In-Depth Examination of E-Scooter Safety: A Case Study of Austin, Texas

August 2023 | Final Report

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While gaining widespread popularity in cities worldwide, electric scooters (e-scooters) have also raised significant safety and other concerns since their emergence in the United States in late 2017. This study addressed these concerns by examining e-scooter safety using multiple data sources. The study utilized data collected from two main sources in Austin, Texas, spanning a period of 4 years (2018 to 2021): hospital emergency room patient records obtained from Dell Seton Medical Center and crash data obtained from Texas Department of Transportation's Crash Records Information System. Further, field-based micro-level built environment data from the study area as well as macro-level demographic, socioeconomic, and built environment data from publicly available sources was collected. The findings highlighted the importance of improving consistency in incident and injury reporting as well as the development and integration of data from different sources. The exploratory analysis revealed key insights on injured e-scooter riders as well as injury and crash patterns. The findings underscored the importance of targeted safety education, interventions addressing alcohol and drug use, infrastructure planning, and time/location-specific measures to enhance e-scooter safety and reduce incidents. A notable finding pertained to intersections, underscoring the need for improvements in visibility, implementation of traffic calming measures, and provision of education specifically tailored for micromobility riders.</td></tr>
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Abstract

While gaining widespread popularity in cities worldwide, electric scooters (e-scooters) have also raised significant safety and other concerns since their emergence in the United States in late 2017. This study addressed these concerns by examining e-scooter safety using multiple data sources. The study utilized data collected from two main sources in Austin, Texas, spanning a period of 4 years (2018 to 2021): hospital emergency room patient records obtained from Dell Seton Medical Center and crash data obtained from Texas Department of Transportation's Crash Records Information System. Further, field-based micro-level built environment data from the study area as well as macro-level demographic, socioeconomic, and built environment data from publicly available sources was collected. The findings highlighted the importance of improving consistency in incident and injury reporting as well as the development and integration of data from different sources. The exploratory analysis revealed key insights on injured e-scooter riders as well as injury and crash patterns. The findings underscored the importance of targeted safety education, interventions addressing alcohol and drug use, infrastructure planning, and time/location-specific measures to enhance e-scooter safety and reduce incidents. A notable finding pertained to intersections, underscoring the need for improvements in visibility, implementation of traffic calming measures, and provision of education specifically tailored for micromobility riders.

Acknowledgments

This project was funded by the Safety through Disruption (Safe-D) National University Transportation Center, a grant from the U.S. Department of Transportation—Office of the Assistant Secretary for Research and Technology, University Transportation Centers Program.

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We would also like to acknowledge TTI researchers Brittney Gick for conducting a preliminary literature review, Marcie Perez for her support in accessing and understanding the CRIS data, and Rahul Sahu (formerly with TTI as a student researcher) for his work in the initial stage of this project. We also thank Dr. Yunlong Zhang (Texas A&M University) for his support and discussions during the execution of this project.

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Introduction

Micromobility, which is defined as any small, low-speed, human- or electric-powered transportation device, has become critical in urban transportation planning. Among micromobility devices, dockless electric scooters (e-scooters) are one of the fastest-growing modes of transportation emerging in the U.S. market. Lime—a micromobility provider—first introduced its shared e-scooter system in San Francisco, California, in June 2017. Since then, e-scooter systems have proliferated in numerous cities across the country and have become the most popular form of shared micromobility in many cities (DuPuis et al., 2018). Figure 1 shows mainland U.S. cities with shared e-scooter systems/stations based on data from the U.S. Department of Transportation's Bureau of Transportation Statistics (2022).

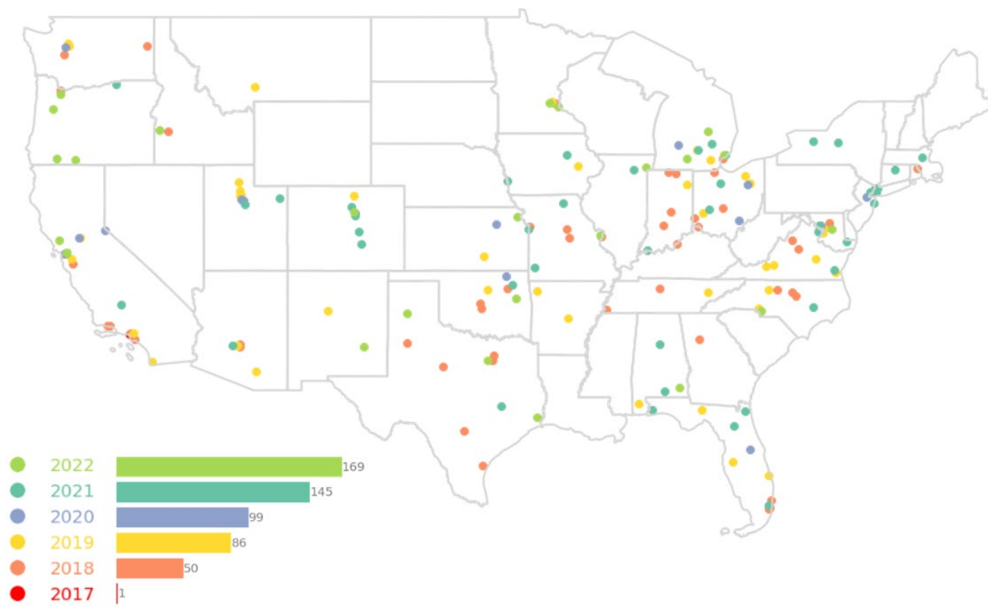

Figure 1. U.S. Cities with shared e-scooter systems/stations color-coded by implementation year (Bureau of Transportation Statistics, 2022).

E-scooters offer a convenient and environmentally friendly alternative to cars for short trips (Abduljabbar et al., 2021; Milakis et al., 2020; Sun & Ertz, 2022). A nationwide survey conducted in early 2018 indicated positive views toward e-scooters, given their potential to "expand transportation options, enable a car-free lifestyle, [be] a convenient replacement for short trips in a personal vehicle or ride-hailing service (i.e., Uber or Lyft), and [be] a complement to public transit" (Populus, 2018).

However, the unpredictable adoption and unmanageable operations of some of the e-scooter systems have raised concerns from both the public and city officials. E-scooters quickly evolved from being an exciting new mobility option to a transportation mode with numerous safety and other concerns, as highlighted in various studies (e.g., Azimian & Jiao, 2022; Iroz-Elardo & Currans, 2021; Karpinski et al., 2022; Shah et al., 2021; Stigson et al., 2021; Yang et al., 2020).

To address these concerns, many cities, including Austin, Texas, have implemented regulations and guidelines for e-scooter use to address safety for riders and pedestrians alike. The sudden emergence of e-scooters on Austin streets in April 2018 was met with an initial ban by city authorities (Albright, 2018), which was later rescinded after the city introduced a permitting process that allowed operations to resume under certain conditions (Winkle & Goard, 2018). Another early initiative undertaken by the City of Austin was to commission a study conducted by Austin Public Health (2019), in cooperation with the Centers for Disease Control and Prevention and others, to investigate e-scooter-related injuries. The study identified potential e-scooter-related injury incidents in Austin, Texas, from September 5, 2018, to November 30, 2018, using Austin-Travis County Emergency Medical Services incident reports as well as hospital emergency department syndromic surveillance chief complaint data from nine area hospitals. Although this study provided valuable first insights, the results also highlighted the need to better understand the safety patterns and concerns associated with e-scooters. According to a recent study by Badia and Jenelius (2023), shared e-scooter services "have not become a transport alternative for everyday mobility needs, for which a main hindrance is the unsafe feeling."

