Understanding factors influencing e-scooterist crash risk: A naturalistic study of rental e-scooters in an urban area

Citation for the original published paper (version of record):
Pai, R., Dozza, M. (2025). Understanding factors influencing e-scooterist crash risk: A naturalistic study of rental
e-scooters in an urban area. Accident Analysis and Prevention, 209.
http://dx.doi.org/10.1016/j.aap.2024.107839

Accident Analysis and Prevention 209 (2025) 107839

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Understanding factors influencing e-scooterist crash risk: A naturalistic study of rental e-scooters in an urban area

Rahul Rajendra Pai *, Marco Dozza

Department of Mechanics and Maritime Sciences, Division of Vehicle Safety, Chalmers University of Technology, Hörsalsvägen 7, 41258 Göteborg, Sweden

A R T I C L E I N F O

Keywords:
E-Scooter Safety
Naturalistic Data Analysis
Micro-mobility Crashes
Rider Behavior
Electric Scooter

A B S T R A C T

In recent years, micromobility has seen unprecedented growth, especially with the introduction of dockless e-scooters. However, the rapid emergence of e-scooters has led to an increase in crashes, resulting in injuries and fatalities, highlighting the need for in-depth analysis to understand the underlying mechanisms. While helpful in quantifying the problem, traditional crash database analysis cannot fully explain the causation mechanisms, e.g., human adaptation failures leading to safety–critical events. Naturalistic data have proven extremely valuable for understanding why crashes happen, but most studies have addressed cars and trucks.

This study is the first to systematically analyze factors contributing to crashes and near-crashes involving rental e-scooters in an urban environment, utilizing naturalistic data. The collected dataset included 6868 trips, covering 9930 km over 709 h with 4694 unique participants. We identified 61 safety–critical events, including 19 crashes and 42 near-crashes, and subsequently labeled variables associated with each event according to the codebook using video data.

Our odds ratio analysis identified that rider experience and behavior (e.g., phone usage, single-handed riding, and pack riding) significantly increase the crash risk. Given the accessibility of rental e-scooters to individuals regardless of their experience, our findings emphasize the need for rider training in addition to education. Influenced by their experience with bicycles, riders may anticipate a similar self-stabilizing mechanism in e-scooters. We found that single-handed riding, which compromises balance, poses a heightened risk, underscoring the crucial role of balance in safe e-scooter operation. Furthermore, the purpose (leisure or commute) and directness (point-to-point or detour) of the trip were also identified as factors influencing the risk, suggesting that user intent plays a role in safety–critical events. Interestingly, our analysis underscores the importance of adapting the crash and near-crash definitions when working with two-wheeled vehicles, especially those in the shared mobility system.

1. Introduction

Micromobility, characterized as a light and sustainable transport alternative to traditional means, has grown in popularity due to its potential to reduce emissions, traffic congestion, and parking constraints. Dockless electric scooters, or e-scooters, have become popular among young adults, primarily due to the convenience and accessibility of sharing services (Guo and Zhang, 2021). However, the unprecedented growth has brought challenges, including increased crashes and, consequently, deaths and injuries involving e-scooters. Research indicates that e-scooters, often perceived and regulated similarly to bicycles (Transportstyrelsen, 2021), exhibit distinct behavior (Dozza et al., 2023; Li et al., 2023), and usage patterns compared to bicycles, with e-scooter riders facing ten times higher risk of crashes (Fearnley et al., 2020). The distinct characteristics inherent to e-scooters necessitates specific research to understand the mechanisms and factors underlying the e-scooter crashes, as extrapolating findings from bicycle crash studies may not yield accurate insights. Despite the growing body of literature on e-scooter safety, there remains a significant gap in understanding the specific mechanisms and factors leading to e-scooter crashes. For instance, most existing studies rely on police and hospital reports, which often lack detailed insights into the behaviors that lead to crashes. The lack of nuanced behavioral data and risk factors in e-scooter crashes limits our ability to develop targeted interventions to improve e-scooter safety.

This paper presents the first study of shared e-scooter usage in an

* Corresponding author.
E-mail addresses: rahul.pai@chalmers.se (R.R. Pai), marco.dozza@chalmers.se (M. Dozza).

https://doi.org/10.1016/j.aap.2024.107839
Received 14 June 2024; Received in revised form 27 October 2024; Accepted 7 November 2024
Available online 12 November 2024

urban environment which utilizes naturalistic data to identify prevalent factors in Safety Critical Event (SCE: i.e., a crash or a near-crash). By analyzing data gathered from 4694 unique e-scooterists in Gothenburg, we aimed to calculate Odds Ratio (OR) and thereby identify any distinctions between SCE and regular e-scooter trips, as well as factors influencing crash risks. Unlike previous studies, our study mitigates population bias and uses non-intrusive equipment, ensuring a representative sample and preserving rider dynamics.

2. Literature review

This literature review is organized into three sections. The first subsection provides a detailed review of the current state of e-scooter research, covering various studies on crash mechanisms, temporal and spatial crash patterns, and the role of rider experience. The second subsection discusses the methodologies and challenges of naturalistic data collection, emphasizing the importance of accurately defining SCEs. Finally, the third subsection describes the application and complications of OR analysis in traffic safety research, highlighting the selection of baseline events and their impact on the analysis. Together, these sections not only identify the gaps in previous literature but also provide the necessary background for the methodology used in our study.

2.1. E-scooter safety and crash analysis

Several studies based on hospital reports and crash databases (Mehranfar and Jones, 2024; Sanders and Nelson, 2023; Stigson et al., 2021; Trivedi et al., 2019) indicate the magnitude of the safety issue pertaining to e-scooters and outline injury patterns, but do not describe the behavioral mechanisms leading to the crashes. Research by Stigson et al. (2021) and Uluk et al. (2022) reported on temporal crash patterns, with over half of e-scooter crashes occurring during the weekend. When considering daily temporal trends, Shah et al. (2021) reported that 69 % of e-scooter crashes happen in daylight. In contrast, Stigson et al. (2021) noted that half of the crashes they studied occurred at night. Moreover, Uluk et al. (2022) identified the peak period for crashes between 12:00 and 18:00, implying a complex role of time in crash occurrences. Spatial analysis of e-scooter crashes by Shah et al. (2021) reveals that 67 % of e-scooter crashes with motorized vehicles occur at intersections. Complementarily, Stigson et al. (2024) indicated that 59 % of e-scooter crashes involving passenger cars take place at intersections. Studies by the Austin Public Health (2019) and Cicchino et al. (2021) highlighted the high injury risk for first-time e-scooter riders, with one-third suffering an injury during their first e-scooter ride. Such a significant share emphasizes the crucial role of experience in safe e-scooter operation. Interestingly, research by Uluk et al. (2022) reveals that experienced riders are three times more likely to suffer from traumatic brain injuries when involved in crashes, signifying that the relationship between crash risk and experience is multifaceted.

Previous studies involving data collection from e-scooters were mainly conducted in controlled environments with recruited participants rather than adopting a naturalistic approach. Notably, the analyses by Leoni et al. (2023) and Ma et al. (2021) focused on road surface identification, with the latter requiring the participants take a specified route. On the other hand, Prabu et al. (2021), explored e-scooter interactions with vehicles and required participants to wear a portable data logger weighing 9 kg (which may have affected the balance and kinematics).

White et al. (2023) conducted one of the few studies on e-scooters using naturalistic data, analyzing collected data from 50 e-scooters, identifying 85 crashes and 69 near-crashes. The study revealed a significant increase in risk for infrastructure factors such as riding on gravel and grass. Furthermore, the authors indicated that behavioral factors, such as aggressive riding and group riding, increased the risk of SCEs. However, the data collection was confined to the Virginia Tech campus, potentially biasing the population to university employees and students.

2.2. Naturalistic data collection in traffic safety research

In traffic safety research, naturalistic data collection, which involves the use of instrumented vehicles, typically recording kinematics and video data, has served as a pivotal resource in understanding the mechanisms leading up to an SCE. Defining an SCE is crucial when analyzing naturalistic data because the definition severely impacts the results. In traditional naturalistic studies, a crash was defined as any contact between the subject vehicle (often referred to as the ego vehicle) and another road user or the infrastructure (Dingus et al., 2006). This definition of a crash notably included tire strikes, a contentious point within the traffic research community, as they are perceived to have no significant impact on safety. A fundamental challenge in naturalistic studies is the low number of crashes (Guo et al., 2010a), leading researchers to consider near-crashes as surrogates (Dozza, 2020; Guo et al., 2010b) despite the lack of a clear, objective definition of what constitutes a near-crash event (Dozza and González, 2013). In the 100-car study, a near-crash was defined as a conflict scenario that involved a *rapid evasive maneuver* (Dingus et al., 2006). However, the inherent subjectivity in defining a rapid evasive maneuver introduces inconsistencies in near-crash identification, an issue that continues to be explored within the research community. Given that micromobility vehicles are used and controlled differently from motorized vehicles (i.e., cars and trucks) and include balancing tasks, the definition of an SCE in these scenarios may require some revisions to better reflect the distinct nature of micromobility.

