there were 150+ classes, as depicted in Figure 7. This trend could be attributed to people commuting for lunch, and students with morning and evening classes leaving and coming to the campuses around this time, respectively.

We also discovered (Figure 6) that predicted encounters in atomic segments with high encounters 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 encounters (as the observed average signal strength of the BLE packets in the encounters is relatively weaker) for Lime and Bird brand e-scooters. This suggests that e-scooter related pedestrian collisions are more likely to occur in spatio-temporal zones with high encounters than in the ones with low encounters.

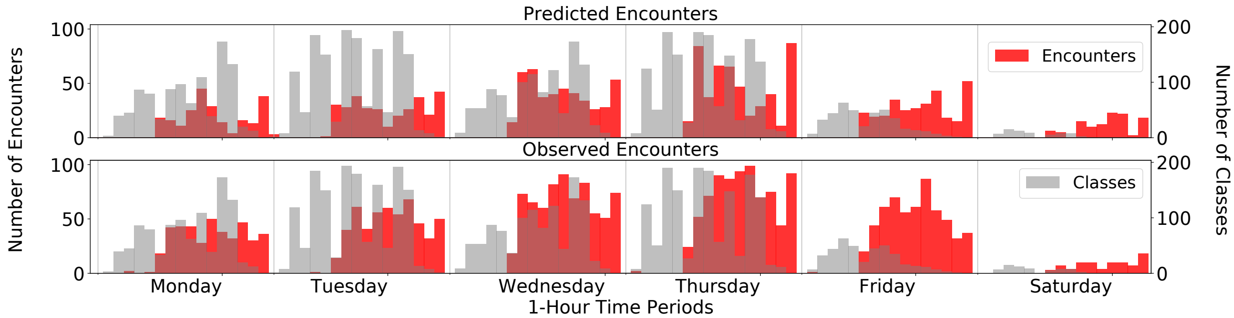

Fig. 7: Number of predicted (E_P) and observed (E_O) encounters in each of the 102 1-hour periods (sorted chronologically), between 06:00-23:00 for six days of a week, plotted with the number of classes scheduled in the corresponding time periods.

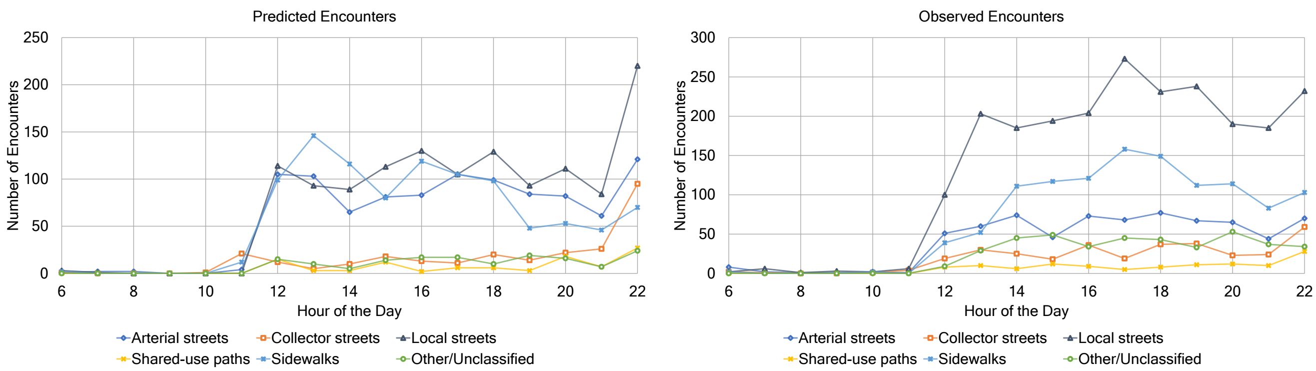

Fig. 8: Number of predicted (E_P) and observed (E_O) encounters in each 1-hour time period between 06:00-23:00, plotted for each functional classification of road network segments. The x-axis unit represents the next 1-hour time period.

VI. Conclusion

In this study, we crowd-sensed encounters between e-scooters and pedestrians on two distinct urban university campuses over a three-month period by using wrist-wearables such as smartwatches. We analyzed and used specific spatio-temporal metrics as benchmarks to understand the impact on pedestrian safety from e-scooter services. Our analysis uncovered mobility trends and potentially unsafe spatio-temporal zones for pedestrians with respect to e-scooters. We show that such crowd-sensing experiments using mobile and wearable devices can aid in planning and infrastructure improvements which could reduce pedestrian safety risks due to modern transportation modes such as e-scooters.

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