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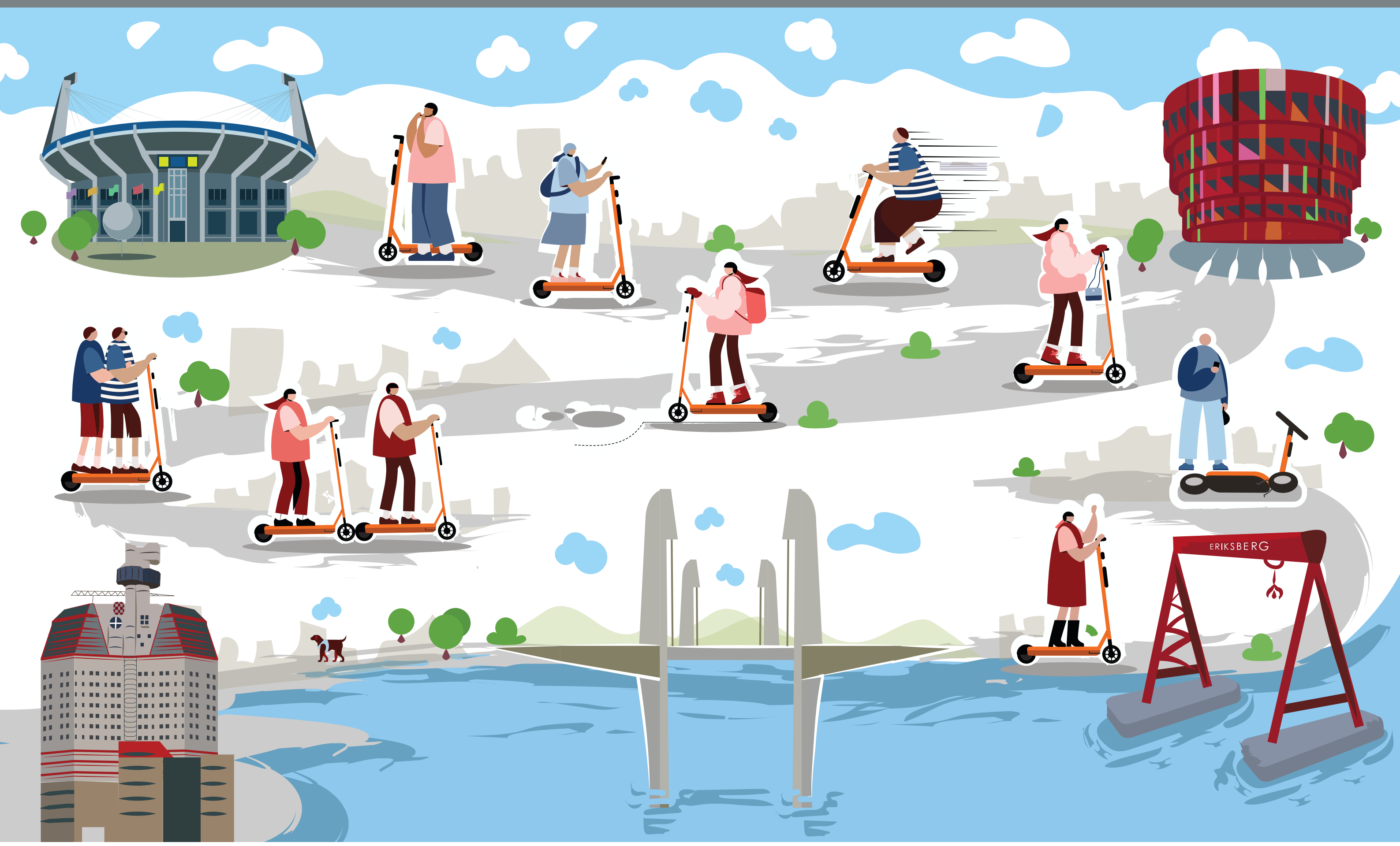

Is the risk worth the ride? Crash causation analyses of naturalistic e-scooter data

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THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

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CRASH CAUSATION ANALYSES OF NATURALISTIC E-SCOOTER DATA

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Göteborg, Sweden-2025

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Cover: Illustration by Deepthi Pai.

Illustration of e-scooter riders displaying unsafe behaviour with the city of Gothenburg as the backdrop.

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Abstract

The rapid increase in e-scooter popularity has brought an increase in crashes resulting in injuries and fatalities, creating growing concern about e-scooter safety. The aim of this thesis is to investigate which limitations in human behaviour, vehicle design, riding environment, and infrastructure contribute to e-scooter crashes. The two included studies address the limitations of conventional crash databases, using naturalistic riding data from instrumented rental e-scooters in an urban environment. The high-frequency kinematic and video data elucidated behaviours and factors contributing to safety-critical events (SCEs: crashes and near-crashes). The studies focused on two topics: identifying the key risk factors for e-scooters and evaluating the impact of methodological choices on the risk assessment. This unprecedented research used kinematic triggers to identify trips with at least one SCE, which were then verified through manual review of video footage. The identified events were labelled and relevant variables related to the rider, infrastructure, environment, and trip characteristics were extracted.

The results highlight the need to adapt definitions of crashes and near-crashes to reflect the unique characteristics of e-scooters (and perhaps other forms of micromobility). The results also show the need to prioritise safety interventions based on both crash risk and crash prevalence to optimise their impact on safety. In fact, the factors such as riders using the e-scooter for leisure trips, the presence of intersections, trips taken on Fridays and Saturdays, pack riding, and inexperienced riding—listed in decreasing order of prevalence—were nonetheless all significant contributors to risk. The results challenge assumption derived from conventional crash databases; for example, if nighttime riding is not as risky as previously believed, nighttime bans might not be necessary. Identifying risk factors from SCEs requires a baseline for comparison, which captures typical riding scenarios with no SCEs. In this thesis, two different approaches to baseline selection (random and matched) were compared. The results indicate that both random and matched baselines are necessary to get the full picture of crash causation.

In conclusion, this thesis contributes to the field of micromobility safety by identifying several factors influencing e-scooter crashes and evaluating the impact of baseline selection. Additionally, the need for tailored definitions of e-scooter SCEs was identified. These insights can guide the development of suitable interventions, such as rider training programs, targeted campaigns, risky-riding detection systems, and intelligent communication systems, to enhance e-scooter safety.

Keywords: Micromobility safety, naturalistic data analysis, rider behaviour, e-scooter crash causation analysis

Publications

This thesis is based on the following appended papers:

Paper I:

Rahul Rajendra Pai, Marco Dozza
Understanding factors influencing e-scooterist crash risk: A naturalistic study of rental e-scooters in an urban area
Published in Accident Analysis and Prevention
vol 209, no. 107839, Jan 2025
DOI: 10.1016/j.aap.2024.107839

Author's contribution: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft, Writing – review & editing.

Paper II:

Rahul Rajendra Pai, Marco Dozza
What Influences Crash Risk and Crash Prevalence for E-scootering? Insights from a Naturalistic Riding Study
Under review at Transportation Research Part F

Author's contribution: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft, Writing – review & editing.