2.3. Quantifying crash risk through odds ratio analysis

Typically, OR analysis (Agresti, 1999) is used to determine the impact that various factors have on the occurrence of an SCE. The non-crash (i.e., baseline) events influence OR calculation and require careful selection. For instance, randomly selected baseline events may include stationary ego-vehicle, biasing the data and skewing the results (because the chance of a crash is clearly limited). Therefore, many strategies have been used to find the "perfect" baseline. Victor et al. (2014), who, in their analysis of SHRP2 naturalistic data, matched individual SCEs with baselines based on driver, stationary duration, presence of surrounding road users, speed, weather, and lighting conditions. Similarly, Klauer et al. (2010), in their study of the 100-car data, identified baseline events by matching the driver, time of day, day of the week, and surrounding infrastructure.

Another issue in OR analysis is the number of baseline events in relation to the number of SCEs. Increasing the proportion of baseline events to SCEs potentially improves the accuracy of the analysis albeit with the caveat that an increased number of baselines may not always be feasible, as some SCEs may lack sufficient matching baseline events, leading to skewed comparisons and potentially inaccurate conclusions.

3. Methods

Fig. 1 shows the overall process of data collection and analysis. The process commenced with the data collection using instrumented e-scooters. The collected dataset underwent pre-processing to ensure synchronization between the kinematic and video data. Following synchronization, we identified and reviewed potential events of interest to determine the critical events. For each identified critical event, reference baseline events were established. Labeling the baseline and critical events was followed by an OR analysis to verify whether the prevalence of several factors was statistically significantly different between baseline and critical events.

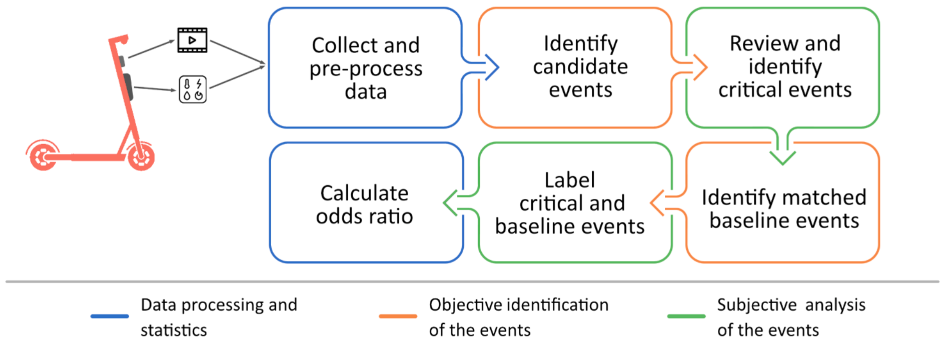

Fig. 1. Methodological steps from collection to statistical analysis.

3.1. Data collection and pre-processing

In this study, we collected naturalistic data from 17 instrumented Voi e-scooters (Boda et al., 2023; Pai, 2022), which were a part of the fleet that Voi deploys in Gothenburg, Sweden. Voi is a micromobility-sharing company with over 100 thousand e-scooters worldwide.

A data logger mounted on the e-scooter sampled data at 10 Hz. The data included 3-axis acceleration, 3-axis angular speed, Global Navigation Satellite Systems (GNSS) coordinates, wheel speed, and the positions of the two handlebar-mounted brake levers. As illustrated in Fig. 2 and Fig. 3, a camera with a 220-degree field of view (FoV) captured videos with 0.4 MP at 30 fps. The wide FoV provided a visual representation of the road, the handlebar, the front wheel, and objects at the sides of the e-scooter. The data was stored in an encrypted format and uploaded when the e-scooter connected to the mobile network. Within the operational area (spanning 4 km radially from the city center), these e-scooters were permitted to be ridden at a max speed of 20 km/h.

3.2. Candidate event identification

As illustrated in Fig. 1, the subsequent step involved the identification of the SCEs. Similar to the 100-car, SHRP2, and K-100NRS (Cho et al., 2023; Dingus et al., 2006; Victor et al., 2014), we relied primarily on kinematic triggers (Table 1) to identify the candidate SCEs. Thresholds on accelerations, speed, and brake activation determined anomalous (potentially critical) events (Gelmini et al., 2021). For instance, if the speed of the e-scooter was greater than 5 km/h, we flagged an event as a toppled e-scooter when the absolute lateral acceleration exceeded 6 m/s^2. Similarly, for the same speed condition, a harsh braking event was identified when the longitudinal deceleration exceeded 3 m/s^2 and the brake lever was engaged at the start of the deceleration (Li et al., 2023). Additionally, a swerving maneuver was determined when the absolute angular speed along the steering column axis exceeded 100 degrees/s while the speed was above 5 km/h. Any trip with kinematics exceeding the set threshold was marked as a candidate event, resulting in 1801 candidate SCEs. We used an iterative approach to determine thresholds for identifying toppled e-scooters and swerving maneuvers. For angular speed we considered thresholds from 10 degrees/s and in 10 degrees/s increments, and lateral acceleration thresholds starting at one m/s^2, increasing by one m/s^2. For both parameters, we identified instances exceeding these thresholds and randomly sampled 25 detections. If at least one sample respectively indicated a toppled e-scooter or swerving, we considered the threshold for detecting candidate SCEs. Although the incremental approach was intended to minimize the false negative rate, it resulted in a conservative threshold and a high false positive rate.

3.3. Review and critical event identification

This study adapted the definitions of crash and near-crash from the naturalistic data studies on bicycles (Dozza et al., 2016; Dozza and Werneke, 2014). A crash was defined as a non-intended event in which the ego e-scooter collided with other objects or the rider fell off the standing deck while the e-scooter was in motion. The non-intended events which involved a rapid evasive maneuver by the ego e-scooter or the surrounding road users were identified as near-crashes.

The context and patterns of each event were analyzed to identify intentional crashes or near-crashes. Intentional SCEs were characterized by deliberate actions that led to a crash, such as an e-scooter starting from a standstill and crashing into a wall or other stationary objects. These events were identified by reviewing videos, focusing on the

Fig. 2. Camera mounted on the e-scooter and visualization of the camera's field-of-view (area colored in blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Frame from a video captured by the e-scooter.

Table 1
Candidate event type and the identifiers used.

Candidate event type	Variables used
Topple	Lateral accelerations in combination with the speed profile
Braking	Longitudinal accelerations in combination with the speed profile and brake activation
Swerving	Angular speed of the steering column in combination with the speed profile

absence of spontaneity and the presence of premeditated actions. Additionally, the behavior of the rider before the event, such as repeated attempts to crash into objects or perform unsafe maneuvers, which indicated a deliberate intent rather than an accident, was considered. These intentional collisions were excluded from the analysis to maintain consistency with previous naturalistic micromobility studies (Dozza and Werneke, 2014), aligning with the approach used in traffic safety research to exclude self-induced crashes, such as suicides, from crash databases.

Using the data visualization tool developed for this study, shown in Fig. 4, two analysts reviewed all the potential SCEs. The analysts, by

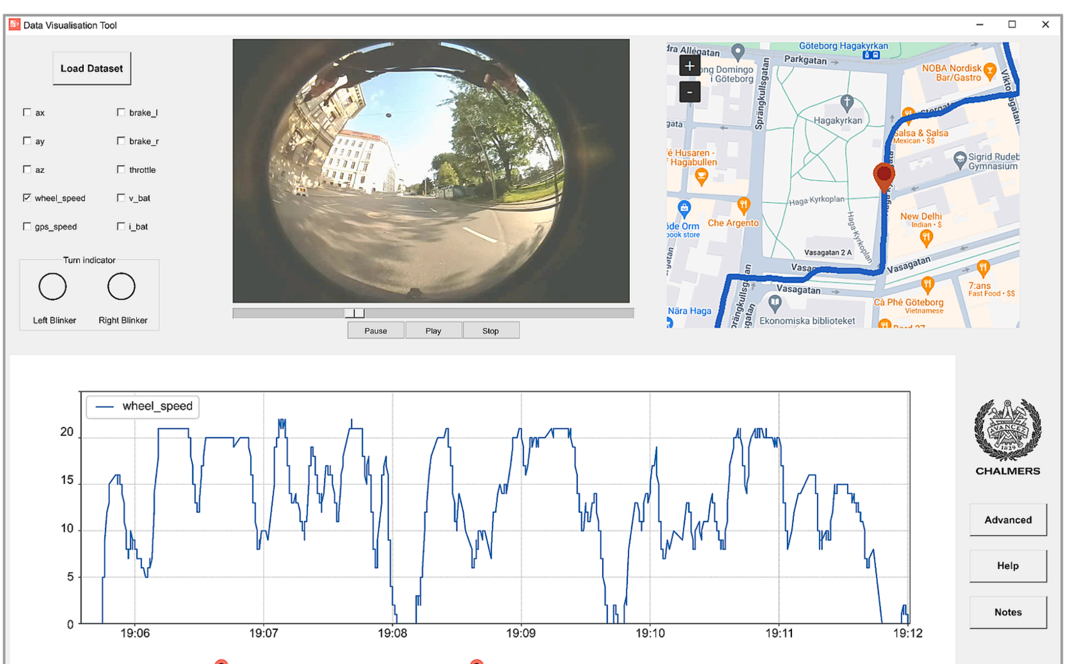

Fig. 4. Screenshot of the data visualization tool used in the study.

inspecting the video and verifying the conformity to the definitions of crash and near-crash, classified the candidate events into SCEs and non-SCEs. In case of disagreement among the analysts, two more members from our research group stepped in to examine the events and resolve the disagreement. As indicated in Fig. 1, this step involved a subjective analysis of the events.

