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Modelling E-scooterist Braking and Steering for Collision Avoidance

TIANYOU LI

Department of Mechanics and Maritime Sciences

CHALMERS UNIVERSITY OF TECHNOLOGY

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TIANYOU LI

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Department of Mechanics and Maritime Sciences
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 3694

Cover:
Drawing of a rider riding an electric kick scooter (e-scooter) crossing an intersection. Image created by the author, with part of the background visual elements generated by artificial intelligence model Fotor M2 (fotor.com).

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ABSTRACT

Introduction: In the last few years, new road safety issues have emerged with the growing popularity of novel micromobility vehicles (MMVs). The term 'novel MMV' includes, in addition to electrically assisted bicycles, electric kick scooters (e-scooters) and Segway balance scooters (Segways)—which are usually distinct in appearance and operation from traditional MMVs (conventional bicycles). Developing validated models that offer a comprehensive understanding of the behavior of these new types of MMVs is crucial to inform the design of new, safer MMVs, active safety systems, infrastructure, and the making of regulations. This licentiate thesis includes two studies that shed light on how MMV riders perform longitudinal and lateral control of both traditional and novel MMVs at an operational and tactical level.

Methods: Study 1 analyzed field test data and compared the longitudinal control (i.e., accelerating and braking) of bicycles, an electrically-assisted bicycles (e-bicycle/e-bike), a light personal electric kick scooters, and a Segway balance scooters. Study 2 conducted field tests and compared both the longitudinal and lateral (i.e., steering) maneuvers in a rear-end collision avoidance scenario. A larger e-scooter from the public sharing systems replaced the Segway in the test. Comparisons were made among different types of vehicles, maneuvers, and urgency levels (i.e., maneuver comfortably as daily riding, or harshly as avoiding close danger), to determine the extent to which these novel MMVs, compared to traditional bicycles, demonstrate constraints in maneuverability, safety, and comfort.

Results: The results showed differences in longitudinal performance across vehicles, while no statistically significant differences were observed in lateral performance. Novel MMVs demonstrated poorer braking capability than bicycles and were perceived as less safe and maneuverable. Among the two e-scooters, the larger one could achieve shorter braking distances. Additionally, riders were able to improve their collision-avoidance performance by compromising comfort when urgency increased. Two kinematic models, linear and arctangent, were derived to predict MMV trajectories.

Conclusion: Compared to bicycles, novel MMVs demonstrate statistically significantly poorer in braking performance, which usually constrains the rider's collision avoidance capability. No statistically significant difference was observed in steering. The findings of this thesis have implications for improving road safety for MMVs by informing MMV design, infrastructure planning, policy-making, and consumer assessment programs. For example, EuroNCAP can incorporate the findings to design test scenarios for this new group of vulnerable road users (VRUs). They can also support the development of active safety systems and automated driving features for automobiles, enabling more accurate and acceptable system activations with respect to timing and magnitude in interactions with MMVs.

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1. INTRODUCTION

This chapter introduces the background of this licentiate thesis and presents a brief literature review focused on micromobility crashes and their causes and countermeasures, addressing several research gaps in existing studies. The aims and objectives, as well as the project outline, are also presented.

1.1. Micromobility vehicles and road traffic crashes

The term micromobility vehicle (MMV) can refer to a wide range of transportation products and solutions but has no commonly agreed definition or classification criteria. Several authoritative organizations define and categorize MMVs by considering a human-powered or electrically-assisted vehicle's curb weight and maximum speed as key criteria. According to SAE International [SAE, 2019], an MMV should have a curb weight ≤ 500 lb. (227 kg) with a top speed of 30 mph (48 km/h). The International Transport Forum (ITF) defines an MMV as a vehicle with no more than 350 kg mass and a top speed of 45 km/h [ITF, 2020]. In this licentiate thesis, a 'traditional MMV' is a human-powered bicycle; 'novel MMV' refers to electrically assisted bicycles (e-bikes), electric kick scooters (e-scooters), and Segway balance scooters (Segways).

Micromobility solutions as a means of personal transportation have seen rapid growth in recent years. Compared to motorized vehicles, MMVs such as electric bicycles and electric kick scooters (and their sharing systems) can offer cheaper, more flexible, and more sustainable travel compared with privately-owned motorized vehicle [Abduljabbar et al., 2021]. MMVs are particularly efficient for first-mile and last-mile trips within urban areas. Additionally, compared to mobility by walking, MMVs can offer reduced transport time and less muscle effort.