In response to this concern, this study aimed to provide an in-depth examination of e-scooter safety through a case study of Austin, Texas. The study started with a review of completed pilot studies and other research to determine the current state of the practice for e-scooter use. The review also included a thorough review of research related to e-scooter-related injuries, contributing factors to e-scooter incidents, and public perceptions and concerns regarding e-scooters. Based on the rich information revealed in this review, the study employed an evidence-based multi-level analysis to derive conclusions and informed recommendations for enhancing e-scooter safety. The study used data originated primarily from two sources in Austin, Texas, spanning a period of 4 years (2018 to 2021): (1) hospital emergency room patient records obtained from Dell Seton Medical Center, and (2) the Crash Records Information System (CRIS) maintained by the Texas Department of Transportation's Traffic Safety Division. These primary data sources were supplemented with other data sources such as field-based micro-level built environment data as well as macro-level data of demographic, socioeconomic, and built environment data obtained from publicly available sources (e.g., city's open databases and U.S. census).

The remaining sections of this report delve into the distinctive characteristics of the data sources utilized in this study, highlighting the insights derived from the conducted analysis. Following the presentation of the primary research efforts, the report concludes by providing a description of additional products generated within the project, including Education and Workforce Development as well as Technology Transfer components.

It is important to note that this report offers a condensed summary of the research endeavors and key highlights of the findings due to space limitations. Detailed findings from the literature review, along with in-depth data analysis and modeling conducted during this study, will be made available through technical papers, currently being developed for publication (Koirala et al., 2023; Koirala & Sener, 2023), as described in the Additional Products section.

Analysis of E-Scooter-Related Patient Records

Hospital Emergency Room Patient Records

The hospital data used in this study was obtained through a collaborative effort with the injury coordinator of trauma services and the physicians at the Dell Seton Medical Center at the University of Texas. The process involved multiple years of coordination and documentation to ensure data access, sharing, and use[1].

After completing the necessary documentation for data access, the researchers obtained Institutional Review Board (IRB) approval from the Texas A&M Transportation Institute (TTI) through the Texas A&M University System. The approved documentation was then submitted to the Dell Medical Center for their evaluation and preparation of the requested data, which also required their own internal IRB approval process. Once the entire process was completed, legal procedures were finalized to ensure data confidentiality and sharing for research purposes.

Hospital emergency room patient records were obtained for 369 e-scooter-related injury patients. Appendix A provides variables from the hospital emergency room patient records used for analysis in this study. Specifically, we incorporated a range of variables from the hospital data encompassing demographic characteristics, such as age, race, ethnicity, and gender. Additionally, we considered factors related to the injury, including the type and mechanism of injury. Medical indicators such as ICU days, length of stay, and condition on discharge were also examined. The study further accounted for lifestyle choices, such as smoking and alcohol consumption (whether above or below the legal limit), as well as drug use (positive or negative drug test). The injury severity score provided a measure of the severity of injuries. Finally, temporal factors such as the year and day of the week were taken into account.

Additional variables that were not included comprise variables related to the understanding of various aspects of patients' conditions, treatments, and healthcare pathways, such as vital signs, blood-related measurements, and discharge-related information.

Exploratory Analysis of Patient Records

Descriptive statistical analyses of the hospital emergency room data provided a general understanding of the characteristics of patients admitted to the hospital due to e-scooter-related injuries. Subsequent statistical analyses allowed for relationships between variables to be confirmed as they pertain to e-scooter-related crashes. Notable findings from these analyses are discussed below, including insights related to demographic characteristics, temporal characteristics, alcohol and drug use, injury mechanism, and injury severity.

[1] Note that the project encountered additional delays in accessing data as all resources in the hospital were reallocated to address the influx of COVID-19 cases. Accordingly, the temporary suspension of various activities, including the necessary processes to access the data utilized in this study, contributed to the extended timeline.

Figure 2 shows the age distribution of patients in total and segregated by gender. Most of the injured patients fell within the age range of 21–30, with a mean age of 33.88 ± 12.01. The age distribution is skewed towards the younger population. In terms of gender, approximately 65% were male, while 35% were female. The analysis using a student's t-test revealed no significant difference in age between genders.

Figure 3 provides a cross-table heatmap of patients admitted to the hospital by age and day of the week. The majority of e-scooter crashes occurred on Saturdays. Furthermore, results from Fisher's exact test demonstrated a statistically significant association (p-value < 0.01) between the day of crashes (weekday crashes, excluding Fridays, vs. weekend crashes, including Fridays) and the age groups of e-scooter patients (below 40 vs. above 40). However, no significant relationship was observed across genders (p-value = 0.865).

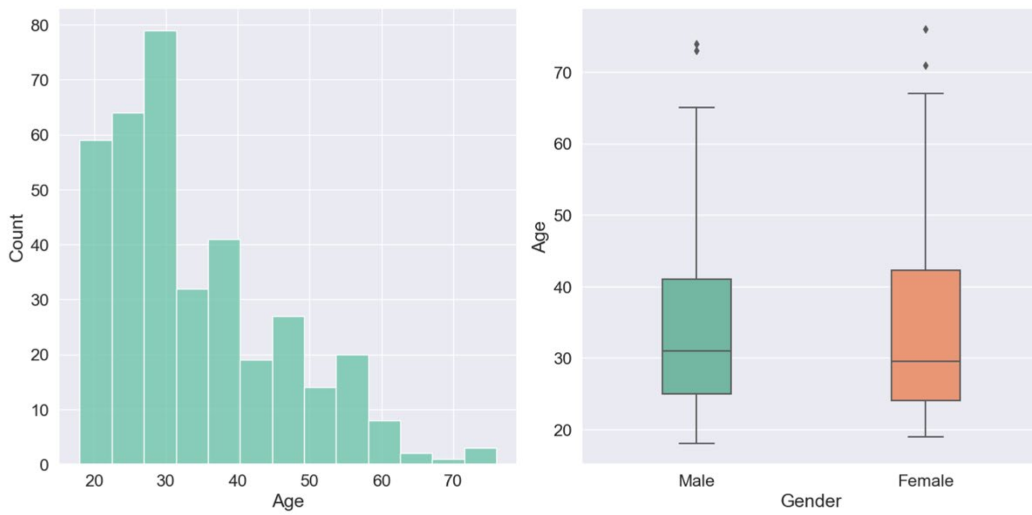

Figure 2. Age of patients admitted to the hospital in total (left) and by gender (right).

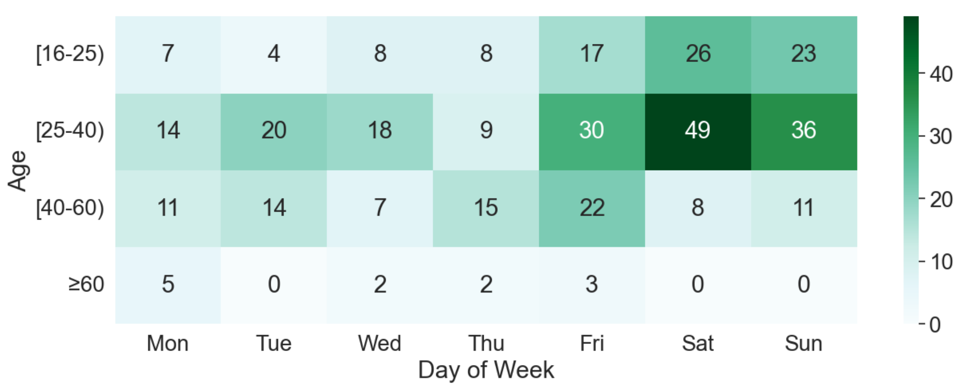

Figure 3. Patients admitted to the hospital by age and day of week.

The highest number of e-scooter-related admissions occurred in 2021, followed by 2019. Fall had the highest number of e-scooter-related injuries, followed by spring, summer, and winter. Nearly twice as many injuries occurred on weekends and Fridays compared to days of the week, with the maximum number of injuries occurring on Saturdays (see Figure 4).