3.4. Matched baseline event identification

The analysis of SCEs involved the establishment of corresponding baselines, adhering to a set of predefined criteria. For each SCE, the corresponding baseline was identified at the same location, primarily using GNSS coordinates (latitude and longitude) for the matching process. Additional optional matching criteria were defined (in descending order of importance): e-scooter speed, weather conditions, lighting conditions, time of the day, and trip date. When no baselines were found to meet all criteria for a particular SCE, the matches that met the most criteria, guided by the order of importance of the criteria, were selected. Our study adopted a 3:1 ratio for baseline-to-SCE events to balance precision and cost. While a higher ratio could potentially increase precision, it also comes with the risk that some SCEs do not have enough matching baselines, which could compromise the robustness of the OR analysis.

3.5. Critical and baseline event labeling

As illustrated in Fig. 1, labeling the critical and baseline events involved subjective analysis of the data. The codebook (a detailed description of the variables that have been labeled primarily using video data; see Appendix A) has been adapted from the BikeSAFE study (Werneke et al., 2015) to include e-scooter-specific variables. Our codebook initially covered 27 variables pertaining to five key areas: rider, infrastructure, environment, trip characteristics, and conflict partner. Except for GNSS coordinates and the type of road user, which were used for descriptive statistical purposes, most variables were considered potential influencers of crash risk. However, upon further analysis, only 16 of these variables proved to be of interest and were subsequently utilized in the study. Given the matched baseline approach of the study, the effect of variables such as type of road, weather conditions, would be nullified and hence were excluded from further analysis. For each SCE and its corresponding baseline events, segments of 30 s were extracted and labeled in accordance with the codebook. For SCEs, the segments included 20 s before and 10 s after the event, while for baselines, segments consisted of 20 s before and 10 s after passing the location of the corresponding SCE. The same two analysts who examined the candidate events independently reviewed the clips in a randomized sequence to minimize the influence of personal bias. Additionally, continuous variables, such as surface type, were labeled at the 20-second mark for each clip. When analysts disagreed over the interpretation of certain variables for specific events, a systematic process was implemented to resolve the discrepancies. The research group, drawing on the members' expertise, reviewed each of the specific instances. The review was followed by a discussion in which the analysts explained their perspectives and the labels were finalized based on consensus.

3.6. Description of the novel variables

While most of the 16 variables used in our analysis are self-explanatory and have been used in previous naturalistic driving studies, this study introduces five novel variables which are less intuitive. The *experience of the rider* corresponds to the number of trips previously taken on Voi e-scooters, and the *mean speed* refers to the average of speed values greater than zero. *Pack riding*, a widely observed phenomenon, indicates whether the ego e-scooter was part of a group of e-scooters or bicycles. The *directness factor* is a measure indicating the extent to which a trip was point-to-point or detour. This approach is similar to Aarhaug et al. (2023), who identified trips not made for the purpose of travel when the distance traveled exceeded the trip planner map distance by a predetermined limit. The measure was calculated as the ratio of the recommended distance from the origin to the destination of the trip (from OpenStreetMap) to the actual distance traveled during the trip. Initially, we aimed to adopt the threshold of 0.5 for classifying trips as detours, based on the value used by Aarhaug et al. (2023); however, found the threshold to be too low for our data. Consequently, we adjusted the threshold to 0.6, classifying trips with a value lower than the threshold as detour. In other words, it was considered a detour trip if the distance traveled was greater than 1.7 times the recommended distance. The adjusted threshold still leaves a margin for personal choice of routes and potential disruptions in traffic.

We utilized OpenStreetMap to determine the proximity of the origin and destination of the trips to specific points of interest: public transit stations, restaurants, and educational institutions. The proximity was calculated using the Euclidean distance between the trip's origin or destination and the nearest point of interest. A trip was considered to be in the proximity of a point of interest if the calculated Euclidean distance was less than a threshold of 25 m, an approach similar to that used by Li et al. (2022). These proximities, in conjunction with the directness factor, served as a crucial determinant in identifying the *purpose of the trip*.

To categorize the trips according to the purpose, we implemented an unsupervised machine-learning technique of k-means clustering. This method of categorizing trips was based on the approaches implemented by Shah et al. (2023) and Liu et al. (2020). The clustering process took into account various factors, including the directness factor, proximity to points of interest, trip distance, mean speed, day of the week, and speed above zero (the percentage of the trip where the speed was greater than zero). The optimal number of clusters was determined based on the Davies-Bouldin index and Silhouette scores (Davies and Bouldin, 1979; Rousseeuw, 1987), which led us to a model with seven clusters for further interpretation. These clusters were further combined into two broader categories, representing leisure and commute trips (for a detailed description of clustering, see Appendix B).

3.7. Odds ratio (OR) calculation

The ORs were calculated to assess the effect of each labeled variable on the occurrence of an SCE. A 95 % confidence interval estimated the statistical significance of the ORs. Consider the variable *phone usage*: let $\text{SCE}_{\text{phone}}$ and $\text{Baseline}_{\text{phone}}$ represent the number of SCE and baseline events with phone usage, respectively. Similarly, let $\text{SCE}_{\text{no-phone}}$ and $\text{Baseline}_{\text{no-phone}}$ represent the number of SCE and baseline events without phone usage, respectively. The OR for phone usage is then calculated as $OR = \frac{SCE_{\text{phone}}}{SCE_{\text{no-phone}}} \times \frac{Baseline_{\text{no-phone}}}{Baseline_{\text{phone}}}$.

It is worth noting that in our study the sum of $\text{Baseline}_{\text{phone}}$ and $\text{Baseline}_{\text{no-phone}}$ was three times the sum of $\text{SCE}_{\text{phone}}$ and $\text{SCE}_{\text{no-phone}}$. An OR that exceeds one signifies an increased risk, while an OR less than one signifies a decreased risk. The OR is deemed statistically significant if its confidence interval does not include the value one.

4. Results

4.1. Description of the dataset

From July 2022 to December 2023, 4694 unique participants took 6868 trips, covering 9930 km in 709 h. The average trip distance was 1.45 km, and the average trip duration was 6.19 min. Fig. 5 shows the overall geographic coverage of all the trips and illustrates all the routes taken. Notably, each e-scooter traversed a substantial part of the operation zone, indicating that the entire zone was well covered by the individual e-scooters. It is worth noting that although we initially deployed 17 e-scooters for data collection, some e-scooters were

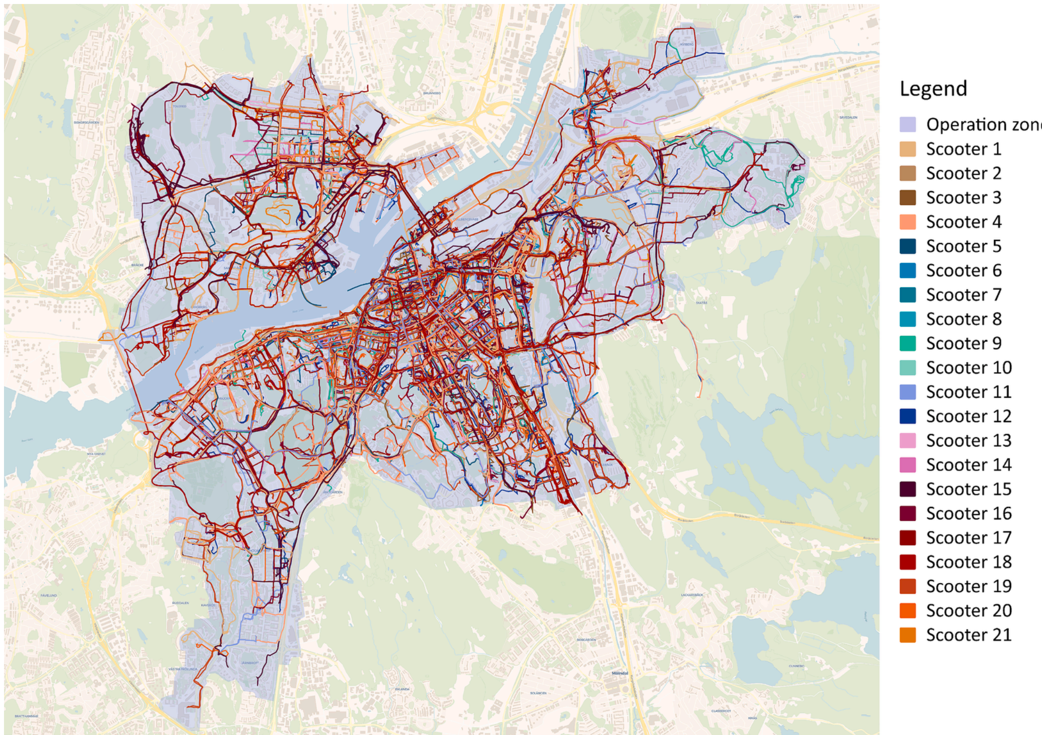

Fig. 5. Geographic coverage of all the trips in the dataset (the map representing Gothenburg city center was generated using Kepler.gl).

rendered unusable due to vandalism and subsequently replaced during the study. As a result, a total of 21 e-scooters were included, although at any given point in time, no more than 17 e-scooters were operative.