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Contents

CHAPTER 1

Introduction

Micromobility, a relatively new term within the transport sector, refers to low-speed, lightweight, personal transportation vehicles (Santacreu, 2020). Once a niche concept, this new segment of transport has witnessed unprecedented growth since the introduction of the first dockless e-scooter-sharing systems to the public in Santa Monica and San Francisco in 2017 (Hawkins, 2018). Rental e-scooters offer a flexible and often more efficient option for short-distance travel compared to public transport or walking. The popularity of e-scooters has surged, with 69 million trips recorded in the USA during 2023 alone (NACTO, 2024). However, this growth in popularity has caused safety concerns, resulting in drastic measures like complete bans in some areas (Guéron-Gabrielle, 2023).

1.1 Crashes on e-scooters

The increasing popularity of e-scooters has brought significant challenges, especially concerning safety, with the notable rise in e-scooter crashes resulting in injuries and fatalities. According to a study by Stigson et al. (2021), most e-scooter crashes are single-vehicle incidents, with approximately half of the crashes occurring during the weekend and 46% of those requiring emergency department visits happening at night. The study also reports that one-third of the crashes are related to road surface or infrastructure issues, a finding similar to that of Cicchino et al. (2021a). Multiple studies have found that a significant portion of riders were injured during their first few trips (Austin Public Health, 2019; Trivedi et al., 2019). Sanders and Nelson (2023) explored the circumstances of e-scooter critical events and found that 35% of those reporting critical events while riding mentioned speed or loss of control as a factor.

These studies often rely on crash databases, hospital records, and police reports to assess the magnitude of the problem. However, these traditional data sources do not fully capture its complexity. Hospital data tend to include only severe injuries, potentially underrepresenting the full scope of e-scooter-related safety-critical events (SCEs), assuming that SCEs follow the Heinrich's triangle (Heinrich, 1941). Further, traditional crash data analysis, while helpful in quantifying the problem, cannot fully explain the behaviours and causation mechanisms, such as delayed rider reactions, distraction, and other rider impairments.

In response to growing safety concerns surrounding e-scooters, authorities have implemented various measures to mitigate risks. These measures range from complete bans on e-scooter use, as seen in Paris (Guéron-Gabrielle, 2023), to more specific restrictions such as nighttime bans (Sprangers, 2021), geofencing for speed regulation (Field & Jon, 2021), and prohibitions on sidewalk riding to protect pedestrians (Department for Transport, 2022; Transportstyrelsen, 2021). Additionally, some authorities have introduced licensing requirements and mandatory education programs for e-scooter riders (Department for Transport, 2022; *Electric Scooters - Transport for London*, n.d.). Beyond regulatory and policy measures, e-scooter design and handling have been improved with better brakes and enhanced stability features (Li et al., 2023). While these initiatives reflect efforts to address safety, the rising number of crashes highlights a clear need for more data in order to obtain a deeper understanding of e-scooter crashes and devise effective countermeasures.

1.2 Crash causation analysis

Existing measures to address e-scooter safety, consist of bans and restrictions. However, there is a fundamental gap in our understanding of e-scooter crashes, since current data sources do not provide the necessary depth of information about the causation mechanisms, behaviours and factors that lead to crashes. The absence of nuanced pre-crash data limits our ability to understand the chain of events leading to crashes and to develop targeted safety interventions. This issue necessitates a shift towards naturalistic data, which capture real-world pre-crash behaviour.

In other modes of transport, analysing causal mechanisms has led to significant safety improvements in the past. For instance, identifying the strong link between cell phone use while driving and increased collision risk led to regulations in many countries that restrict or ban the use of cell phones while driving (Olson et al., 2009; Redelmeier & Tibshirani, 1997). Similarly, understanding that driver distraction increases the crash risk threefold has led to the development of advanced driver-assistance systems, such as driver monitoring systems that actively assist the driver and improve safety (Vegega et al., 2013). Furthermore, crash causation analysis has been crucial in creating targeted safety campaigns and educational programs that raise awareness of and promote safe driving behaviour. Braitman et al. (2008) identified key factors contributing to crashes among novice teenage drivers: inattention, speeding, and failure to detect other vehicles. Numerous educational programs addressing these risk factors among young drivers have proven effective at promoting safer driving behaviours and reducing crash rates (Fohr et al., 2005).

Research on bicycle crash mechanisms has identified that poor road conditions, such as potholes and slippery surfaces due to rain or ice, can cause cyclists to lose control, increasing the risk of crashes (Dozza et al., 2016a; Dozza & Werneke, 2014). In addition, certain cyclist behaviours, such as speeding and distracted riding, also contribute to crashes. While these insights are valuable, it is important to note that e-scooterists and cyclists exhibit distinct behaviours (Dozza et al., 2023; Li et al., 2023) and injury patterns (Cicchino et al., 2021a), despite often being perceived and regulated similarly (Transportstyrelsen, 2021). Therefore, the findings from bicycle crash analyses may not translate directly to e-scooters. One of the few studies on e-scooter safety, by White et al. (2023), identified riding on gravel or grass, aggressive behaviours, and group riding as risk factors. However, the data for their study were collected on the Virginia Tech University campus, which may have introduced population bias, as the participants were primarily students and university employees. Additionally, the controlled environment of the campus, with limited traffic and restricted usage hours, may further limit the generalisability of their findings.

1.3 Research objectives

The overall aim of this PhD is to inform the development of technical, regulatory, educational and infrastructural countermeasures by elucidating the causes, timing, and mechanisms of e-scooter crashes.

To achieve this aim, three objectives have been set:

1. Investigate which limitations in human behaviour, vehicle design, riding environment, and infrastructure contribute to e-scooter crashes.
2. Compare the crash rates and injury incidences of e-scooterists with those of cyclists.
3. Identify factors that contribute to injuries and fatalities in e-scooter crashes by analysing medical reports, thereby enabling countermeasure prioritisation.

The first objective forms the aim of this thesis, and Papers I and II address this by focusing on the contributions of rider behaviour, riding environment, infrastructure, and surrounding road users to crashes (as depicted in Figure 1). Papers III to V are future work for the rest of the PhD. Paper III will address the second objective by comparing the crash risk patterns of e-scooterists with cyclists, focussing specifically on rider-related aspects of these events. Paper IV will address the third objective, using a combination of diverse data sources. Finally, as informed by the findings of Papers I, II, and IV, Paper V will revisit the first objective, providing a deeper dive into infrastructure-related factors.