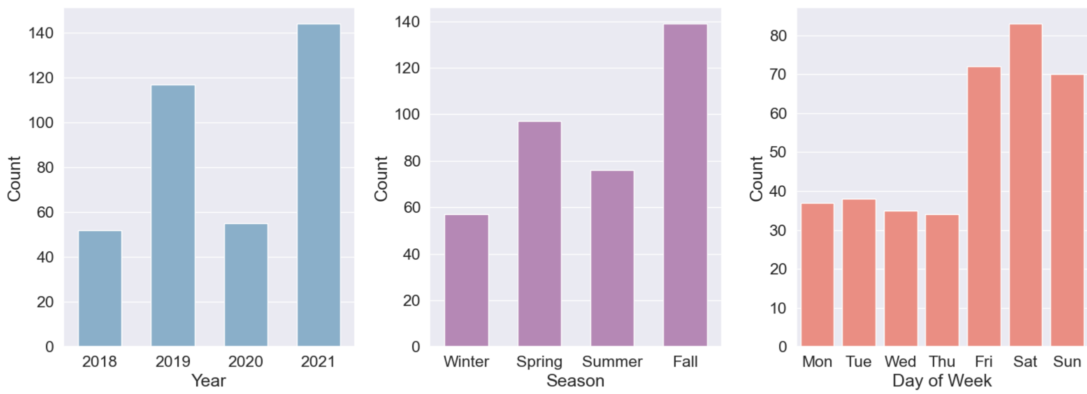

Figure 4. Patients admitted to the hospital by year (left), season (center), and day of week (right).

Nearly half (181 of 369) of the hospital emergency room patient records included alcohol testing; 104 of these records showed patients had blood alcohol levels (BAC) above the legal limit (0.08% in Texas [TxDOT, 2023]). It's important to note that alcohol testing was not available for all patients and was likely administered only to those suspected of alcohol influence. Differences were found in BAC levels between weekends (including Friday) and weekdays (excluding Friday), with higher BAC levels observed on weekends, which was statistically significant at a significance level of 0.1. Descriptive findings showed an uneven distribution of alcohol use among patients by gender and ethnicity, although the differences were not statistically significant.

Interestingly, contrasting trends were observed regarding the distribution of alcohol and drug use among injured patients by age. A Fisher's exact test was performed to examine differences in drug use based on age, using two age categories: less than 40 years old and 40 years old or older. Alcohol use was slightly higher among younger patients, but the difference was not statistically significant, whereas drug use was more common among older patients and was statistically significant at a significance level of 0.05.

Finally, most injuries (87%) were caused by falls under 1 meter in height. Crashes with other pedestrians accounted for 8.7% of injuries, while crashes by striking other nonmoving objects represented 4.3%. Similarly, the neck was the most injured region on the body, followed by the upper extremity, lower extremity, and head regions.

While the chi-squared contingency test did not indicate any statistical significance between the Abbreviated Injury Scale (AIS)[2] of patients for head injury and other characteristics including gender, alcohol use, drug use, or day of the week (weekend vs. weekday), there were some notable

[2] AIS is an anatomical-based coding system developed by the Association for the Advancement of Automotive Medicine and used to classify and quantify the severity of individual injuries. The AIS score ranges from 1 to 6, where 1 indicates minor injuries, and 6 represents the most severe (maximal) injuries. For this study, we have classified AIS scores of 4, 5, and 6 as severe injuries.

differences in percentage shares. Specifically, results showed that a higher percentage of patients with alcohol use (above legal limits) and drug use had serious head injuries (AIS score > 3) compared to those without alcohol or drug use. Similarly, among patients with head injuries, males had a higher proportion of higher AIS scores. Lastly, there was a higher occurrence of serious injuries on weekends compared to weekdays.

Analysis of E-Scooter-Related Crash Records

TxDOT CRIS Data

Maintained by TxDOT's Traffic Safety Division, the CRIS includes all traffic crash reports in Texas. The TxDOT CRIS database includes crashes involving a motor vehicle occurring on public roadways that resulted in a death, injury, or $1,000 in damages (i.e., TxDOT reportable crashes). The database contains information related to the individuals and vehicles involved in a crash and the environment in which the crash occurred. On-scene information, including crash cause and circumstances, is collected by law enforcement officers (e.g., police officers or state troopers). Environmental information, such as the lighting and weather conditions, is also collected.

The final dataset comprised 153 e-scooter-related crashes. Appendix B provides the variables from the TxDOT CRIS data used for analysis in this study. Demographic characteristics such as age and ethnicity were considered, along with specific factors such as riders' alcohol and helmet use. The study also examined environmental factors, such as roadway system, presence of traffic control devices, roadway type, light condition, weather condition, and season. Temporal factors such as the day of the week and intersection, were taken into account. Vehicle-related variables, such as vehicle body style, and contributing factors involving e-scooter riders and motor vehicle drivers were also included. Lastly, the study considered injury severity as an important variable for analysis.

It is worth noting that for certain variables (such as lighting conditions), the collected data consisted of more categories. However, due to the low sample size, these categories were aggregated (such as into binary forms like with lighting and without lighting) before conducting the analysis to ensure statistical reliability.

Extracting E-scooter Data from Crash Reports

A total of 2,195 crash records were available for analysis, including crashes involving bicycle, pedestrian, or motorized conveyance. Based on internal discussions with the administrators of CRIS data (at TTI), during the time of this analysis (between the years of 2018 and 2021), the police crash reports identified crashes involving bicyclists and pedestrians, but not e-scooters specifically.

It was also noted, during discussions, that the category of motorized conveyance crashes includes e-scooters[3]. Instead of requesting just the motorized conveyance data, we requested data from bicycle, pedestrian, and motorized conveyance crashes specifically to review and ensure that e-scooters were not mistakenly categorized or included within the bicycle or pedestrian crash database.

An initial review of 68 unique police crash reports from the TxDOT CRIS database that included *motorized conveyance* was manually scanned to determine if an e-scooter was involved in the crash. During this preliminary review, we noted the various common keywords (e.g., scooter, wheels, e-scooter, Lime, Uber, Bird) used to describe e-scooters in support of the subsequent text mining analysis (that included the entire crash dataset as discussed earlier). Common punctuation marks were also included when recording the common keywords used to describe e-scooters. Among the 68 police crash reports manually reviewed, 50 reports specifically mentioned the involvement of e-scooters in the crash.

A more extensive review of the remaining 2,127 police reports contained in the TxDOT CRIS database was performed using text-mining techniques. The descriptive narratives in the police reports from the TxDOT CRIS were digitized and stored in the computer. The sentences in the narratives were split into words, and the words were searched for the aforementioned keywords related to e-scooters. Among the 2,127 police reports analyzed, 104 reports were found to include one or more of the keywords. Each of these additional reports was also manually reviewed for accuracy. In cases where e-scooters were identified within those databases, we added them to our e-scooter database.

In total, 153 police crash reports were identified as e-scooter related. The following additional data was also collected using manual review and text mining techniques: the position of both the e-scooter and motor vehicle involved, the manner of movement (or maneuver) of both the e-scooter and the motor vehicle involved, the type of collision, and the contributing factor and fault in the crash

Exploratory Analysis of TxDOT CRIS Data

Descriptive statistical analyses of the TxDOT CRIS data provided a broader understanding of e-scooter-related crash characteristics. Statistical tools were utilized to assess relationships between different variables and to identify underlying trends. Findings related to temporal and demographic characteristics, maneuvers and damage estimates, roadway characteristics, and injury severity are detailed below.

Figure 5 shows the age distribution of e-scooter-related crash victims in total and segregated by gender. Most of the crashes involved individuals aged 21–30, with a mean of 31.18 ± 11.27. The

[3] Please note that this data collection information is specific to the time period of the requested and analyzed crashes and may no longer be applicable. Changes have been made to the crash report options, which might have also impacted how the data are recorded and categorized.

sample of e-scooter-related crash victims comprised 66% males and 34% females; however, the results from the t-test indicated that this difference was not statistically significant.

Figure 6 provides a cross-table heatmap of e-scooter-related crashes by victim age and day of the week. Most crashes occurred on Saturdays. Results from a Fisher's exact test confirmed no significant differences between crashes occurring on weekdays/weekends or between different age groups (e.g., rider age groups below and above 40)[4]. This lack of significant association remained consistent when tests were performed for weekday crashes (excluding Fridays) and weekend crashes (including Fridays).