As MMVs continue to evolve and are introduced to the market in ever larger numbers, new types of crashes and injuries have also begun to emerge, creating new concerns and challenges [Abduljabbar et al., 2021]. A recent study has shown that the crash risk of riding an e-scooter is ten times higher than riding a bicycle [Fearnley et al., 2020]. E-scooter crashes often result in serious injuries which are different from the injuries experienced by cyclists; a high percentage of the former involve head injuries and concussions with loss of consciousness [Cicchino et al., 2021; Yang et al., 2020]. Upper and lower extremities are also commonly injured in e-scooter crashes [Serra et al., 2021]. Further, overcrowding and parking-rule violations caused by dockless MMVs (which can be left anywhere within a defined area) create safety concerns for other road users (e.g., pedestrians) in addition to being a public nuisance [Bai et al., 2022]. Thus, novel MMVs, especially e-scooters, face significant opposition from both the administration and other road users who share the infrastructure [Glavić et al., 2021; Maiti et al., 2022].

1.2. Existing research

In this section, existing research from various aspects (i.e., MMV users, crashes, and potential countermeasures) is briefly introduced. At the end, several existing literature reviews are recommended, and current research gaps are addressed.

1.2.1. Demographic profile of MMV users

Studies from different parts of the world have profiled MMV users. Reck et al. (2021) conducted a large-scale survey of shared e-scooter users in Zürich, Switzerland. They found that although shared e-scooters were the most expensive MMV option, they remained popular, which suggests that disposable income and price are not the main factors in the choice of transportation mode. The study's results also confirm previous research showing that innovators (i.e., the group of people who have the lowest threshold of resistance to the adoption of new ideas [Roggers, 1995]) and early adopters are often young, educated, relatively wealthy males. Additionally, dockless e-bikes and e-scooters included more older users than the docked sharing services; vehicle (i.e., e-bikes and e-scooters) owners and (public transport) season ticket owners of public transport are also more likely to use shared MMVs (both docked and dockless) than non-owners. Another study conducted in Taiwan has shown that young adults who are seen as potential catalysts for change toward travel by e-scooters. Additionally, females were found to be more likely to adopt and maintain the use of sharing e-scooters [Eccarius et al., 2020]. It was also found that the motivation for e-scooter use was balanced between necessity and leisure. "Necessity" users were more likely to live in urban areas with over 100,000 inhabitants, while "leisure" users were more likely to live in smaller areas [della Mura et al., 2022].

1.2.2. MMV Crash causation

Studies have found that MMV crashes often occur due to hazardous road surfaces, loss of balance, or vehicle malfunctions; e-scooter crashes are more frequent during summer, on weekends, and between noon and 9:00 p.m. The incidence of serious crashes increases after 7:00 p.m., suggesting that poor visibility (i.e., insufficient lighting, obstruction on the road), impairment caused by alcohol, and adverse weather conditions each play a role [Karpinski et al., 2022; Cicchino et al., 2021; Shah et al., 2021; Stigson et al., 2021; Liu et al., 2019]. However, when analyzing and interpreting MMV crashes, it is important to consider exposure as well (e.g., MMV exposure, hazard exposure, etc.). In traffic safety research, 'exposure' is the frequency, time, or spatial coverage of certain traffic events (e.g., number of MMVs per population, number of kilometers riden on MMVs, percent of time riding MMVs on sidewalk, the number of collisions per the number of vehicles present, etc.), some of which may create risk and opportunities for a crash to occur. By relating both the crash and exposure data to the risk assessment, we can better understand the causative factors of the crashes and develop countermeasures [Wolfe, 1982].

In Sweden, many MMV crashes occur during recreational activities or school commutes, particularly among youth and children who use bikes as toys, perform stunts, or lack biking skills [Axelsson et al., 2019]. Maintenance issues or distractions may also result in crashes [Kröyer, 2021]. Collisions between bicyclists and motorized vehicles usually occur in urban areas, where bicycle exposure is greatest [Boufous et al., 2011; Isaksson-Hellman, 2012]. Right turns by large vehicles pose a significant threat to MMV riders, primarily due to blind spots, and these crashes tend to be severe [Pokorny et al., 2017]. On the other hand, for novel MMVs, crashes which involve only the users themselves are the most common type [Schepers et al., 2018; Stigson et al., 2020]. For e-scooter crashes in particular, only around 10% of the injuries involved other road users (such as pedestrians), which are often due to collisions or falling caused by improperly parked scooters [Stigson et al., 2020] and collisions with e-scooters in wrong-way-riding [Das et al., 2023]; in half of these cases, pedestrians were hit by the e-scooter [Trivedi et al., 2019].