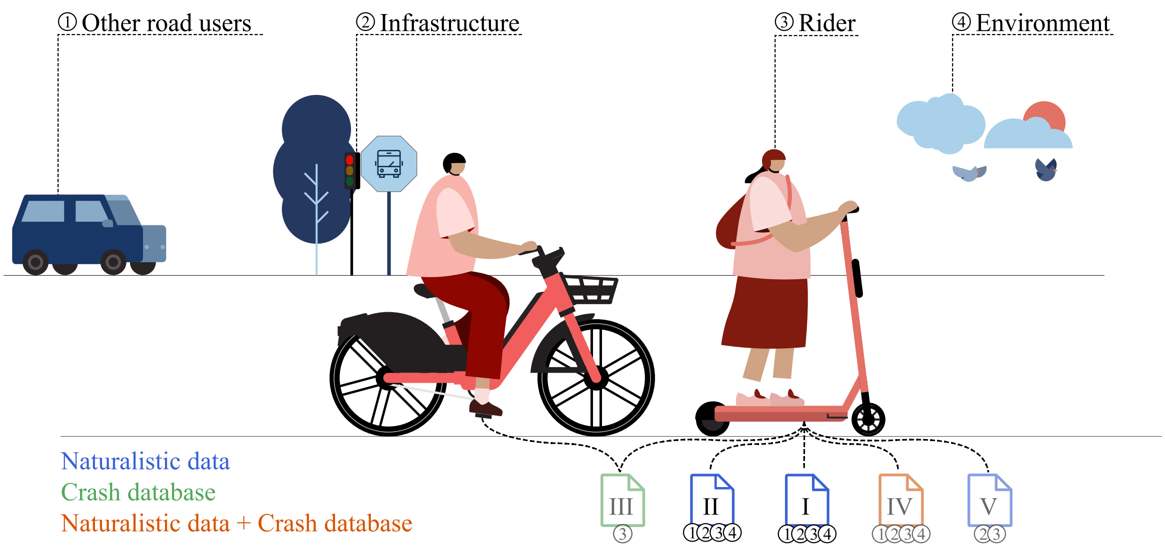

Figure 1. Overall outline of the PhD studies comprising five papers, illustrating the types of micromobility riders analysed and the data sources. Papers I and II are included in this thesis; Papers III to V are future work.

CHAPTER 2

Methodology

This thesis leverages naturalistic data to statistically analyse crash risk for e-scooters. Naturalistic data are real-world data collected unobtrusively and systematically from participants using the vehicle for their day-to-day activities, thereby capturing a detailed view of interactions and rider behaviours. Figure 2 illustrates the typical process of naturalistic data analysis, consisting of five steps: data collection, critical event identification, baseline selection, video reduction and labelling, and statistical analysis. The study was reviewed and approved by the Swedish Ethical Review Authority (Etikprövningsmyndigheten) (Ref. 2023-04671-01).

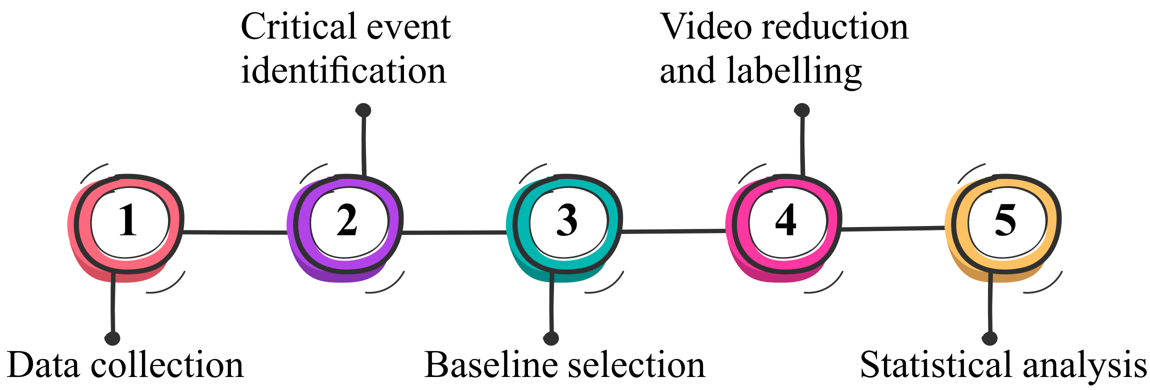

Figure 2. Methodological steps from data collection to statistical analysis.

2.1 Data collection

Naturalistic data can be collected through various methods. One common approach is site-based, wherein sensors and cameras are strategically installed at specific locations to monitor traffic and rider behaviour (Mohammadi et al., 2023). The other, more traditional method for collecting naturalistic data involves instrumented vehicles, the same approach utilised in this thesis. These instrumented vehicles are outfitted with a diverse set of monitoring tools that capture detailed data on vehicle dynamics, rider behaviour, and environmental conditions. By recording data, these vehicles facilitate the collection of pre-crash information, offering crucial insights into the moments preceding an SCE. The granular data allows researchers to analyse typical riding patterns and identify deviations that could potentially lead to crashes. This vehicle-based approach has been widely used in studies focussing on cars and trucks (Barnard et al., 2016; Dingus et al., 2006; Victor et al., 2015). More recent studies have expanded to include bicycles (Dozza et al., 2016a; Dozza & Werneke, 2014), but only one study to date has focused on e-scooters (White et al., 2023).

Naturalistic data collection can be either trigger-based or continuous. Trigger-based data are saved only when specific events or conditions occur, such as sudden braking or rapid acceleration. While this method efficiently captures critical events, it does not record normal riding scenarios, limiting the ability to measure exposure and establish baselines. Continuous data collection, on the other hand, saves uninterrupted data over a period of time, capturing all aspects of riding. This thesis collected data continuously, necessitating higher storage capacity and data processing resources due to the larger volumes of data generated (compared to the trigger-based data collection).

Naturalistic data were collected from 17 instrumented e-scooters; see Figure 3 (Boda et al., 2023; Pai, 2022). These customised e-scooters, part of a fleet in Gothenburg were available to customers of a micromobility company and limited to a maximum speed of 20 km/h in compliance with local regulations. Additionally, geofencing (Reclus & Drouard, 2009) restricted the e-scooters to an operational area of approximately four km^2 around the city centre. The data from the sensors (Figure 3) were logged at 10 Hz. In addition, a 220° fisheye camera recorded video at 30 frames per second. The advantage of such a wide field of view is that it can record peripheral information, such as the position of the rider's hands (Figure 3). The discreet data logging setup ensured that the recording equipment did not influence the rider's behaviour.

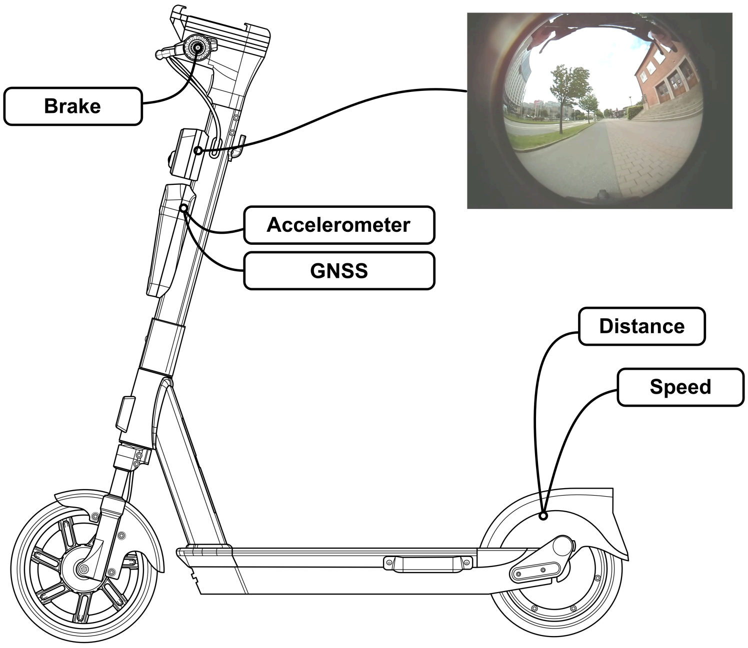

Figure 3. Instrumentation on the e-scooters used for data collection, including Global Navigation Satellite System (GNSS).