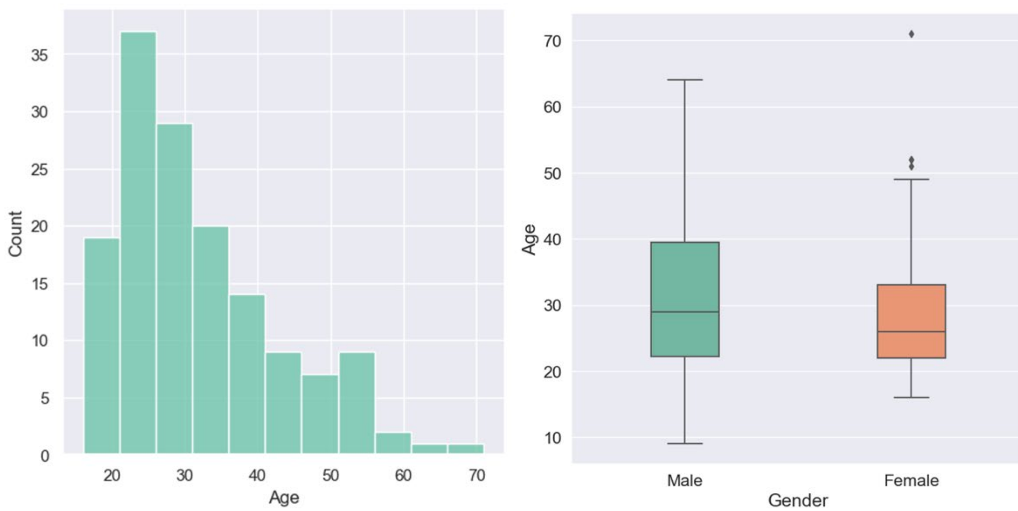

Figure 5. Age of e-scooter-related crash victims in total (left) and by gender (right).

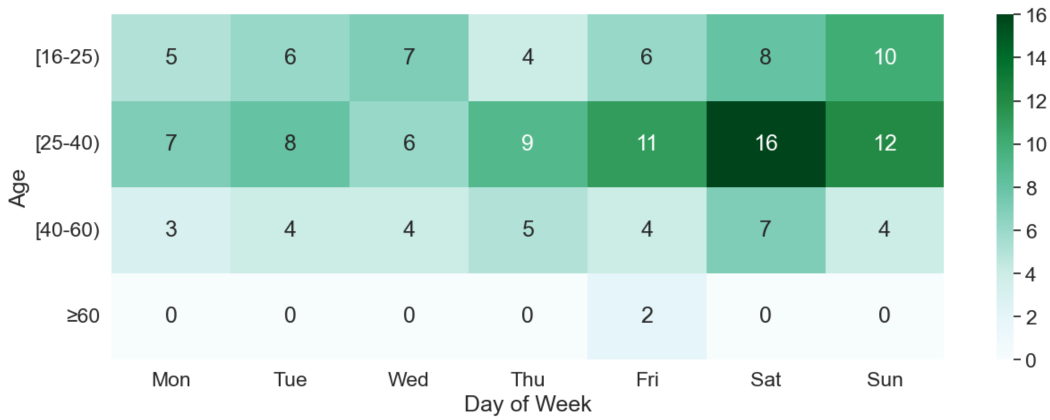

Figure 6. E-scooter-related crashes by victim age and day of week.

[4] Note that different functional forms were utilized for the variables during the analysis reported in this study. For instance, age was examined both as a continuous variable and in different categorical forms. Consequently, various tests were applied to accommodate these different forms and sample sizes (e.g., Student's t-test, Pearson $\chi 2$ test, or analysis of variance test). However, due to space constraints, only select findings are presented in this report. Further details on additional findings can be found in Koirala and Sener (2023), as noted in the Additional Products section.

The highest number of e-scooter-related crashes occurred in 2019, in the fall season, and on weekends, especially on Saturdays (see Figure 7). Results from Fisher's exact test confirmed significant differences in the time of day and day of the week for e-scooter-related crashes, with the majority occurring during nighttime hours and on weekends.

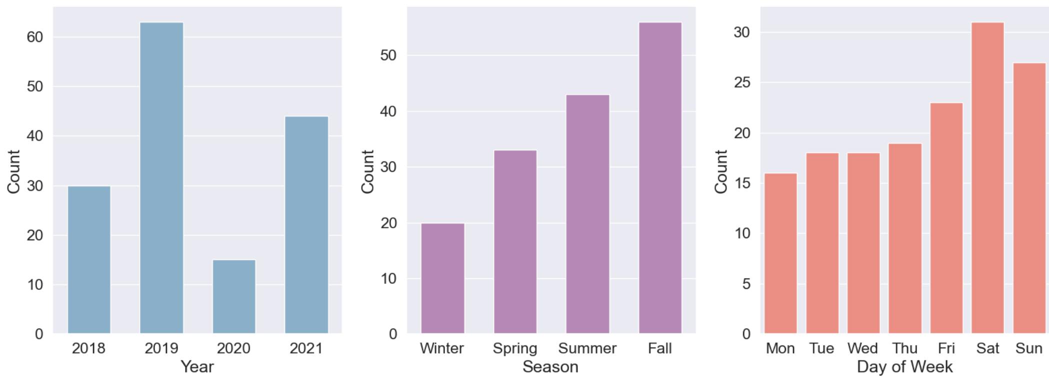

Figure 7. E-scooter-related crashes by year (left), season (center), and day of week (right).

Furthermore, the findings showed that more than 90% of e-scooter crashes occurred on local roads and streets (streets, roads, avenues, boulevards, etc.), with a small number occurring on highways (interstate highway frontage roads, state highways, U.S. highway, etc.). Further investigation revealed that crashes on interstate highway frontage roads most often occurred on weekends around midnight, involved white male riders in their 30s, and had a high incidence of severe injuries (that prevented continuation of normal activities) or fatal injuries.

Finally, the crash data contained in the TxDOT CRIS database characterize injury severity according to the KABCOU injury classification scale (K = fatal injury, A = incapacitating/suspected serious injury, B = non-incapacitating injury/suspected minor injury, C = possible injury, O = not injured, and U = unknown).

Figure 8 shows the distribution of injury severity among e-scooter riders in the CRIS dataset, with non-incapacitating and possible injuries being the most prevalent. The severe injury category comprised incapacitating and fatal injuries, accounting for approximately 14% of all injuries.

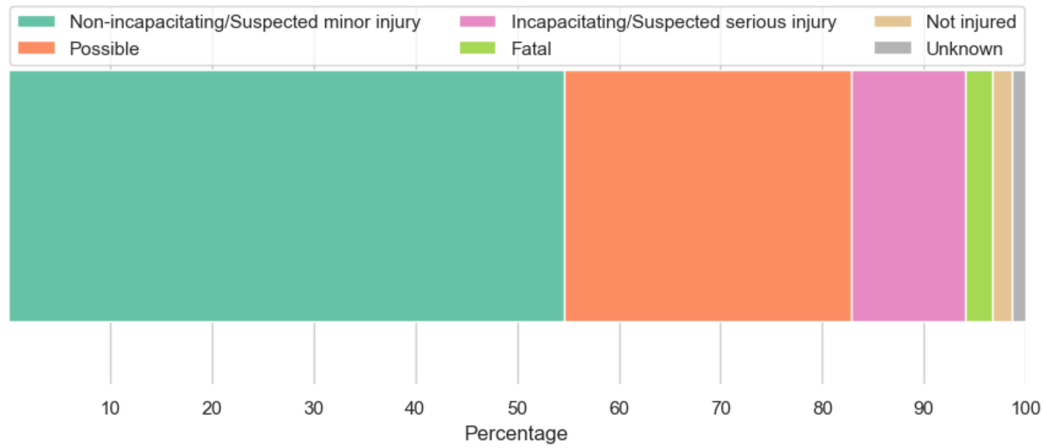

Figure 8. E-scooter-related crashes by injury severity.

Analysis of the Narrative Section of the Crash Reports

The narrative section of the crash report was manually reviewed, and data were collected regarding various aspects such as the fault of the vehicle driver or e-scooter rider, the maneuver involved, and the location of the crash.

The findings showed that vehicle drivers were at fault in 56% of the crashes, while e-scooter riders were at fault in 44% of the crashes. Figure 9 shows the various maneuvers performed by e-scooter riders and vehicle drivers just prior to the crash.