Fig. 6 illustrates the distribution of the trips over the course of the week, revealing usage peaks (particularly in the late afternoon), with Wednesdays and Fridays showing the highest trip frequencies. Conversely, Sundays recorded the lowest number of trips. Panel A of Fig. 7 presents a histogram of trip distances, showing that most trips fall within the 0–2 km range: as the distance increases beyond 2 km, there is a noticeable decline in the number of trips. Panel B of Fig. 7 illustrates a histogram of trip durations, showing that most trips last less than ten minutes: few trips exceeding this duration. Fig. 8 shows the geographical distribution of the 61 SCEs (19 crashes and 42 near-crashes). The light markers indicate near-crashes and the dark ones, crashes. Given that the baseline events and SCEs were matched based on GNSS coordinates, the positions of the baselines are identical to those of the SCEs.

Fig. 9 illustrates the distribution of conflicting road users: light motor vehicles were the most common. Notably, heavy vehicles were not present in any safety–critical interactions, and only two events involved multiple conflicting road users. In 28.6 % of the SCEs, no road users were involved. Of the 19 crashes, only two involved evasive maneuvers: one involved braking and the other, swerving. In contrast, all but one of the 42 near-crashes involved evasive maneuvers: 28 involved braking, five swerving, and eight both braking and swerving.

4.2. *Factors contributing to increased risk*

Table 2 reports the ORs and the confidence intervals for the variables in the codebook (Appendix A).

As reported in Table 2, a rider with an experience of less than or

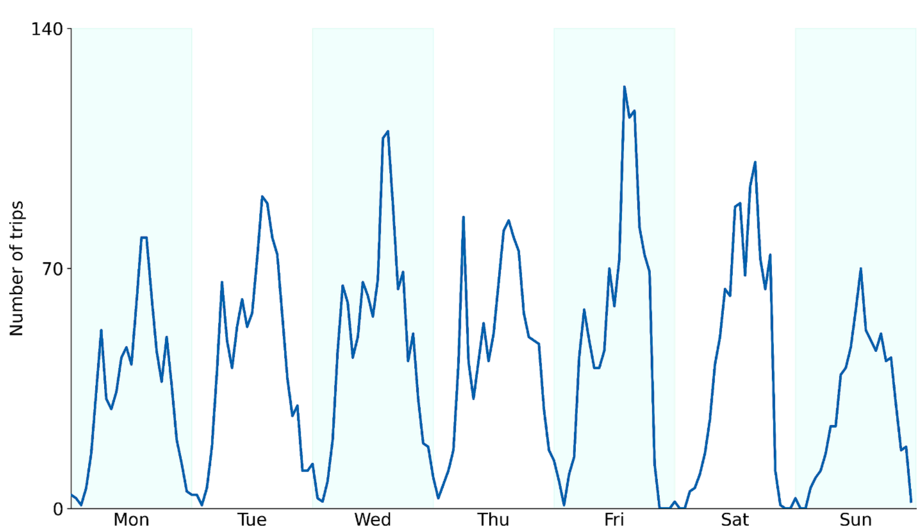

Fig. 6. Number of trips by day of the week.

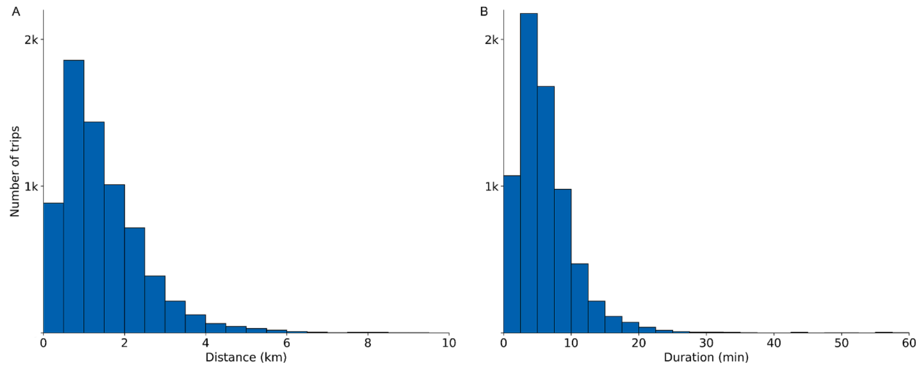

Fig. 7. Panel A: Distribution of the distance of the trips. Panel B: Distribution of the duration of the trips.

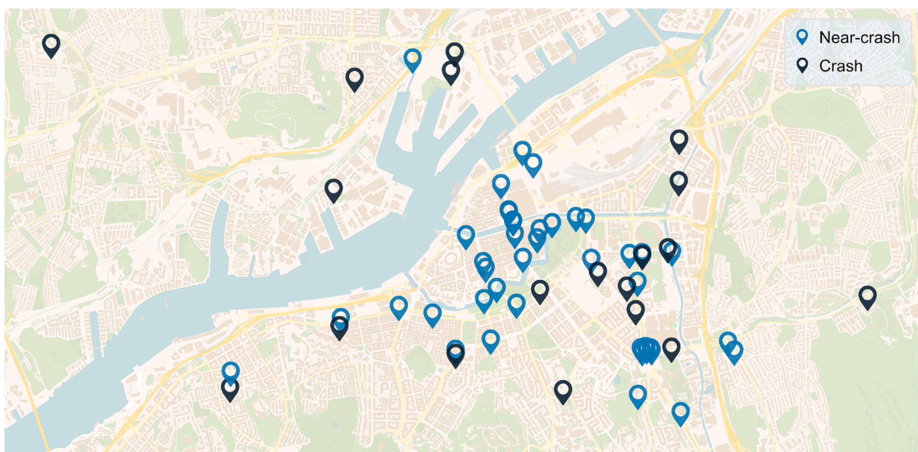

Fig. 8. Geographical location of critical events in Gothenburg (the map was generated using Kepler.gl).

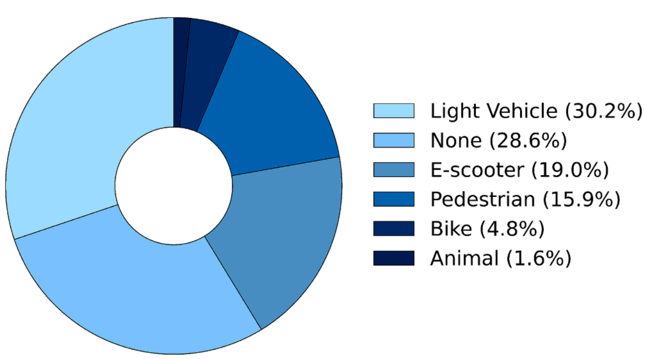

Fig. 9. Road users conflicting with the e-scooterist in the safety–critical events.

equal to 5 trips was twice as likely to experience a critical event as those with more experience. Further, e-scooterists with an experience lower or equal to 5 trips were responsible for 28 % of the SCEs. Pack riding was associated with 2.7 times increased risk compared to riding alone. Phone usage and single-handed riding significantly increase risk by factors of 2.67 and 6.51, respectively. Fig. 10 illustrates the relationship between the OR and mean speed in relation to the experience of riders. At each point on the x-axis, we computed the OR using the corresponding experience level as a threshold. Simultaneously, we calculated the average of the mean speeds for all trips up to and including the respective experience levels. It may seem counterintuitive that riders traveling at an average speed of 11 km/h or lower were over three times more likely to experience an SCE (Table 2). This observation may be explained by the positive correlation between experience and mean speed, as indicated in Fig. 10.

Table 2
Odds ratios and confidence intervals for the variables.