2.2 Critical event identification

Critical events and their severity follow the Heinrich triangle (Heinrich, 1941), which posits that for every fatality, there are many minor injuries and even more near-crash events. This model suggests that by addressing and reducing the number of minor incidents and near-crashes, the occurrence of more severe outcomes, including fatalities, can be minimized. Given this framework, the use of near-crashes as surrogates for crashes becomes particularly valuable, especially in the context of e-scooter research where recorded crashes are relatively few. The use of near-crashes as proxies for crashes has been debated and discussed in several previous studies (Dozza, 2020; Guo, Klauer, Hankey, et al., 2010; Knipling, 2015). While near-crashes may not always accurately represent the conditions leading to crashes, some studies have argued that they serve as proxies for crashes (Guo, Klauer, Hankey, et al., 2010; Guo, Klauer, McGill, et al., 2010). Considering both near-crashes and crashes to be SCEs offers a larger dataset for analysis than the use of crashes alone. As a result, crash risk estimations may be more precise, albeit conservative. However, this approach has been contentious, and there is no formal agreement on its validity (Knipling, 2015).

Similar to the approach within previous naturalistic studies (Dingus et al., 2006; Victor et al., 2015), this thesis used kinematic triggers to flag trips that included potential SCEs (Figure 4). Kinematic thresholds were set for the e-scooter's accelerations, speed, and brake lever position. Consequently, 1801 trips were identified as potential SCEs; each flagged as a candidate event for exceeding the set thresholds. Two analysts inspected the video footage of all candidate SCEs, determining if each event conformed to the definition of crash or near-crash. The definitions of SCEs in this thesis were derived from naturalistic data studies on bicycles (Dozza et al., 2016b; Dozza & Werneke, 2014). Crashes were identified as unintended events in which the ego e-scooter collided with other objects or road users, or the rider fell off the standing deck during motion. Unintended events that involved rapid evasive manoeuvres by the ego e-scooter or surrounding road users were classified as near-crashes.

Figure 4. Types of events flagged as candidate SCEs in this thesis.

2.3 Baseline selection

In crash risk analysis, establishing a baseline is crucial for identifying deviations in patterns and behaviours that may indicate increased risk. A baseline refers to a data point representing normal riding or driving in a non-SCE trip. Comparing SCEs to these baselines helps in isolating and identifying risk factors that contribute to unsafe situations. Baselines serve as reference points, allowing for a clearer understanding of what constitutes normal riding versus conditions that lead to SCEs. Baseline can be selected using various techniques, including random sampling and matching (Lash et al., 2021). Random sampling involves selecting baseline trips randomly, providing a broad and diverse set of data points. On the other hand, matching involves selecting baseline trips that closely resemble certain conditions of SCE trips, such as location and speed. Figure 5 illustrates the SCE and the corresponding scenarios identified using the two baseline sampling methods. This thesis employed both random and matched baselines; the paragraphs 2.3.1 and 2.3.2 below explain the details.

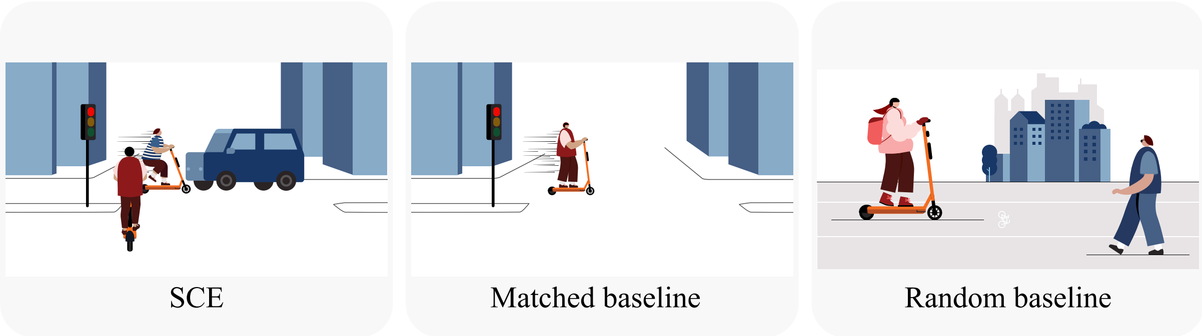

Figure 5. Visualising SCE and sampling methods (matched by location and random).

2.3.1 Random baseline selection

For each SCE, six baseline trips were randomly selected. Within each baseline trip, a random timestamp was identified as the baseline data point. Each baseline trip was uniquely associated with a single SCE to ensure data independence. To avoid bias from stationary periods, if the e-scooter was not in motion at the baseline data point, that timestamp was discarded, and a new timestamp was chosen. Additionally, to analyse the impact of different baseline-to-SCE ratios, we further refined our sample by selecting three and, subsequently, one baseline per SCE from the initial six. Random sampling offers a broad and general approach, providing a diverse set of baseline data points. While random baselines are straightforward and not resource-intensive (Checkoway et al., 1989), they may not control for confounding variables and introduce bias affecting the accuracy of risk estimates.

2.3.2 Matched baseline selection

To establish matched baselines for each SCE, we utilised the Global Navigation Satellite System (GNSS) data to pinpoint trips that traversed the exact SCE location. Additional matching criteria were then applied in a prioritised sequence: speed, weather conditions, lighting conditions, time of day, and trip date. Trips that met the highest number of these criteria were selected as baselines. As shown in Figure 5, the matching ensures the similarity of the baseline data point to the SCE.

Given the stringent requirements for matched baselines, we limited the selection to three baselines per SCE to ensure that each SCE had the same number of baseline events. Unlike randomly selected baselines, matching helps control for confounding variables by ensuring that the distribution of baseline trips is similar to SCE trips (Lash et al., 2021). However, by definition, matching can mask the effect of those variables on crash risk. For instance, if the SCE and baseline trips are matched for weather conditions, then the specific impact of a specific weather condition on crash risk may be less apparent.

2.4 Video reduction and labelling

The primary purpose of video reduction and labelling is to systematically categorise and describe the rider behaviours, environmental conditions, and interactions captured within the SCEs and baselines. Variables were primarily identified using video data; a codebook (see Appendix A) which provides detailed descriptions of each variable was used to ensure consistent labelling across different analysts. Variables were classified as either subjective or objective. Subjective variables, such as lighting conditions (see Appendix A), required interpretation of the video by the analysts. Objective variables, such as the speed of the vehicle (see Appendix A), were quantifiable and could be determined directly from the data. The reliability of the labelling process was further enhanced by having multiple analysts independently label the video segments and data points. Inter-rater reliability for the subjective variables was measured quantitatively using statistical metrics, ensuring that the labels were applied consistently and accurately across analysts. Variables were labelled manually by analysts to ensure high accuracy and context-specific understanding, which automated methods or machine learning models may not fully achieve. While automation helps process large data volumes, nuanced interpretations, especially for the subjective variables, often require human judgment.