The findings also revealed that when e-scooters were moving straight, the majority of fault was with the vehicle drivers. Conversely, when vehicles were moving straight, the fault was predominantly attributed to e-scooter riders. Moreover, vehicle drivers exhibited a higher proportion of fault when making right or left turns. To further explore this relationship, the vehicle maneuver variable was divided into two categories: turning and not turning. A chi-square statistical test was then conducted, revealing a significant association between a vehicle making a turn and a higher likelihood of being at fault in collisions with e-scooters ($p < 0.0001$).

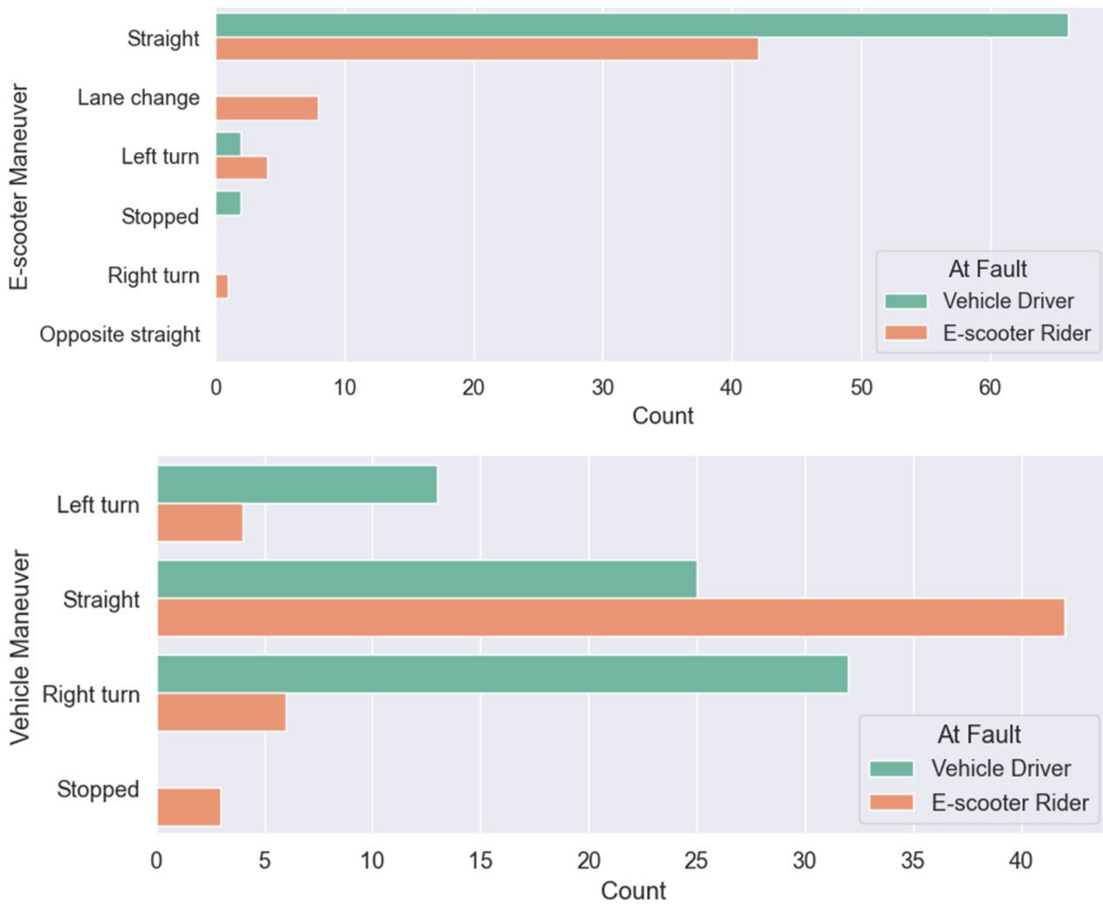

Figure 9. Frequency of e-scooter-related crashes by maneuver of e-scooters (top) and vehicles (bottom) with respect to at-fault mode of transportation.

Figure 10 illustrates the relationship between the location of e-scooters and vehicles in relation to the at-fault mode of transportation. The results showed that when e-scooters were involved in crashes at intersections, the fault tended to lie with the e-scooters. Conversely, if an e-scooter was positioned at an intersection crossing, it was more likely that the vehicle driver was at fault. Similarly, when an e-scooter was in a bike lane or sidewalk, the fault was more likely attributed to the vehicle driver. Likewise, when a vehicle was present at an intersection, a higher number of vehicle drivers were found to be at fault. Interestingly, when an e-scooter was in an outer lane, it was the e-scooter rider who was at fault. Notably, in all cases where the crashes involved vehicles in a driveway, it was the vehicle driver who was at fault.

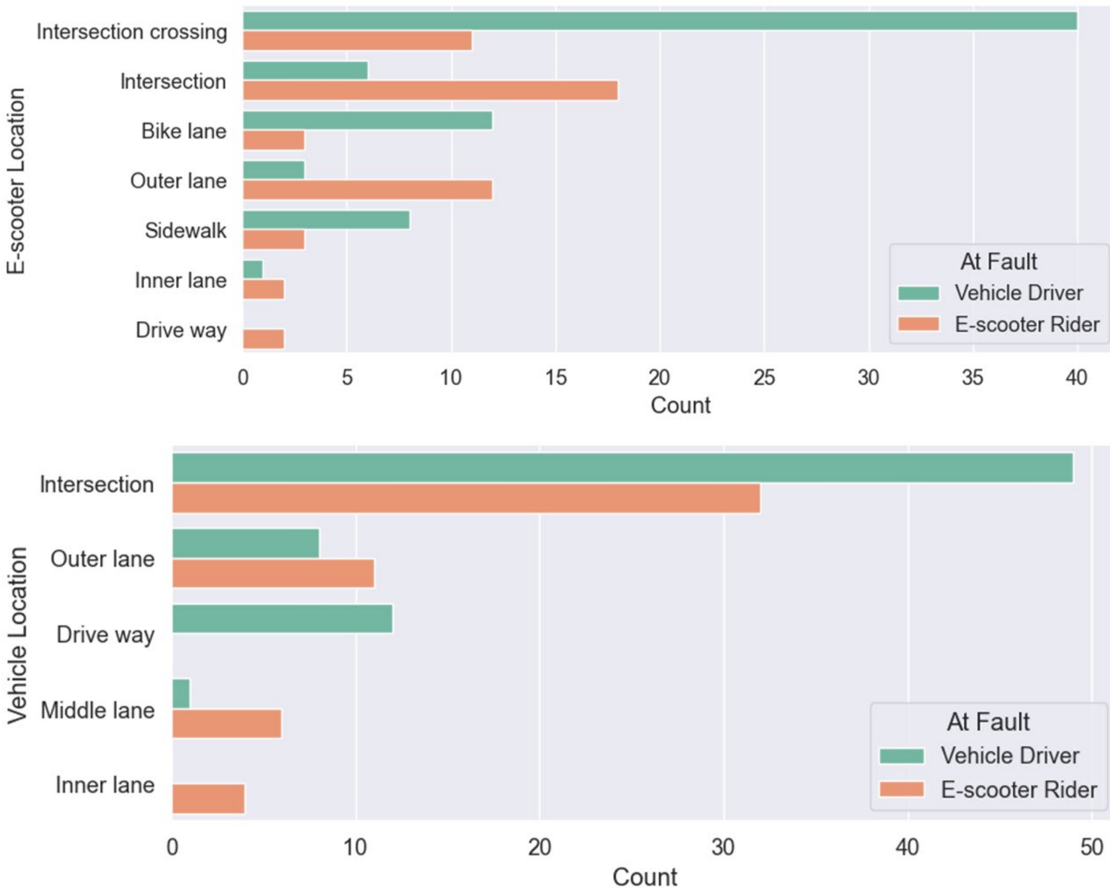

Figure 10. E-scooter-related crashes by location of e-scooters (top) and vehicles (bottom) with respect to at-fault mode of transportation.