Variable	Odds ratio	Confidence interval
Rider factors		
Rider experience $\leq$ 5 trips	2.23*	[1.12, 4.46]
Phone usage	2.67*	[1.05, 6.81]
Pack riding	2.68*	[1.39, 5.17]
Single-handed riding	6.51*	[1.58, 26.89]
Object on handlebar	1.61	[0.73, 3.55]
Infrastructure factors		
Intersection	0.98	[0.53, 1.73]
Construction work	1.00	[0.20, 5.09]
Visual occlusion	1.00	[0.20, 5.09]
Environmental factors		
Temperature $\leq$ 5 °C	1.54	[0.72, 3.31]
Trip characteristics		
Detour vs point-to-point trips	4.93*	[1.79, 13.60]
Leisure vs commute trips	2.40*	[1.33, 4.35]
Weekend trips	1.27	[0.65, 2.48]
Trip distance $\leq$ 1.45 km	1.25	[0.68, 2.29]
Trip duration $\leq$ 371 s	1.16	[0.63, 2.17]
Mean speed $\leq$ 11 km/h	3.69*	[1.81, 7.53]
Instantaneous speed $\leq$ 11 km/h	0.75	[0.31, 1.82]

* indicates statistical significance.

Detour trips, which increased the risk of incurring an SCE by a factor of 4.93, accounted for 16 % of the SCEs. On the other hand, leisure trips increased the risk by 2.4 and contributed to 51 % of the SCEs.

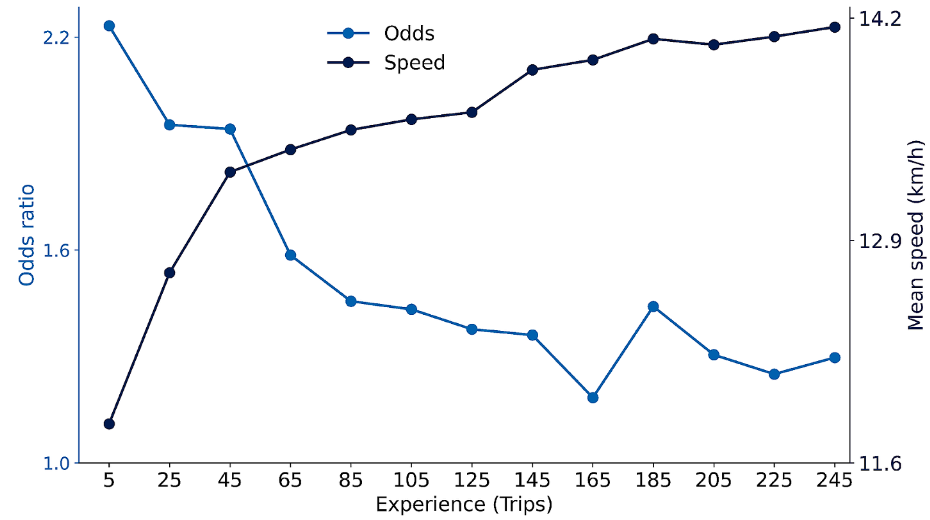

Fig. 10. Mean speed and OR as functions of experience.

Table 2 includes additional variables that are not described in detail here. While these additional variables contribute to the description of the dataset, the lack of statistical significance limits their potential impact, therefore they are not further discussed in this paper.

5. Discussions

In this study, we used naturalistic data to identify which factors were most prevalent in SCEs involving rental e-scooters and thus possibly get new insights into crash causation for micromobility vehicles. However, the definition of crashes and near-crashes are not straightforward and even less so for micromobility.

5.1. Crashes and near-crashes

The proportion of crashes to near-crashes in this study follows the widely accepted Heinrich triangle (Heinrich, 1941). However, the distribution differs from that observed in the previous naturalistic study on e-scooters by White et al. (2023), in which the number of crashes was notably higher than near-crashes. The reason for the difference may lie in the different definitions of crashes and near-crashes, different environments (university campus vs. urban), and/or different populations (university students vs. road users traveling in the city center).

While crash identification is typically unambiguous, some e-scooter crashes involved intentional collisions with other road users, particularly vulnerable road users and infrastructure. These intentional crashes, such as a scooter starting from standstill and crashing into wall were deemed not to be incidental but rather deliberate. Although this identification was subjective, these voluntary crashes exhibited a distinct pattern of non-spontaneity which was hard to miss. In order to maintain comparability with previous naturalistic data studies (Dozza et al., 2016; Dozza and Werneke, 2014), we have excluded these intentional collisions even if they may fit the definition of a crash. Voluntary crashing, which involved the use of e-scooters in such a manner that was more akin to vandalism than transport, could be influenced by a multitude of factors, including but not limited to the lack of personal ownership of the vehicles and the absence of established social norms around e-scooter usage. The exclusion of voluntary crashes from our analysis is not unusual in traffic safety research and can be likened to the exclusion of suicides or self-induced crashes from crash databases. Unlike crashes, the identification of near-crashes has always been subjective (Dingus et al., 2006; Dozza and González, 2013). The pre-meditated crash tendencies displayed by e-scooter riders have increased the complexity of identifying near crashes.

Alongside the challenge of identifying self-induced critical events, another challenge arises when considering minor, inconsequential collisions. In the SHRP2 and the 100-car naturalistic driving study, a large share of the crashes were tire strikes with curbs (Dingus et al., 2006; Kidd and McCartt, 2015). E-scooter riders in Gothenburg tend to switch between pavement, bicycle lanes, and roadways, leading to a high incidence of tire strikes. The frequent transitions between different road types often lead to minor, inconsequential collisions. Although these low-risk tire strikes technically fit the crash definition, they were also excluded from the analysis because the rider maintained complete control of the vehicle during the collision.

One notable difference between the crashes and near-crashes was the presence or absence of evasive maneuvers. Riders did not attempt evasive maneuvers in 89 % of the crashes, which suggests that the riders either did not have the opportunity or did not even try to avoid the crash. These findings are consistent with those from the 100-car naturalistic study: evasive maneuvers were far more common in near-crashes than crashes (Dozza, 2013). Only in one of the 42 near-crashes no evasive maneuver was attempted by the rider. The prevalence of evasive maneuvers in near-crash situations starkly contrasts with crash incidents, implying that these maneuvers may often prevent near-crashes from escalating into actual crashes.

5.2. Factors influencing crash risk

Our findings suggest that riders using e-scooters for leisure activities are more prone to be involved in SCEs. Our methodology builds upon the work by Shah et al. (2023) and Liu et al. (2020) and categorizes e-scooter riders into two categories: those using e-scooters for leisure and those using them for commuting, providing novel insights into these categories for the first time. In our clustering inputs, we considered the proximity of e-scooter trips to specific points of interest, such as public transit stations, restaurants, and educational institutions. A trip was considered in proximity if the calculated Euclidean distance to the nearest point of interest was less than a certain threshold. Given that e-scooter use was concentrated in city centers, we set our proximity threshold at 25 m, in contrast to the approach by Li et al. (2022), who set this threshold at 50 m. A larger threshold could potentially lead to a higher rate of false positives, incorrectly classifying trips not in proximity to points of interest.

The directness factor, an indicator of riding pattern, also influences safety, with detour trips subject to five times increased risk. Rider profiling is a potential strategy to understand and mitigate these risks. Identifying riders who frequently engage in detour trips or use e-scooters for leisure activities would facilitate targeted nudges to promote safer riding behavior. For our study, we employed a threshold of 0.6 to classify trips as either point-to-point or detour, a modification from the previously published limit of 0.5 (Aarhaug et al., 2023). This update was necessary as the earlier threshold proved too lenient, leading to misclassifications in our data. The new threshold was chosen to more accurately reflect the variability in riders' choice of route, which could be influenced by several factors, including a preference for specific infrastructure types, ongoing construction work, or traffic congestion.

Our findings indicate a statistically significant increase in risk associated with single-handed riding (OR 6.51). Unlike a bicycle, which has the ability to self-stabilize (Kooijman et al., 2011), e-scooters' current geometry does not result in the same inherent balancing mechanism (Paudel and Fah Yap, 2021). Thus, single-handed riding on e-scooters may compromise the rider's ability to steer and maintain balance effectively, thereby increasing the likelihood of SCEs. Implementing a computer-vision-based rider monitoring system may help prevent these crashes, if not reduce their severity. The system could monitor the rider's hands and disable the throttle when single-handed operation is detected, effectively reducing the speed of the e-scooter. Similar to the observations in the previous naturalistic studies (Klauer et al., 2014; Victor et al., 2014), engagement in a secondary task was also associated with heightened risk. Notably, phone usage (OR 2.67), which coincided with single-handed riding in many cases, contributed to an increased risk of crashes. Riders unlock the e-scooter with a mobile application, which could be used to detect phone usage during the ride. This information could then be used to limit the top speed of the e-scooter, in addition to alerting the rider about the potential risks when phone use is detected.