In this thesis, the codebook, which describes variables related to the rider, infrastructure, environmental factors, trip characteristics, and conflict partners, was adapted from the BikeSAFE study (Werneke et al., 2015) to include variables specific to e-scooters. For each SCE and the corresponding baseline events, 30-second video segments were extracted and labelled according to the codebook. The segments comprised 20 seconds before and ten seconds after the event for SCEs, the same timeframe around the location of interest for matched baselines, and around the randomly selected timestamp for random baselines. Continuous variables, such as single-handed riding, were labelled at the 20-second mark for each clip. Two analysts independently reviewed the clips in a randomised sequence, minimising the influence of personal bias. The inter-rater reliability for subjective variables was quantitatively assessed using Cohen's kappa (Cohen, 1960). Following the inter-rate reliability estimation, the analysts in cases where they disagreed on the interpretation of certain variables, they discussed their differences and reached an agreement. If discrepancies could not be resolved, the research group members were consulted to finalise the labels.

2.5 Statistical analysis

In naturalistic studies, statistical analysis transforms labelled data into meaningful insights about the significance of different risk factors by identifying patterns and quantifying relationships, to determine the significance of different risk factors. First, the labelled data is organized into contingency tables (2x2 tables) that summarise the number of SCEs and baselines exposed to a particular factor and the number that were not. Each 2x2 table facilitates the straightforward calculation of multiple statistical metrics. The two key metrics used in this thesis were the Odds Ratio (OR) and the Population Attributable Risk Percentage (PARP).

The OR quantifies the association between exposure and SCEs; in other words, it compares the odds of the occurrence of an SCE in the presence of a particular factor against the odds of its occurrence without that factor (Agresti, 1999; Bishop et al., 2007). For instance, an OR estimate of e-scooter crashes at intersections would compare the odds of crashes occurring at intersections versus the odds of their occurrence at non-intersections. An OR greater than one would indicate an increased risk, while an OR less than one would indicate the factor having a protective effect. However, this metric fails to convey the broader impact of a factor within the population. A risk factor with a high OR might imply an increased likelihood of SCEs, but if the factor is rare in the population, its overall contribution to crash risk is minimal. Fundamentally, OR can sometimes overemphasise the significance of an uncommon risk factor that increase the crash risk.

PARP estimates the proportion of the SCEs in the population that can be attributed to a specific risk factor (Cole & Macmahon, 1971; Levin, 1953). For instance, if intersections are associated with an increased risk, the PARP would provide an estimate of the prevalence of intersection in the SCEs and baselines combined. Thus, PARP helps rank the factors' contributions to the incidence of SCEs. This thesis combines OR and PARP, ensuring that the significant risk factors are identified and prioritised according to their overall contribution to the incidence of SCEs, thereby guiding effective intervention strategies.

CHAPTER 3

Summary of papers

3.1 Paper I:

Rahul Rajendra Pai, Marco Dozza
Understanding factors influencing e-scooterist crash risk: A naturalistic study of rental e-scooters in an urban area
Published in Accident Analysis and Prevention
vol 209, no. 107839, Jan 2025
DOI: 10.1016/j.aap.2024.107839

3.1.1 Background

With the rise in popularity of e-scooters, there has been a corresponding increase in crashes, injuries, and fatalities. Retrospective analyses based on hospital records and crash databases have demonstrated the magnitude of the safety issues. However, these studies have failed to capture the underlying mechanisms of e-scooter crashes. Additionally, to date the research on e-scooters has been conducted in controlled environments, which do not fully reflect the intricate dynamics of e-scooter usage in real-world settings.

3.1.2 Aim

This paper presented the first systematic analysis of shared e-scooter usage in an urban environment. The study analysed naturalistic data to identify the factors prevalent in SCEs.

3.1.3 Methods

A naturalistic dataset was collected using instrumented rental e-scooters in Gothenburg, Sweden. The identification of SCEs was based on kinematic triggers derived from the onboard sensor data. For each SCE, three matched baselines were identified to account for exposure. The matching process used GNSS coordinates (latitude and longitude) of each SCE to find baselines at the same location. Additional matching criteria (applied in descending order of importance) included e-scooter speed, weather conditions, lighting conditions, time of day, and day of the week. The SCEs and baselines were then labelled according to the codebook, which included 29 variables. The OR was calculated for each labelled variable to assess its effect on the occurrence of an SCE.

3.1.4 Results

Data from 6868 trips, which covered 9930 km over 709 hours and involved 4694 unique participants, were analysed. Sixty-one SCEs (19 crashes and 42 near-crashes) were identified and labelled. The findings revealed several significant factors contributing to SCEs. For instance, riders with experience of five trips or fewer were twice as likely to encounter a critical event as their more experienced counterparts. Pack riding posed a 2.7-fold higher risk than riding alone. Certain behaviours, such as phone usage and single-handed riding, escalated the risk by factors of 2.67 and 6.51, respectively. The type of trip also influenced the risk, with detour trips amplifying the likelihood of a safety-critical event by a factor of 4.93 relative to point-to-point trips. Similarly, leisure trips were riskier (albeit at a lower rate of 2.4) than commute trips. (Each of the factors mentioned above was determined to be statistically significant.)

3.1.5 Discussion and conclusions

The study not only underscores the importance of adapting the definitions of "crash" and "near-crash" but also provided an objective definition for these terms when working with two-wheeled vehicles, especially those in the shared mobility system. Although balancing on e-scooters and bicycles may feel similar, e-scooters are inherently less stable and demand greater effort to control during sudden changes. This over-reliance on bicycle experience can lead to a loss in balance, which can result in an SCE when the rider releases one hand. The accessibility of the rental e-scooter system allows individuals of varying experience levels to operate the e-scooters.

Many rental companies provide virtual education on safe e-scooter riding; however, because the system is accessible to individuals of varying experience levels, moving from rider education to rider training may be essential to improve the safety for novice riders. The results also revealed risks associated with different usage patterns (such as using e-scooters for detour trips rather than for point-to-point travel). The purpose for which riders use e-scooters largely determines the associated risk, highlighting the importance of further research into the impact of different usage patterns on safety.

3.2 Paper II:

Rahul Rajendra Pai, Marco Dozza
What Influences Crash Risk and Crash Prevalence for E-scootering? Insights from a Naturalistic Riding Study
Under review at Transportation Research Part F

3.2.1 Background

The increasing use of e-scooters in urban areas has introduced both benefits and safety challenges. Unlike traditional data sources like crash databases, naturalistic data, are collected in the real-world traffic, offering a unique opportunity to understand rider behaviour and crash causation. Baselines, segments of trips without SCEs, are crucial for naturalistic data analysis; they can be selected randomly or matched to the characteristics of SCEs. The OR is commonly used to measure the relationship between exposure and SCEs, but they do not indicate the prevalence of risk factors within the population. The PARP, on the other hand, quantifies the proportion of crashes attributable to specific risk factors. In addition to the baseline sampling method, the baseline per SCE considered in the analysis will likely influence the accuracy and reliability of the risk estimates.

3.2.2 Aim

The study aimed to investigate baseline selection methods on the estimation of crash risk and crash prevalence in e-scootering. Specifically, results from random and matched baselines were compared, and the effects of changing the baseline-to-SCE ratio were assessed.