The e-scooter location data was divided into two categories: e-scooters at intersections and those not at intersections. A chi-square contingency test was performed using the at-fault mode variable. The results of the chi-square test indicated a statistically significant relationship between e-scooters being at an intersection and being at fault ($p = 0.0015$). This suggests that intersections pose a higher risk for e-scooter crashes, with e-scooters being primarily at fault in these situations. The findings also highlight the increased risk to e-scooters when vehicles are making turning maneuvers.

The observed fault patterns in e-scooter crashes can be influenced by numerous factors. For instance, when e-scooters are involved in crashes at intersections, the rider's fault could be for various reasons such as improper lane use, failure to yield right-of-way, or not adhering to traffic signals or stop signs. On the other hand, when e-scooters are positioned at intersection crossings, it is more likely that vehicle drivers are at fault, possibly due to their failure to notice or yield to e-scooters while making turns or crossing the intersection. Additionally, e-scooter riders might be at fault in outer lanes due to challenges in keeping up with traffic flow or improper lane usage; perhaps these crashes were either sideswipe or rear-end type collisions. More research is needed to comprehensively understand the underlying causes contributing to these fault patterns.

However, these findings emphasize the need for intersection designs that are more accommodating to micromobility devices, as well as awareness and training programs focusing on the safe use of e-scooters.

Predictive Analysis of TxDOT CRIS Data

Following the descriptive statistical and narrative analyses, three different (statistical and machine learning) models were developed using only the TxDOT CRIS dataset to predict injury severity and examine the effect of various variables in distinguishing the level of injury severity in e-scooter related crashes. Additional data were gathered and appended to the crash dataset, including demographic, socioeconomic, and built environment data. Topic modeling was performed to extract new features related to the use of different words in the crash reports.

The results provided a greater understanding of the similarities and differences in factors affecting crash injury severities and emphasized the importance of targeted interventions to improve safety, such as those related to the demographic and temporal characteristics of e-scooter crashes, along with enhancements in e-scooter infrastructure and the design of micromobility-friendly intersections in urban areas.

A comprehensive explanation of the data, methods, findings, and policy evaluations related to the injury severity modeling efforts can be found in Koirala et al. (2023)—as described in the Additional Products section. To maintain brevity in the remaining report, these details will not be discussed further.

Comparative Analysis of E-Scooter-Related Patient and Crash Records and Integration Efforts

Table 1 compares descriptive statistics for the hospital emergency room and TxDOT CRIS datasets. Both datasets indicated increased activity (i.e., crashes and patient admissions) from 2018 to 2019, followed by a decrease in activity in 2020. The decreased activity in 2020 can be attributed to the COVID-19 pandemic; however, hospital patient numbers were higher in 2020 than in 2018, probably suggesting that e-scooter-related crashes not involving vehicles may have increased during the pandemic. The level of activity (i.e., crashes and patient admissions) also varied by season. Seasonal data from 2020 was excluded due to uneven travel restrictions. With respect to gender and race/ethnicity, both datasets showed higher levels of e-scooter-related crash involvement for white males.

Table 1. Descriptive Comparison of Hospital Emergency Room and TxDOT CRIS Data

Variable	Hospital	CRIS
Crashes in 2018	14.09%	19.61%
Crashes in 2019	31.71%	41.18%
Crashes in 2020	14.91%	10.46%
Crashes in 2021	39.02%	28.76%
Crashes in winter	15.44%	10.22%
Crashes in spring	26.28%	23.36%
Crashes in summer	20.59%	29.20%
Crashes in fall	37.69%	37.23%
Age-mean	34	31
Age-median	30	28
Female	34.69%	34.21%
Male	65.31%	65.78%
Age-male (median)	30	28
Age-female (median)	31	29
White (non-Hispanic)	64.23%	59.86%
Hispanic	20.86%	17.00%
Black	7.04%	14.96%

Different techniques were used to combine the e-scooter crash data from the hospital emergency room crash data and the TxDOT CRIS data. The hospital emergency room crash data contained rich information about the patient's condition, injury, and demographics but lacked information about the crash location. Common variables across the two datasets were used to combine the data, allowing some margin of error for select variables. The data in each dataset was first matched by date of occurrence. Next, information related to the patient involved in the crash was matched. New variables—such as the travel time from the crash scene to the hospital—were calculated for each data point in the TxDOT CRIS to support comparisons with the hospital emergency room data. Because the travel time to reach the emergency room by ambulance was only available in the hospital emergency room patient records and the crash location information was only available in the TxDOT CRIS, an open-source application programming interface (API)—openrouteservice API V2—was used to calculate the travel time between the crash location and the hospital (The Heidelberg Institute for Geoinformation Technology, 2020).

Common variables, taking into account the margin of error during the combination process, including date, gender, age (±5 years), travel time (±5 minutes), and race/ethnicity were used to combine the datasets. Table 2 shows the number of matched data points by variable, with *1* indicating a match and *0* indicating no match.

Table 2. Number of Matched Data Points by Variable

Date	Gender	Age	Travel Time	Race/Ethnicity	Matched Data Points
1	1	1	1	1	3
1	1	1	1	0	3
1	1	1	0	0	4
1	1	1	0	1	4
1	1	0	1	1	6
1	1	0	1	0	18

In addition to the category of "vehicle," there are various other categories used to indicate transportation mode in the CRIS data, including "pedalcyclist," "driver_motorcycle," "pedestrian," "pass_motorcycle," and "other." We attempted to match the hospital emergency room dataset with the complete TxDOT CRIS dataset initially, and then, using the TxDOT CRIS dataset parsed to include only the *other* category for transportation mode. When using the TxDOT CRIS dataset parsed by *other* transportation mode, only four data points could be matched to the hospital emergency room dataset. Because only four data points were able to be matched across all five variables, we concluded that the two datasets could not be combined and performed separate analyses for each dataset.

The inability to combine the hospital emergency room dataset with the TxDOT CRIS dataset may be explained by the following:

- Not all the e-scooter-related crashes occurring in Austin, Texas, from 2018 to 2021 required an emergency room visit.
- Not all individuals who were injured in e-scooter-related crashes occurring in Austin, Texas, from 2018 to 2021 who required an emergency room visit sought treatment at this particular hospital.
- The injury records from the TxDOT CRIS report pertain to crashes involving a motor vehicle occurring on public roadways that resulted in a death, injury, or $1,000 in damages.
- The hospital emergency data did not contain information regarding whether the crash involved a motor vehicle or not. It is possible that the two datasets represent different crash occurrences.

This study's attempt to combine these two datasets revealed the importance of enhancing the consistency in injury and incident reporting as well as developing and integrating data from different sources.

Analysis of Field-based Built Environment Data

To further understand the effects of infrastructure features on the injury severity in e-scooter-related crashes, we supplemented the injury severity data from the TxDOT CRIS database with built-environment data collected directly in the field. Field data collection procedures included taking photos and completing standardized questionnaires regarding environmental features and conditions for each location of interest. Table 3 summarizes the specific variables collected from the field.

Table 3. Variables Collected from the Field

Category	Features	Entry Code	Description
Sidewalk	Sidewalk presence	0 1 2	Not present On one side of the road On both sides of the road
Sidewalk	Condition	0 1	Uneven or broken Even and continuous
Bike lane	Bike lane presence	0 1 2	Not present On one side of the road On both sides of the road
Bike lane	Condition	0 1	Uneven or broken Even and continuous
Other	Traffic signal presence	0 1	Not present Present
Other	Parking condition	0 1 2	None On one side of the road On both sides of the road
Other	Lighting condition	0 1 2	No lighting Partial lighting Fully lit
Other	High rise condition	0 1 2	No high-rise buildings Partial high-rise buildings Surronded by high-rise buildings
Other	Abandoned buildings/ plots frequency	0,1,2…	Number of abandoned buildings/plots

A total of 131 crash locations in the City of Austin were visited, allowing for detailed information on the built environment and infrastructure features. Select images captured from the field visit are displayed in Figure 11. To optimize the visit to all 131 locations, a travel plan was created using Google My Maps, including 19 different routes. For example, Route 1, which included 10 locations, took approximately 133 minutes, accounting for driving time, data collection, and parking.