Consistent with the findings of White et al. (2023), our study found that pack riding also escalates the crash risk by a factor of 2.68. The riders' heightened risk may be due to reduced safety margins (Bärgman et al., 2015; Gibson and Crooks, 1938) or becoming overly focused on the leading riders, a phenomenon referred to as *target fixation*. Although some rental companies offer a group ride feature to discourage tandem riding and increase ridership, such an option was not available to Voi users in Gothenburg at the time of our data collection. In light of these findings, providing all users with comprehensive information at the outset of each trip is crucial. This information, which could include best practices for pack riding, may complement technical solutions to detect behaviors such as tailgating.

The rider's experience plays a crucial role in the likelihood of being involved in an SCE, a finding that aligns with observations from previous studies on e-scooters and bicycles (Austin Public Health, 2019; Cicchino et al., 2021; Dozza et al., 2023). E-scooter riders with more experience not only face lower risks but also tend to maintain higher average speeds during their trips as illustrated in Fig. 10. Recognizing the significant impact of rider experience on mitigating risks, rental e-scooter companies offer online traffic schools or educational programs. These initiatives encourage the riders to acquire the necessary knowledge and skills for safe riding before they hit the road. However, moving from rider education to rider training may be essential to improve safety for new riders. Interestingly, according to Uluk et al. (2022), riders with experience have a three times the odds of traumatic brain injury, suggesting that the experience factor introduces complex risk dynamics.

Fig. 6 reveals a lack of e-scooter operation between 22:00 and 05:00 on Fridays and Saturdays; in fact, city regulations ban e-scooters from riding at those times. Consequently, the impact of nighttime riding during the weekend could not be estimated. In line with the findings of Peci et al.'s (2022) study in Gothenburg and the comprehensive review by Badia and Jenelius (2023), our data (presented in Fig. 7) also indicate that e-scooters are predominantly used for short distances (less than 2 km) and durations (less than 10 min).

5.3. Ecological validity of data collection

In this study, the logging of sensors onboard the e-scooter allowed for unintrusive data collection, unlike previous naturalistic studies in which the user was required to carry heavy instrumentation during data collection (Prabu et al., 2021). While including a rider-facing camera in the setup could have offered additional insights into behavior and distractions, challenges in system integration as well as legal and privacy considerations led to its exclusion.

A unique aspect of this study is that the participants were not recruited and covered a wide range of e-scooter riders, thereby making it more representative of the rider population. Further, participants were not directed to take specific routes or travel within a specified location, as they were in studies by Ma et al. (2021) and Prabu et al. (2021). While their method provides researchers with better control over the data, it could potentially lead to riders exhibiting slightly more cautious riding behavior.

5.4. SCE and baseline identification

Identifying candidate events and, subsequently, SCEs depends on the presence of an anomaly in the sensor data from the e-scooter. While anomalies in the sensor data will be present during a crash, they may not be in near-crashes. The data mining process will not flag the trip as an SCE if the rider does not conduct any strong evasive maneuver. The exclusion of such instances introduces a bias. Additionally, the bias is further compounded by the fact that setting the threshold for anomaly detection is a tradeoff between sensitivity and specificity. If the threshold is set too low, more SCEs might be flagged (high sensitivity), but there is also a risk of classifying non-critical events as SCEs (low specificity). On the other hand, if the threshold is set too high, most non-critical events might be accurately determined (high specificity), but many SCEs could be omitted (low sensitivity). Notably, this study is the first to objectively define the anomaly detection thresholds used to identify candidate events on an e-scooter.

Inspired by the case-crossover approach used by Victor et al. (2014) and Klauer et al. (2010), we used matched baselines to account for confounding factors and ensure similar conditions for both the baselines and SCEs. Traditionally, in a case-crossover approach, trips from the same participant are used as baselines to compensate for rider-specific confounding factors, and additional constraints on other variables are implemented in the matching process. However, such an approach was not feasible for our study given the limited number of trips per participant in the dataset. Opting for a matched baseline approach led to the exclusion of only one crash and one near-crash from the analysis due to the absence of corresponding baseline events. Our conservative approach ensured a fair comparison but may have influenced the results, potentially underestimating the statistical significance of some factors.

5.5. Future studies

The matched baseline approach used in this study might obscure the effects of the variables used for matching on crash causation. In other words, variables such as presence of intersection, road type, and travel time cannot be associated with crash risk because of our study design. Future studies may benefit from adopting a random baseline methodology to gain a clearer view of how these factors influence crash risks. Furthermore, the crude OR analysis used in this study assumes the independence of each contributing factor. Transitioning to logistic regression could allow the estimation of adjusted odds ratios, capturing the complex interdependencies between risk factors. Additionally, calculating metrics such as population attributable risk percentage could further enhance our understanding of the potential reduction in crashes that could be achieved by addressing each factor.

6. Conclusions

In this study, we have examined the factors contributing to e-scooter crashes and near-crashes, offering the most ecologically valid insights into e-scooter crash causation to date. By analyzing naturalistic data, we have redefined what constitutes crashes and near-crashes for these unique two-wheeled vehicles, highlighting the inadequacy of traditional definitions based on cars and trucks. Our findings reveal that deliberate e-scooter crashes and near-crashes, often resembling acts of vandalism, are a significant concern. These incidents may arise from the lack of ownership and established social norms around e-scooter usage. Future research should analyze these intentional crashes to obtain a deeper understanding of what triggers these events.

This study is the first to highlight the heightened risk associated with detour trips, which pose a greater risk compared to point-to-point travel. Our findings underscore the importance of distinguishing between leisure and commuting e-scooter trips, as leisure trips are associated with a higher risk of SCEs. Additionally, our analysis indicates that the rider's experience plays a crucial role in safety; colloquially, inexperienced riders are more susceptible to SCEs. The study also reveals that single-handed riding, phone usage, and pack riding significantly increase crash risk, suggesting the need for targeted interventions such as rider monitoring systems and speed limitations based on phone usage detection.

In conclusion, this study makes substantial contributions to the understanding of e-scooter safety and offers practical recommendations for improving rider safety through targeted interventions and advanced monitoring technologies. The findings of this study can be useful to city administrations, planners, and micromobility operators. Decision-makers and transportation planners can develop policies and infrastructure, such as dedicated e-scooter lanes, to ensure safe and efficient operation. Micromobility operators can optimize e-scooter distribution and implement rider monitoring systems to detect risky behaviors and set speed limitations.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and Microsoft Copilot to correct grammar and review language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Rahul Rajendra Pai: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Marco Dozza:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We thank the team at Voi Technology AB for the naturalistic data collection. We also extend our heartfelt thanks to André Dankert for his invaluable insights on critical event detection techniques and his constructive discussions throughout the analysis. We further thank Rikard Fredriksson for participating in various discussions throughout the project. We thank Dr. K. Mayberry for the language review of the manuscript.

This work was conducted as part of the project Safe Integration of Micro-mobility in the Transport System (SIMT), funded by Trafikverket (Swedish Transport Administration) through the Forskning och innovation (FoI) program under grant 2022/32014. The data collection was supported by the project e-SAFER funded jointly by Vinnova, the Swedish Energy Agency, the Swedish Transport Administration, and the Swedish vehicle industry through the Strategic Vehicle Research and Innovation (FFI) Program under grant 2022-01641. The work was carried out at Chalmers University of Technology, Gothenburg, Sweden.

Appendix A. Codebook

.

Table A1
Description of variables in the codebook.

Category	Variable	Subcategory/Entry type	Description
Rider	Rider experience		The number of trips previously taken on Voi e-scooters
	Phone usage	Handheld Using the phone holder No phone usage	If there was any phone usage involved.
	Pack riding	Present Absent	If the ego e-scooter rider was riding alongside other e-scooters or bicycles.
	Hand position	Both hands on One hand on No hands on	The position of both the hands.
	Object on handlebar	Present Absent	If there was any type of object on the handlebar or the stem of the e-scooter.
	Gloves	Yes No	If the rider was wearing gloves.
Infrastructure	Type of road	Bicycle lane Sidewalk Roadway Shared Other	

(continued on next page)

Table A1 (*continued*)