3.2.3 Methods

Naturalistic riding data, including both kinematic and video data, were collected from instrumented rental e-scooters and analysed. The SCEs were identified by first looking for anomalies in the kinematic data and then reviewing the corresponding video footage. Two distinct baseline selection methods were implemented to investigate the factors contributing to SCEs: random sampling and matched sampling. Random baselines were chosen by randomly selecting a point in time from trips without SCEs. Matched baselines, on the other hand, involved identifying trips that passed through the same location as an SCE while also matching other criteria like speed, weather, lighting, and time of day. After both SCEs and baselines were identified, two analysts independently labelled each event according to predefined criteria. The crash risk was calculated using OR and crash prevalence was calculated using PARP for 14 factors. The crash risk analysis was repeated for random baselines, using different baseline-to-SCE ratios to evaluate the impact of the baseline choices on the results.

3.2.4 Results

The study found that certain factors exhibited consistent and statistically significant crash risks across both random and matched baselines: limited rider experience (five or fewer trips), phone usage while riding, single-handed riding, pack riding, leisure trips, detour trips, and trips with a mean speed of 11 km/h or lower. In contrast, factors influenced by the matching criteria, such as the presence of intersections and road types, showed different crash risks, depending on the baseline selection method. For example, intersections increased crash risk threefold in the random baseline analysis but had a negligible effect in the matched baseline analysis. Similarly, riding in pedestrian lanes was safer in the random baseline analysis but not in the matched baseline analysis. Additionally, nighttime trips were associated with a lower risk of SCEs compared to daytime trips (with a significant OR) in the random baseline analysis. The PARP results indicated that leisure trips and pack riding had high PARP values, suggesting significant risk and prevalence compared to commute trips and riding alone, respectively. On the other hand, single-handed riding had a high OR but low PARP value. Increasing the baseline-to-SCE ratio resulted in narrower confidence intervals and more statistically significant variables, enhancing the precision of the risk estimates.

3.2.5 Discussion and conclusions

The study demonstrates the need to prioritise safety interventions based on both crash risk (OR) and prevalence (PARP). Focusing solely on factors with a high OR, such as single-handed riding, is not optimal for enhancing safety, as these behaviours might not be widespread among e-scooter riders. The findings challenge assumptions based on traditional crash databases and hospital reports; nighttime e-scooter usage might be safer than previously thought, which brings into question the necessity of nighttime bans. However, the dataset did not include trips on weekend nights, potentially masking the influence of alcohol on crash risk. Random baselines are easier to implement and can uncover the influence of a broader set of variables but are more susceptible to confounding. Ideally, using both sampling methods together provides a complete picture of crash dynamics.

This study's results highlight prioritising safety interventions according to their crash risk and prevalence. Specifically, recommended countermeasures must include those targeting leisure trips, intersections, trips on Fridays and Saturdays, pack riding, and inexperienced riding since addressing the other factors considered in the study is expected to be less impactful.

CHAPTER 4

Discussion

4.1 Definition of safety-critical event

Similar to most previous naturalistic driving and riding studies, this study initially defined a crash as any collision of the ego e-scooter with another object or road user. While the crash identification process is typically unambiguous, e-scooters pose a unique challenge due to the occurrence of self-induced or intentional crashes. Rather than the result of a loss of control, these events are deliberate, often resembling vandalism. Although they fit the initial definition of a crash, they represent something beyond e-scooters as a mode of transport—and thereby fall beyond the focus of traffic safety research. As pointed out in Paper I, the definition of an SCE needed to be adapted to exclude these intentional acts. The use of near-crashes as proxies for crashes (Guo, Klauer, Hankey, et al., 2010; Knipling, 2015) and even the definition of near-crashes (International Organization for Standardization, 2018)—is not straightforward. In fact, the correct interpretation of near-crashes is a contentious topic in traffic safety research. The premeditated nature of these self-induced events further complicates the identification of near-crashes.

Paper I was the first study to objectively define SCEs involving e-scooters. As indicated in Section 2.2, crashes were defined as unintended events in which the ego e-scooter collided with other objects or road users, or the rider fell off the standing deck during motion; near-crashes were defined as unintended events that involved rapid evasive manoeuvres by the ego e-scooter or surrounding road users. The distinct behaviour of e-scooter riders, which deviates from that of other road users necessitates the development of countermeasures that specifically address these unique behavioural patterns.

4.2 Risk factors and their prevalence

In this study, numerous rider-related factors have been identified as significantly influencing the risk of e-scooter crashes. Among these, rider inexperience is the most notable factor. This finding is consistent with previous research (Austin Public Health, 2019; Cicchino et al., 2021a; Dozza et al., 2023), although it is important to note that when calculating the crude OR, potential interactions between the different factors are not controlled for. For example, single-handed riding and phone usage were identified in this study as significantly increasing crash risk; while a rider might use only one hand for a number of reasons, phone usage often occurs in conjunction with single-handed riding. Operating an e-scooter with one hand poses more significant challenges than when riding a bicycle with one hand. Unlike bicycles, which can remain stable with minimal rider input (Kooijman et al., 2011), e-scooters require more effort to maintain balance at typical riding speeds (Paudel & Fah Yap, 2021), particularly when perturbed (Li et al., 2023). Moreover, the crash avoidance techniques differ between e-scooters and bicycles (Dozza et al., 2023; Li et al., 2023). Riders may mistakenly apply their bicycle-riding experience to e-scooters, underestimating the unique risks involved. In this thesis, pack riding was also found to increase risk, possibly due to distraction, reduced safety margins, or riders being overly focused on leading riders.

Trip characteristics also play a significant role in e-scooter safety. In this thesis, leisure trips were associated with a higher risk of SCEs than commuting trips. Similarly, detour trips, which do not follow a direct point-to-point route, were identified as having an increased risk of SCEs. Both leisure and detour trips may reflect e-scooters activity beyond simple travel or transport, leading to less cautious behaviour and perhaps more risk-taking. Study by Shah et al. (2023), classified trips as leisure or commute and detour or point-to-point. However, Paper I of this thesis is the first to associate these trip characteristics with SCEs. Interestingly, in this thesis the trips with a lower mean speed were also associated with an increased risk, perhaps because less experienced riders travel at lower speeds.

Temporal factors were also shown to influence crash risk. Trips taken on Fridays and Saturdays were associated with a higher risk of crashes irrespective of baseline type, aligning with previous studies (Cicchino et al., 2021b; Stigson et al., 2021). Surprisingly, trips taken during the late evening hours (21:00 to 00:00) showed a reduced risk, a finding that contrasts with previous studies, which reported higher crash rates at night (Shah & Cherry, 2022; Stigson et al., 2021). It is important to note that this thesis did not include possible interactions with alcohol. In Gothenburg, where our data were collected, e-scooter trips are prohibited on Saturday and Sunday nights, resulting in a lack of data for these periods. The lowered risk suggests a need to reassess nighttime bans on e-scooters (City of Atlanta, 2019; Oslo kommune, 2022; Sprangers, 2021), as more balanced regulations may enhance safety without unnecessary restrictions. Future studies should aim to combine crash databases and hospital reports with naturalistic data to provide a more comprehensive picture of crash risk across different times of the day and severity levels.