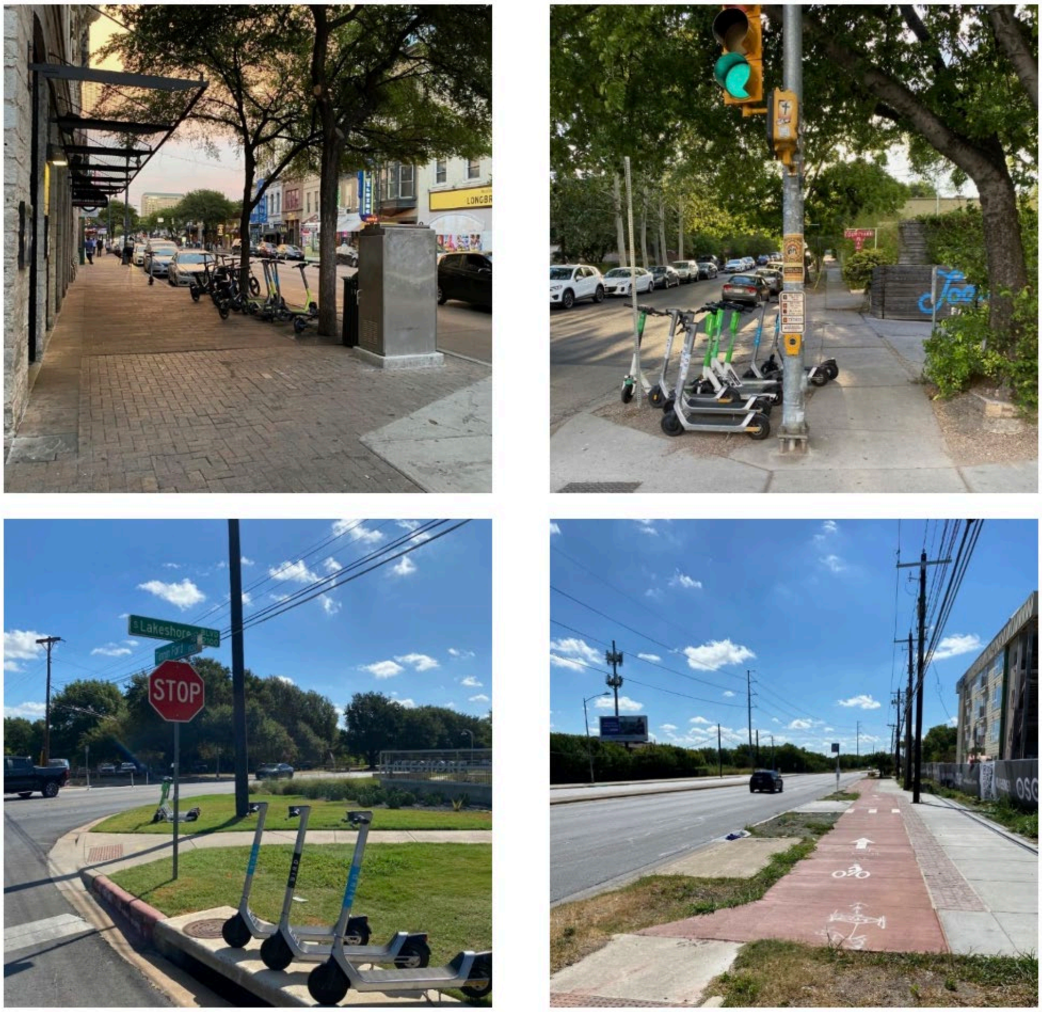

Figure 11. E-scooter crash locations in the City of Austin: field-based built environment data collection.

At each crash location, we implemented a systematic procedure for data collection. Photographs of the crash site were taken from multiple angles to ensure thorough documentation of relevant features. Subsequently, a pre-designed survey questionnaire was completed for each location, gathering data on the condition of the crash site and the surrounding infrastructure. Finally, information related to e-scooter usage, such as proper parking and e-scooter availability, was recorded. Figure 12 showcases the infrastructure features observed in the field. Various statistical analyses were conducted to assess the relationship between infrastructure features and injury severity in e-scooter crashes.

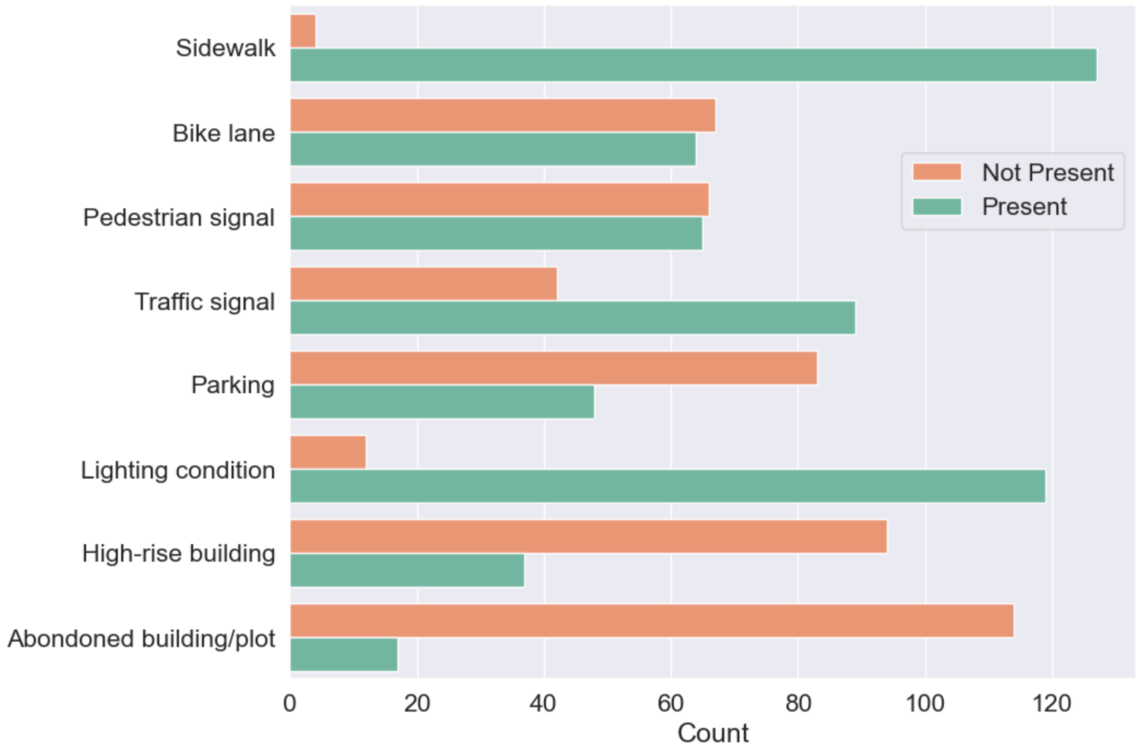

Figure 12. Infrastructure features observed in the field.

The results of Fisher's exact test revealed no statistically significant relationship between sidewalk presence and injury severity in e-scooter-related crashes (p = 0.410). Similarly, the presence of parking (p = 0.165) and abandoned buildings/plots (p = 1.000) also did not show a significant difference in injury severity. A chi-square contingency test was performed for other infrastructure features such as bike lanes, pedestrian signals, traffic signals, lighting, and high-rise buildings. Except for lightning, none of the remaining infrastructure features showed a statistically significant relationship with injury severity in e-scooter-related crashes.

The findings highlighted the importance of lighting conditions as an important indicator of injury severity in e-scooter-related crashes. Locations with lighting infrastructure were found to have a much lower percentage of serious injuries compared to locations without lighting infrastructure. A statistically significant relationship was found between lighting conditions and injury severity (p = 0.002), suggesting that good lighting conditions may help reduce the severity of injuries in e-scooter-related crashes.

Conclusions

Micromobility plays a pivotal role in urban transportation, and e-scooters have gained widespread popularity in cities across the globe. However, as e-scooters emerged, they quickly transitioned from being an exciting mobility option to a transportation mode with many safety concerns. To address these concerns, this study aimed to provide an in-depth examination of e-scooter safety considerations through an evidence-based approach.