Category	Variable	Subcategory/Entry type	Description
	Type of road surface	Asphalt	
		Cobblestone	
		Wood	
		Gravel	
		Grass	
		Tiles	
		Other	
	Surface condition	Dry	
		Wet	
		Icy	
		Snowy	
		Other	
	Road issues	Potholes	
		Obstructions	
		Other	
	Intersection	Signalized	
		Non-signalized	
		Roundabout	
	Construction	Present	
		Absent	
	Visual occlusion	Present	
		Absent	
Environmental	Lighting conditions	Daylight	
		Dark	
		Dusk	
		Dawn	
	Weather conditions	Sunny	
		Cloudy	
		Rainy	
		Snowy	
		Other	
	Temperature	Value in °C	The hourly temperature recorded by Swedish Meteorological and Hydrological Institute (SMHI)
	Wind speed	Value in m/s	The hourly wind speed recorded by SMHI
	Precipitation	Value in mm	The hourly precipitation value recorded by SMHI
Trip characteristics	Directness factor		The ratio of recommended distance by OpenStreetMap to the actual distance of the trip.
	Trip purpose	Leisure	The trip purpose determined using the k-means clustering.
		Commute	
	Trip day		The day of the week the trip taken.
	Trip distance	Distance in km	The actual distance traveled during the trip.
	Trip duration	Duration in seconds	The duration of the trip.
	Mean speed	Speed in km/h	The average speed the trip
	Instantaneous speed	Speed in km/h	Speed at the precipitating event
	GNSS co-ordinates		The GNSS co-ordinates of the event.
Conflict partner	Road user type	Pedestrian	
		Bicycle	
		E-scooter	
		Light vehicle (Car/Van)	
		Heavy vehicle	
		Animal	
		None	
		Other	

Appendix B. Clustering trips

In our study, we implemented an unsupervised machine-learning technique of k-means clustering to categorize the trips according to the purpose. The clustering process took into account the directness factor, mean speed, speed above zero (the percentage of the trip where the speed was greater than zero), day of the week, trip duration, trip distance, and proximity to points of interest. (public transit stations, restaurants, and educational institutions). A trip was considered in proximity if the Euclidean distance between the origin/destination of the trip and the nearest point of interest was less than 25 m.

The optimal number of clusters was determined based on the Davies-Bouldin (DB) index and Silhouette scores. The 7 K-means model was selected for further analysis as it had the optimal combination of high silhouette score and low DB index, as shown in Figure B.1.

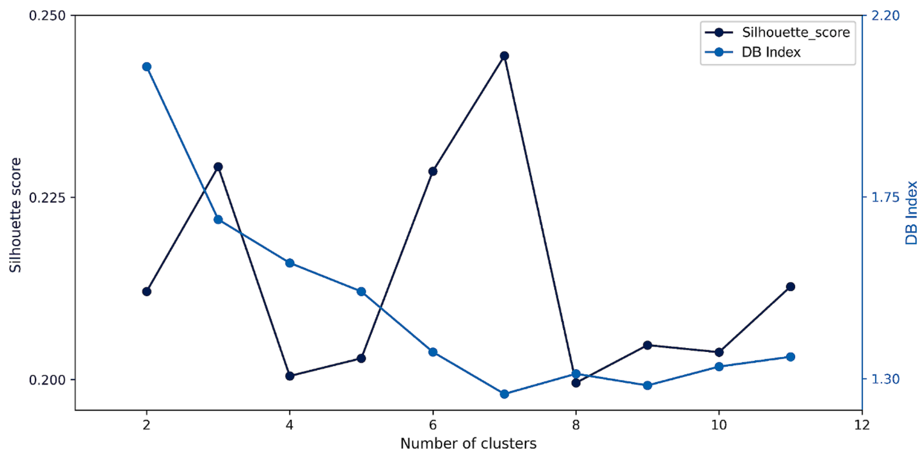

Fig. B1. DB index and silhouette score for different K-means cluster.

The 7 K-means clusters were further combined into two broader categories, representing leisure and commute trips. Clusters 3, 5, and 6 were classified as leisure trips. Notably, Clusters 3 and 5 had a lower average directness factor of 0.7, compared to 0.9 for the other clusters. Cluster 3 specifically had a lower average speed (7.1 km/h vs 14.1 km/h for other clusters) and low speed above zero percentage (47 % vs 80 % for other clusters). Cluster 5 had trips with an unusually long average trip distance (4.2 km vs 1.5 km). Lastly, Cluster 6 included trips primarily originating or ending in proximity to a restaurant or a pub, with some of those trips taken over the weekend.

Conversely, clusters 1, 2, 4, and 7 were classified as commute trips, all showing similar patterns in terms of average trip distances, speed above zero percentage, average speeds, and directness factor. Specifically, cluster 7 had all trips originating or terminating near a public transit station, suggesting a connection to other trips. Cluster 4 had trips that began or ended at schools or universities. Cluster 2 contains only weekday trips, has a high directness factor, and has the highest average speed and speed above zero percentage. Cluster 1 has features similar to cluster 2 in terms of high average speed, speed above zero percentage, and directness factor, with the key difference that cluster 1 consists of trips taken only on weekends.

It is important to acknowledge that the interpretation of the clusters and their categorization into leisure and commute is subjective. Other researchers might interpret or group the clusters differently. The objective here is to illustrate how crash risk varies with different trip patterns.

Data availability

Raw sensor data cannot be shared. Aggregated data may be made available on request.

References

Aarhaug, J., Fearnley, N., Johnsson, E., 2023. E-scooters and public transport – complement or competition? Res. Transp. Econ. 98, 101279. https://doi.org/10.1016/J.RETREC.2023.101279.

Agresti, A., 1999. On logit confidence intervals for the odds ratio with small samples. Biometrics 55 (2), 597–602. https://doi.org/10.1111/J.0006-341X.1999.00597.X.

Austin Public Health, 2019. *Dockless electric scooter-related injuries study*. https://www.austintexas.gov/sites/default/files/files/Health/Epidemiology/APH_Dockless_Electric_Scooter_Study_5-2-19.pdf.

Badia, H., Jenelius, E., 2023. Shared e-scooter micromobility: review of use patterns, perceptions and environmental impacts. Transp. Rev. 43 (5), 811–837. https://doi.org/10.1080/01441647.2023.2171500.

Bärgman, J., Smith, K., Werneke, J., 2015. Quantifying drivers' comfort-zone and dread-zone boundaries in left turn across path/opposite direction (LTAP/OD) scenarios. Transport. Res. F: Traffic Psychol. Behav. 35, 170–184. https://doi.org/10.1016/J.TRF.2015.10.003.

Boda, C.-N., Ahmed, J., Baluyot, R., Eklöf, K., Pai, R.R., Dankert, A., 2023. *E-safe pre-study*. https://www.vinnova.se/globalassets/mikrosajter/ffi/dokument/slutrapporter-ffi/trafiksakerhet-och-automatiserade-fordon-rapporter/slutrapport-2021-05060engelska.pdf.

Cho, E., Yun, Y., Oh, C., Lee, G., 2023. Derivation of riding risk precursors using 100 delivery motor scooter naturalistic riding study. Accid. Anal. Prev. 190, 107186. https://doi.org/10.1016/J.AAP.2023.107186.

Cicchino, J.B., Kulie, P.E., McCarthy, M.L., 2021. Injuries related to electric scooter and bicycle use in a Washington, DC, emergency department. Traffic Inj. Prev. 22 (5), 401–406. https://doi.org/10.1080/15389588.2021.1913280.

Davies, D.L., Bouldin, D.W., 1979. A cluster separation measure. IEEE Trans. Pattern Anal. Mach. Intell. PAMI-1 (2), 224–227. https://doi.org/10.1109/TPAMI.1979.4766909.

Dingus, T.A., Klauer, S.G., Neale, V.L., Petersen, A., Lee, S.E., Sudweeks, J., Perez, M.A., Hankey, J., Ramsey, D., Gupta, S., Bucher, C., Doerzaph, Z.R., Jermeland, J., Knipling, R.R., 2006. *The 100-car naturalistic driving study – Phase II – Results of the 100-car field experiment*. https://rosap.ntl.bts.gov/view/dot/37370.

Dozza, M., 2013. What factors influence drivers' response time for evasive maneuvers in real traffic? Accid. Anal. Prev. 58, 299–308. https://doi.org/10.1016/J.AAP.2012.06.003.

Dozza, M., 2020. What is the relation between crashes from crash databases and near crashes from naturalistic data? Journal of Transportation Safety & Security 12 (1), 37–51. https://doi.org/10.1080/19439962.2019.1591553.

Dozza, M., Werneke, J., 2014. Introducing naturalistic cycling data: what factors influence bicyclists' safety in the real world? Transport. Res. F: Traffic Psychol. Behav. 24, 83–91. https://doi.org/10.1016/J.TRF.2014.04.001.

Dozza, M., Bianchi Piccinini, G.F., Werneke, J., 2016. Using naturalistic data to assess e-cyclist behavior. Transport. Res. F: Traffic Psychol. Behav. 41, 217–226. https://doi.org/10.1016/J.TRF.2015.04.003.

Dozza, M., González, N.P., 2013. Recognising safety critical events: can automatic video processing improve naturalistic data analyses? Accid. Anal. Prev. 60, 298–304. https://doi.org/10.1016/J.AAP.2013.02.014.

Dozza, M., Li, T., Billstein, L., Svernlöv, C., Rasch, A., 2023. How do different micro-mobility vehicles affect longitudinal control? Results from a field experiment. J. Saf. Res. 84, 24–32. https://doi.org/10.1016/J.JSR.2022.10.005.

Fearnley, N., Berge, S.H., Johnsson, E., 2020. *Delte elsparkesykler i Oslo*. https://www.toi.no/getfile.php?mmfileid=52254.