Several countermeasures can be implemented to mitigate the crash risks identified in this study. While many e-scooter companies provide educational programs for new users (*Voi RideSafe Academy*, n.d.), and some municipalities have instituted mandatory education requirements (*Electric Scooters - Transport for London*, n.d.), the increased risk for inexperienced riders suggests these measures alone may be insufficient. Our findings indicate that hands-on training could be essential to enhance the safety of novice riders effectively. In addition, since the risk associated with lower mean speeds is correlated with risk for inexperienced riders, the former will be mitigated, if novice riders receive proper training. Papers I and II further indicate that interventions should focus on promoting safer riding practices, such as keeping both hands on the handlebars and avoiding phone use. Micromobility operators can develop technological solutions to detect single-handed riding or phone use while riding and take preventative actions to reduce the risk. The risks associated with leisure and detour trips as well as pack riding could be addressed by profiling riders based on these characteristics, allowing micromobility rental operators to reward safe riders and promote rider-specific campaigns to foster safe riding. Since the detour trips and leisure trips overlap, addressing one will partly address the other.

Developing effective countermeasures is possible only when the full scope of each issue (beyond crash risk alone) is appreciated. Effective allocation of resources and intervention development requires considering how widespread the factors are within the population—in addition to quantifying the magnitude of the increased risk. As pointed out in Paper II, the PARP quantifies the proportion of crashes that can be attributed to a specific risk factor, so that factors can be ranked according to their overall impact on safety. In the 100-car study, a driver reaching for a moving object in the cabin of the car was associated with an eight-fold increased risk, but accounted for only 1% of crashes and near-crashes (Klauer et al., 2006). Similarly, in Paper II of this thesis, although single-handed riding had a high OR, it had a low PARP, which means that other more common factors may have a greater overall impact on safety even if they have lower ORs. Clearly, addressing the factors with the highest risk and prevalence can achieve the most powerful safety improvements. Therefore, the factors leisure trips, the presence of intersections, trips on Fridays and Saturdays, pack riding, and inexperienced riding are to be prioritised. Emphasis should be placed on the following countermeasures: rider profiling to develop targeted safety campaigns, improving intersection interactions with intelligent transportation systems like V2X communication, and providing hands-on training for new riders. PARP calculations, like crash risk estimates, were conducted independently for each factor without accounting for potential interactions. Thus the result should be understood, not as absolute percentages of preventable SCEs, but rather as a metric that augments the OR, offering additional context about the relative contribution of each factor.

4.3 Baseline selection

A reference point for comparison is needed in order to calculate OR and understand the factors contributing to SCEs. This reference point typically is formed by a baseline, which represents a segment of normal riding or driving without any critical events. Just as it is important to have well-defined critical events, appropriate and carefully selected baselines are equally essential for accurate and reliable analysis. The selection of these baselines, both in terms of the method used to choose them and their number relative to the number of SCEs, can significantly influence the results of the analysis.

4.3.1 Baseline sampling

The random baseline method provides a broad and diverse set of baseline data points reflecting general riding conditions, but it may not control for confounding variables and may introduce bias (Lash et al., 2021). The matching process aims to control for confounding variables, ensuring that the baseline events share characteristics similar to the corresponding SCEs (Bharadwaj et al., 2019; Victor et al., 2015). The choice between random and matched baselines has substantial implications on the findings. As observed in Paper II, the presence of intersections significantly increased crash risk when using random baselines. However, when using baselines matched for location (among other factors), the baseline segments also occurred in intersections, and the increased risk was not observed. Similarly, the safety of pedestrian lanes compared to bicycle lanes also showed contradictory results, depending on the baseline type: the random baseline analysis indicated that riding in pedestrian lanes is safer than riding in bicycle lanes, but the opposite was observed with the matched baseline. These examples show that the decision to use random or matched baselines should be made carefully, taking into account the trade-offs between controlling for confounders and capturing a broader range of potential risk factors. Ideally, using both methods in parallel, as was done in Paper II, can provide a more complete understanding of crash dynamics.

4.3.2 Baseline-to-SCE ratio

As explored in Paper II, increasing the baseline-to-SCE ratio leads to narrower confidence intervals and more statistically significant variables, enhancing the precision of the risk estimates. This observation is consistent with the findings of Hennessey et al. (1999) and Kang et al. (2009), who also noted similar improvements. However, this effect has diminishing returns at higher ratios, so the increased resources required for data collection and analysis may not be justified—similar to the effect shown by Hennessy et al. (1999). Video reduction and labelling, a key part of naturalistic data analysis, also require considerable time and resources; hence, the ratio chosen is ultimately a compromise between statistical considerations and available resources.

4.4 Opportunities with micromobility data

Micromobility data offer unprecedented opportunities to transform traffic safety research, moving beyond the constraints of traditional data collection methods that rely on police reports and hospital records, as well as avoiding the high costs of naturalistic data collection in the past. One key advantage is that modern e-scooters are equipped with a plethora of sensors that capture detailed kinematic data. These detailed data allow a granular analysis of rider behaviour before, during, and after SCEs, providing an objective view of the contributing factors. Furthermore, the continuously logged data enable the accurate measurement of exposure, a key aspect of risk assessment. This measurement is often challenging to achieve with other modes of transport, where data collection is limited and often unreliable (Dozza, 2020; Merlin et al., 2020). High-resolution exposure data can help researchers accurately identify usage patterns, providing information about when, where, and under what conditions e-scooters are used. The fact that rental e-scooters are becoming increasingly available in more cities creates unparalleled opportunities for scalability. By compiling large datasets from multiple cities, researchers and policymakers can develop a good understanding of the factors influencing micromobility safety, enabling the design of targeted, evidence-based interventions to improve safety across a wide range of traffic settings.

4.5 Limitations and future work

This licentiate thesis provides valuable insights into the factors influencing e-scooter crash risk using naturalistic data. Leisure trips, pack riding, and inexperienced riders were found to significantly increase crash risk. Additionally, it has explored the methodological implications of baseline selection, demonstrating how both random and matched baselines are necessary to get the full picture of crash dynamics. However, there were some limitations, which could be addressed in future work.

Although bicycles have a long history of research, with a well-established understanding of their operation, crash mechanisms, and associated risks, the relative safety of e-scooters remains less clear. Although this thesis has focused on the crash risk and prevalence of e-scooters, it is crucial to investigate how their crash rates and risks compare with those of cyclists, especially considering the differences in rider behaviour (Dozza et al., 2023; Li et al., 2023) and injury patterns (Cicchino et al., 2021a). This comparison is essential because bicycles are the most prevalent form of micromobility and have widespread acceptance as a relatively safe mode of transport. Previous studies have suggested that e-scooterists face a higher risk of crashes than cyclists, with some reporting that e-scooter riders are four to ten times more likely to be involved in a crash (Bodansky et al., 2022; Færdselsstyrelsens, 2020; Fearnley et al., 2020; Mcguinness et al., 2021). However, these studies often fall short by not accounting for geographical disparities or variations in usage patterns (such as comparing shared e-scooters with private bicycles)—or by employing different samples for crash counts and exposure estimates. As discussed in Section 4.4, the increasing availability of high-resolution exposure data at scale will enable a fair comparison and will be the focus of Paper III, as indicated in Figure 1.

A limitation of this thesis is the inherent challenge of capturing high-severity crashes within the naturalistic data. This is due to the nature of naturalistic data collection, which focuses on observing everyday behaviour and is unlikely to capture severe events which are often rare. Conversely, traditional crash databases, offer data on high-severity crashes, but often lack detailed pre-crash behavioural information and reliable exposure metrics. Paper IV (Figure 1) will address this limitation by focusing on combining crash databases and naturalistic data to determine if specific spatiotemporal factors are prevalent across critical events of varying severity.