This study contributes to our understanding of the characteristics of e-scooter riders and individuals involved in e-scooter-related crashes. A multi-level analysis, spanning a period of 4 years (2018 to 2021), was utilized. Supporting data originated primarily from two sources: (1) emergency room patient records from a hospital in Austin, Texas, and (2) the CRIS data maintained by TxDOT's Traffic Safety Division. The hospital emergency room and TxDOT CRIS datasets included both similar and dissimilar variables related to e-scooter crashes. To acquire micro-level built environment data from the City of Austin, a 3-day field visit was undertaken. Additional macro-level data (including demographic, socioeconomic, and built environment data) from publicly available sources was gathered.

Various methods were employed to explore the potential to merge hospital data with the CRIS datasets. Text mining techniques were used to pinpoint e-scooter-related crashes within the crash reports. Exploratory statistical analyses were conducted to extract insights from all the datasets. Each e-scooter report was individually examined to gather more data and verify the information present in the CRIS dataset. Predictive modeling was performed to examine injury severity as well as the importance of different variables in distinguishing the level of injury severity in e-scooter-related crashes.

The analysis results revealed key insights on e-scooter rider injuries, such as age and gender distributions, factors such as alcohol and drug use, as well as injury and crash patterns. The findings underscored the importance of targeted safety education, interventions addressing alcohol and drug use, infrastructure planning (including enhancements to the design of micromobility-friendly intersections in urban areas), improvements in visibility, implementation of traffic calming measures, and time/location-specific measures to enhance e-scooter safety and reduce incidents. The findings provide valuable insights for policymakers, urban planners, and relevant stakeholders in implementing effective strategies for e-scooter safety and promoting a safer transportation environment for e-scooter riders and other road users.

While the study offers valuable insights, it is important to acknowledge its limitations, which should be considered by future research endeavors. Future studies could incorporate exposure data, if available, to generate more precise results regarding rider characteristics. Additionally, the findings highlighted the need for improving consistency in incident and injury reporting as well as the development and integration of data from different sources, which would help enhance the richness and robustness of data analysis and evaluation.

Additional Products

Education and Workforce Development Products

This project provided support to Pranik Koirala, who served as the student researcher on the project, which constituted the core of his master's thesis, entitled *Understanding the Factors Affecting Safety of E-Scooter and Bicycle Users in Urban Environments: An Injury Severity Analysis Using Machine Learning and Natural Language Processing*.

- Pranik Koirala graduated from the Civil & Environmental Engineering Department of Texas A&M University (TAMU) in May 2023.

The outputs of this research are expected to be helpful to stakeholders with valuable information to make informed decisions regarding micromobility policies and implement appropriate safety measures to improve the urban transportation system.

Technology Transfer Products

The research team is in the process of developing the following manuscripts:

- Koirala, P., Sener, I.N. & Zhang, Y. (2023). *Injury Severity Analysis of Imbalanced E-scooter and Bicycle Crash Data Using Statistical and Machine Learning Models.*
- Koirala, P., Sener, I.N. (2023). *Examining E-Scooter Risk Factors: A Multi-Level Exploratory Analysis for Safer Urban Mobility.*
    - The work from this second paper was presented at the International Professional Association for Transport & Health (IPATH) Annual Meeting 1-Day Conference Series, which was held virtually on Thursday, 29 June 2023.

In addition, the research team developed a slide deck to incorporate materials and knowledge gained from this project into graduate courses/seminars as well as a two-page project brief summarizing the project and presenting the key outcomes.

- The slide deck and the project brief will be available on the project page of the SAFE-D website: Here.

Data Products

The main datasets utilized and described in this study are subject to data confidentiality agreements and adhere to IRB regulations, which prevents them from being shared.

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Appendix A

Select Variables from Hospital Emergency Room Patient Records.

Variable	Definition/Detail	Frequency
Age	18–24	93
	25–39	176
	40–59	88
	>=60	12
Race	White	311
	Black	26
	Asian	22
	Native American	1
	Other	5
	Unknown	4
Ethnicity	Hispanic	77
	Non-Hispanic	284
	Unknown	8
Gender	Male	241
	Female	128
Type of injury	Blunt	368
	Burn	1
Mechanism of injury	Fall <1 m	321
	Other-pedestrian	32
	Other-blunt (striking nonmoving object)	16
ICU days	Unknown	293
	1	17
	2	19
	>2	40
Length of stay	1 day	61
	2 days	151
	3 days	67
	4 days	31
	>4 days	59
Condition on discharge	Unknown	7
	Alive-fully recovered	178
	Alive-excepted moderate recovery	168
	Alive-excepted severe disability	14
	Dead	2
Smoker	Positive	39
	Negative	0
	Unknown	330
Blood alcohol levels (BAC)	Above legal limit in Texas	104
	Below legal limit in Texas	77
	Unknown	188
	No (Not tested)	245

Variable	Definition/Detail	Frequency
Drug (positive/negative drug test)	No (Confirmed by test)	74
	Yes (Confirmed by test – Illegal use drug)	35
	Yes (Confirmed by test – Prescription drug)	14
	Unknown	1
Injury severity score	1–25	360
	25–50	8
	>50	1
Year	2018	52
	2019	117
	2020	55
	2021 (including 1 sample from Jan1, 2022)	145
Day of week	Monday	37
	Tuesday	38
	Wednesday	35
	Thursday	34
	Friday	72
	Saturday	83
	Sunday	70

Appendix B

Select Variables from TxDOT CRIS Data

Variable	Definition/Detail	Frequency
Age	Unknown	3
	<=15	2
	15-25	46
	25–39	69
	40–59	31
	>=60	2
Age (motor)	Unknown	23
	15-25	19
	25–39	55
	40–59	38
	>=60	18
Ethnicity	Unknown	6
	White	88
	Hispanic	25
	Black	22
	Asian	6
	Other	3
Alcohol (above threshold)	Alcohol	2
	No-alcohol	151
Helmet use	Unknown	5
	Worn	3
	Not worn	144
Roadway system	Interstate	10
	US highway	1
	State highway	1
	Farm to market	0
	Local road/street	141
Manner of collision	One motor vehicle-going straight	61
	One motor vehicle-turning right	30
	One motor vehicle-turning left	15
	On motor vehicle-backing	0
	One motor vehicle-other	0
	Both angled	26
	Both same direction	8
	Both opposite direction	13
Traffic control device	None	24
	Signal light	39
	Marked line	34
	Stop sign	16
	Crosswalk	15
	Signal light with red light running camera	8

Variable	Definition/Detail	Frequency
	Center divider	8
	Bike lane	6
	Other	2
	Yield sign	1
	Warning sign	0
Roadway type	Unknown	122
	Other type	0
	Two-lane, two-way	0
	Four or more lanes-divided	19
	Four or more lanes-undivided	12
Light condition	Unknown	1
	Daylight	89
	Dawn	0
	Dark-not lighted	8
	Dark-lighted	54
	Dusk	1
	Dark-unknown lighting	0
Weather condition	Unknown	2
	Rain	8
	Fog	0
	Other	0
	Clear	126
	Cloudy	17
Season	Spring	20
	Summer	33
	Fall	44
	Winter	56
Day of week	Weekday	72
	Weekend	81
Intersection	No	49
	Yes	104
Vehicle body style	Unknown	6
	Passenger car	95
	SUV	27
	Pickup	18
	Van	3
	Heavy vehicle (truck, bus)	4
Contributing factor (e-scooter rider)	None	95
	Failed to yield	9
	Disregarded stop sign or light	6
	Disregarded stop and go	6
	Driver inattention	5
	Other	32
Contributing factor (motor vehicle driver)	None	79
	Field to yield to e-scooter	21
	Driver inattention	13

Variable	Definition/Detail	Frequency
	Failed to yield	3
	Disregarded stop and go	3
	Other	34
Injury severity	Unknown	3
	Incapacitating/Suspected severe injury	3
	Non-incapacitating/suspected minor injury	43
	Possible injury	83
	Fatal	17
	Not injured	4