Gelmini, S., Strada, S.C., Tanelli, M., Savaresi, S.M., De Tommasi, C., 2021. A novel crash detection algorithm for two-wheeled vehicles. IEEE Trans. Intell. Veh. 6 (1), 88–99. https://doi.org/10.1109/TIV.2020.3028462.

Gibson, J.J., Crooks, L.E., 1938. A theoretical field-analysis of automobile-driving. Am. J. Psychol. 51 (3), 453. https://doi.org/10.2307/1416145.

Guo, F., Klauer, S.G., McGill, M.T., Dingus, T.A., 2010. *Evaluating the Relationship Between Near-Crashes and Crashes: Can Near-Crashes Serve as a Surrogate Safety Metric for Crashes?* https://www.nhtsa.gov/sites/nhtsa.gov/files/documents/dot_hs_811_382.pdf.

Guo, F., Klauer, S.G., Hankey, J.M., Dingus, T.A., 2010a. Near crashes as crash surrogate for naturalistic driving studies. Transp. Res. Rec. 2147 (1), 66–74. https://doi.org/10.3141/2147-09.

Guo, Y., Zhang, Y., 2021. Understanding factors influencing shared e-scooter usage and its impact on auto mode substitution. Transp. Res. Part D: Transp. Environ. 99, 102991. https://doi.org/10.1016/J.TRD.2021.102991.

Heinrich, H.W., 1941. Industrial Accident Prevention: A Scientific Approach, (2nd ed.). McGraw-Hill.

Kidd, D.G., McCartt, A.T., 2015. The Relevance of Crash Type and Severity When Estimating Crash Risk Using the SHRP2 Naturalistic Driving Data. 4th International Driver Distraction and Inattention Conference.

Klauer, S.G., Guo, F., Sudweeks, J., Dingus, T.A., 2010. *An Analysis of Driver Inattention Using a Case-Crossover Approach On 100-Car Data: Final Report*. https://www.nhtsa.gov/sites/nhtsa.gov/files/811334.pdf.

Klauer, S.G., Guo, F., Simons-Morton, B.G., Ouimet, M.C., Lee, S.E., Dingus, T.A., 2014. Distracted driving and risk of road crashes among novice and experienced drivers. N. Engl. J. Med. 370 (1), 54–59. https://doi.org/10.1056/NEJMSA1204142.

Kooijman, J.D.G., Meijaard, J.P., Papadopoulos, J.M., Ruina, A., Schwab, A.L., 2011. A bicycle can be self-stable without gyroscopic or caster effects. Science 332 (6027), 339–342. https://doi.org/10.1126/science.1201959.

Leoni, J., Lucchini, A., Strada, S.C., Tanelli, M., Savaresi, S.M., 2023. Active driver assistance systems for e-scooters based on road quality and driving style estimation. IFAC-PapersOnLine 56 (2), 1977–1982. https://doi.org/10.1016/J.IFACOL.2023.10.1091.

Li, T., Kovaceva, J., Dozza, M., 2023. Modeling collision avoidance maneuvers for micromobility vehicles. J. Saf. Res. 87, 232–243. https://doi.org/10.1016/J.JSR.2023.09.019.

Li, A., Zhao, P., Liu, X., Mansourian, A., Axhausen, K.W., Qu, X., 2022. Comprehensive comparison of e-scooter sharing mobility: evidence from 30 European cities. Transp. Res. Part D: Transp. Environ. 105, 103229. https://doi.org/10.1016/J.TRD.2022.103229.

Liu, M., Mathew, J.K., Horton, D., Bullock, D.M., 2020. Analysis of recreational and last mile E-scooter utilization in different land use regions. *IEEE Intelligent Vehicles Symposium, Proceedings (IV)*, 1378–1385. https://doi.org/10.1109/IV47402.2020.9304650.

Ma, Q., Yang, H., Mayhue, A., Sun, Y., Huang, Z., Ma, Y., 2021. E-Scooter safety: the riding risk analysis based on mobile sensing data. Accid. Anal. Prev. 151, 105954. https://doi.org/10.1016/J.AAP.2020.105954.

Mehranfar, V., Jones, C., 2024. Exploring implications and current practices in e-scooter safety: a systematic review. Transport. Res. F: Traffic Psychol. Behav. 107, 321–382. https://doi.org/10.1016/J.TRF.2024.09.004.

Pai, R.R., 2022. *Logging Data From E-Scooters To Improve Traffic Safety* [Chalmers University of Technology]. https://hdl.handle.net/20.500.12380/305446.

Paudel, M., Fah Yap, F., 2021. Front steering design guidelines formulation for e-scooters considering the influence of sitting and standing riders on self-stability and safety performance. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering 235 (9), 2551–2567. https://doi.org/10.1177/0954407021992176.

Peci, G., Ali, S., Fan, J., Zhu, J., 2022. Usage Pattern Analysis of e-scooter Sharing System: A Case Study in Gothenburg, Sweden. In: Bie, Y., Qu, B.X., Howlett, R.J., Jain, L.C. (Eds.), Smart Innovation, Systems and Technologies. Springer, pp. 123–132. https://doi.org/10.1007/978-981-19-2813-0_13.

Prabu, A., Shen, D., Tian, R., Chien, S., Li, L., Chen, Y., Sherony, R., 2021. A wearable data collection system for studying micro-level e-scooter behavior in naturalistic road environment. *Fast-Zero'21*. https://doi.org/10.48550/arXiv.2212.11979.

Rousseeuw, P.J., 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 20 (C), 53–65. https://doi.org/10.1016/0377-0427(87)90125-7.

Sanders, R.L., Nelson, T.A., 2023. Results from a campus population survey of near misses, crashes, and falls while E-scooting, walking, and bicycling. Transp. Res. Rec. 2677 (2), 479–489. https://doi.org/10.1177/03611981221107010.

Shah, N.R., Aryal, S., Wen, Y., Cherry, C.R., 2021. Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology. J. Saf. Res. 77, 217–228. https://doi.org/10.1016/J.JSR.2021.03.005.

Shah, N.R., Guo, J., Han, L.D., Cherry, C.R., 2023. Why do people take e-scooter trips? Insights on temporal and spatial usage patterns of detailed trip data. Transp. Res. A Policy Pract. 173, 103705. https://doi.org/10.1016/J.TRA.2023.103705.

Stigson, H., Malakuti, I., Klingegård, M., 2021. Electric scooters accidents: analyses of two Swedish accident data sets. Accid. Anal. Prev. 163, 106466. https://doi.org/10.1016/J.AAP.2021.106466.

Stigson, H., Kullgren, A., Lubbe, N., 2024. Descriptive statistics on crashes of e-scooters with passenger cars in Sweden. International Research Council on Biomechanics of Injury Europe (IRCOBI Europe) 934–935. https://www.ircobi.org/wordpress/downloads/irc24/pdf-files/24122.pdf.

Transportstyrelsen, 2021. *Utredning behov av förenklade regler för eldrivna enpersonsfordon - slutrapport*. https://www.transportstyrelsen.se/globalassets/global/publikationer-och-rapporter/vag/slutrapport-utredning-regler-eldrivna-enpersonsfordon.pdf.

Trivedi, T.K., Liu, C., Antonio, A.L.M., Wheaton, N., Kreger, V., Yap, A., Schriger, D., Elmore, J.G., 2019. Injuries associated with standing electric scooter use. JAMA Netw. Open 2 (1), e187381. https://doi.org/10.1001/JAMANETWORKOPEN.2018.7381.

Uluk, D., Lindner, T., Dahne, M., Bickelmayer, J.W., Beyer, K., Slagman, A., Jahn, F., Willy, C., Möckel, M., Gerlach, U.A., 2022. E-scooter incidents in Berlin: an evaluation of risk factors and injury patterns. Emerg. Med. J. 39, 295–300. https://doi.org/10.1136/emermed-2020-210268.

Victor, T., Dozza, M., Bärgman, J., Boda, C.-N., Engström, J., Flannagan, C., Lee, J.D., Markkula, G., 2014. Analysis of naturalistic driving study data: safer glances, driver inattention, and crash risk. Transportation Research Board. https://doi.org/10.17226/22297.

Werneke, J., Dozza, M., Karlsson, M., 2015. Safety–critical events in everyday cycling – interviews with bicyclists and video annotation of safety–critical events in a naturalistic cycling study. Transport. Res. F: Traffic Psychol. Behav. 35, 199–212. https://doi.org/10.1016/J.TRF.2015.10.004.

White, E., Guo, F., Han, S., Mollenhauer, M., Broaddus, A., Sweeney, T., Robinson, S., Novotny, A., Buehler, R., 2023. What factors contribute to e-scooter crashes: a first look using a naturalistic riding approach. J. Saf. Res. 85, 182–191. https://doi.org/10.1016/J.JSR.2023.02.002.