It is also important to acknowledge that this thesis assumes that near-crashes can serve as proxies for crashes and thereby uses SCEs to estimate the OR. Knipling (2015) argued that SCEs, while useful, are not always equivalent to crashes, particularly in terms of severity. Therefore, future work may focus on establishing the relationship between SCEs and crashes of different severities, to ensure that this thesis' findings accurately reflect crash risk.

A final limitation of this thesis lies in the geographical area of the data collection, which was confined to Gothenburg, Sweden; the findings may not be generalisable to other cities. While similar naturalistic data collection and analysis in numerous cities might not be feasible due to the substantial time and resource requirements, the knowledge and methods developed in Paper I offer a pathway for broader application. Specifically, the detailed methodology for identifying crashes and near-crashes (as outlined in Section 2.2) allows for a real-time trigger-based detection of critical events (as discussed in Section 2.1). Future studies can leverage this approach to broaden the scope of analysis and facilitate a comparative examination of e-scooter safety across a wider range of infrastructure, as well as across diverse rider populations in various urban environments. The real-time SCE detection enables immediate follow-up questioning the riders while the details are still clear to them which could provide valuable contextual information. Paper V in this PhD will revisit the objective of e-scooters' crash causation by scaling critical event detection across multiple cities to identify patterns, primarily in terms of infrastructure characteristics, that contribute to SCEs.

CHAPTER 5

Conclusions

The risk factors highlighted in Paper I and Paper II strongly suggest that rider behaviour leading to unsafe e-scooter operation is more relevant than intrinsic issues with e-scooters themselves. These findings challenge the perspective that e-scooters are inherently dangerous; instead, the findings point towards the crucial role of rider choices and actions contributing to the occurrence of SCEs.

Papers I and II demonstrate that single-handed riding and phone usage during riding are significant risk factors, emphasising the need for targeted interventions and highlighting the importance of understanding how riders handle e-scooters, in terms of balance, steering, and stability. The high risk associated with single-handed riding suggests the need for micromobility rental companies to implement rider monitoring systems that can detect and prevent such behaviour. Similarly, the correlation between phone usage and increased risk suggests a use for technology-based interventions that limit top speed and/or alert riders when phone use is detected. Additionally, implementing regulations (similar to those for cars) banning phone use while riding could further enhance safety.

Furthermore, the result that leisure and detour trips have a higher risk of SCEs compared to commuting and point-to-point trips, respectively, suggests that the rider's intent and actions are pivotal in determining e-scooter safety. This observation goes beyond traditional notions of exposure-based risk, indicating that a rider's behaviour or activity during the trip is a key variable influencing crash risks. Therefore, micromobility rental companies can create targeted campaigns and educational initiatives for riders who primarily use e-scooters for leisure and detour trips, effectively mitigating potential risks. Rider inexperience is another significant factor in e-scooter safety, as evidenced by the fact that riders with five or fewer trips are more prone to SCEs. This inexperience, which extends beyond the mechanical operation of the e-scooter to a lack of familiarity with e-scooter dynamics and balance, may limit their ability to handle varied road conditions and complex traffic situations, thereby contributing to higher SCE risks. While some cities may require a driving license to ride e-scooters, this does not necessarily guarantee that the rider has the specific training and mastery needed for safe e-scooter operation. Instead, regulators, city officials, or even e-scooter rental companies can offer and mandate a short, targeted safety training program that is specifically tailored to e-scooter riding, which may be a more effective way to assist riders in safely navigating urban environments.

Methodologically, this thesis demonstrates the need to adapt definitions of crashes and near-crashes to suit the specific characteristics and usage patterns of new transport modes. Adapting these definitions is particularly crucial for e-scooters, due to the high incidence of self-induced crashes, which are uncommon in other vehicle types. Paper II revealed that using both matched and random baselines is essential to avoid overlooking key risk factors. While matched baselines may help control confounding variables, they can also mask the impact of significant factors like intersections, which are clearly identified as risks using random baselines. However, relying solely on random baselines may lead to inaccurate assessments of the impact of other variables. This methodological insight demonstrates the need to apply both approaches, when possible, for a more complete understanding of SCE dynamics. Furthermore, effective prioritisation of safety interventions requires considering the prevalence of risk factors. For instance, although single-handed riding may have three times the risk of pack riding, it has a third of the prevalence and therefore addressing it is of little benefit.

In summary, this thesis contributes to the field of micromobility safety by not only capturing the complexities of factors influencing e-scooter crashes but also underlining the need for tailored definitions of safety critical events. Regulators, city planners, and micromobility operators can benefit from the identified risk factors and can implement countermeasures such as rider training and risky-riding detection systems. Additionally, the use of both random and matched baselines in OR analysis provides a more complete picture of the risk factors involved.

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Appendix

A. Codebook (The symbols used in this table indicate the type of each variable as follows: Objective: #, Subjective: ~, Numerical: *, Categorical: +)

Variable	Subcategory/Entry type	Description
Rider experience$^{\#*}$	[Trips]	The number of trips previously taken on e-scooters from the same provider.
Phone usage$^{\sim+}$	Handheld, Using the phone holder, No phone usage	If there was any phone usage involved.
Pack riding$^{\sim+}$	Present, Absent	If the ego e-scooter rider was riding alongside other e-scooters or bikes.
Hand position$^{\sim+}$	Two handed, Single handed, No hands on	The hand positions.
Object on handlebar$^{\sim+}$	Present, Absent	If there was any type of object on the handlebar or the stem of the e-scooter.
Gloves$^{\sim+}$	Yes, No	If the rider was wearing gloves.
Type of road$^{\sim+}$	Bicycle lane, Sidewalk, Roadway, Shared, Other	
Type of road surface$^{\sim+}$	Asphalt, Cobblestone, Wood, Gravel, Grass, Tiles, Other	
Surface condition$^{\sim+}$	Dry, Wet, Icy, Snowy, Other	
Road issues$^{\sim+}$	Potholes, Obstructions, Other	
Intersection$^{\sim+}$	Signalized, Non-signalized, Roundabout	
Construction$^{\sim+}$	Present, Absent	

Visual occlusion~+	Present, Absent	
Lighting conditions~+	Daylight, Dark, Dusk, Dawn	
Weather conditions~+	Sunny, Cloudy, Rainy, Snowy, Other	
Temperature#*	[°C]	The hourly temperature recorded by Swedish Meteorological and Hydrological Institute (SMHI)
Wind speed#*	[m/s]	The hourly wind speed recorded by SMHI
Precipitation#*	[mm]	The hourly precipitation value recorded by SMHI
Directness factor#+	Detour, Point-to-point	The ratio of recommended distance by OpenStreetMap to the actual distance of the trip.
Trip purpose#+	Leisure, Commute	The trip purpose, determined using the k-means clustering.
Trip day#+	Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday	The day of the week the trip taken.
Trip distance#*	[km]	The actual distance travelled during the trip.
Trip duration#*	[s]	The duration of the trip.
Mean speed#*	[km/h]	The average speed the trip
Instantaneous speed#*	[km/h]	Speed at the precipitating event
GNSS co-ordinates#*	[degrees]	The GNSS co-ordinates of the event.
Conflict road user type~+	Pedestrian, Bike, E-scooter, Light vehicle (Car/Van), Heavy vehicle, Animal, None, Other	