Tian et al. (2022) found that males who are frequent e-scooter users had a statistically significantly higher risk of crashes, while female users were more likely to be involved in injury crashes, as they had a greater tendency to ride on sidewalks and unpaved surfaces. In fact, riding an e-scooter on the sidewalk almost doubled the risk of injury, and riding in a bike lane decreased it. However, despite the risks, many riders still prefer to ride on sidewalks—due to a fear of motor vehicles, inaccessibility to bike lanes, and low awareness of regulations [Bloom et al., 2021]. Yang et al. (2020) found that children and senior e-scooter riders were more likely to suffer severe injuries, while the increased risk for the seniors starts at about 40–55 years of age and rises dramatically for older groups. Falling-off incidents and fatal crashes were more likely at night, while female riders were found to be involved in more falling-off crashes than males. Zhao et al. (2022) also found that age groups under 30 and over 60 were at significant risk in MMV-related crashes.

Crashes between MMVs and motorized vehicles were found to be frequent [Fang, 2022]. Even though only partially confirmed, research indicates that car drivers may react more slowly to e-scooters than to cyclists—and that drivers may perceive an e-scooter rider as a pedestrian, which may result in underestimating the rider's speed, thus increasing the collision risk [Das et al., 2023]. Additionally, e-scooters were found to be clearly distinguished from bikes in natural light, but less so in artificial light (i.e., at night) [della Mura, 2022]. MMV crashes involving motorized vehicles always result in more severe injuries [Fang, 2022], and males experience the majority of fatal crashes.

More crowded roads are associated with increased crashes between MMVs and other VRUs or other MMV riders [Gehrke et al., 2022; Folco et al., 2023; Tice, 2019]. Shin et al. (2022) identified road intersections, sidewalks, subway entrances, and land use mix index as significant factors in MMV-pedestrian crashes. According to a study by Maiti et al. (2022), e-scooter-pedestrian collisions are more likely in zones with higher encounter counts, and more unpleasant encounters between pedestrians and MMVs on university campuses were observed during lunch and commuting time than at other times. In Sweden, MMV-pedestrian collisions make up around 1%-2% of crashes, with the pedestrians incurring the majority of injuries [Kröyer, 2021].

Infrequent helmet usage is a grave concern, given the high speeds that these devices can reach (many crashes are reportedly due to excessive speed [Høye, 2018]). A substantial number of crashes involve alcohol and occur at night with bad lighting conditions [Das et al., 2023]. Riding under the influence of alcohol or drugs (RUI) increases the risk of MMV crashes: a significant proportion (7%-21%) of fatally injured bicyclists are intoxicated [Kröyer, 2021]. Depending on the dataset analyzed, the percentage of RUIs in e-scooter crashes ranges from 4.1% [Yang et al. 2020] to 38% [Kobayashi et al., 2019]. However, unified regulations regarding RUI for e-scooter riders are still lacking [Yang et al., 2020].

Infrastructure also plays a significant role in MMV crashes. Asphalt, concrete, and rough-painted tile provide adequate friction for MMV users, with skid resistance values between 55 and 75; asphalt and concrete are preferred, due to lower variability and vibration [López-Molina et al., 2022]. Painted cobblestone and smooth-painted tile pavement have low skid resistance, increasing the risk of crashes and traffic conflicts. Pavement defects such as pebbles, potholes, or cracks often trigger MMV crashes [Fang, 2022]. For e-scooter in particular, this is usually because the vehicle has small wheels and simple suspension which do not dampen vertical vibration very much [della Mura et al., 2022].

In summary, many factors may contribute to the occurrence of MMV crashes: the vehicles themselves, the riders' misbehaviors, the interactions with other road users, insufficient helmet usage, riding under toxication, and the infrastructure. It is also worth noting that safety concerns may evolve as MMV users and other road users gain experience with these means of transport.

1.2.3. Potential crash prevention measures and recommendations

Several studies have proposed potential solutions for MMV safety regarding the abovementioned factors—such as enhanced infrastructure, amended policies (e.g., speed limits, restricted zones, enhanced safety education, and requirement for helmets), and improved MMV designs (e.g., better braking systems and wheels, mandatory turn indicators) [Fang, 2022; della Mura et al., 2022; Prencipe et al., 2022; Glavić et al., 2021; Das et al., 2023; Tian et al., 2022; Tice et al., 2019].

Infrastructure that can better accommodate MMVs is frequently discussed. López-Molina et al. (2022) suggested using appropriate pavement materials for different types of bike lane (e.g., protected bike lane, sidepath) where MMVs are riden, and conducting further research on the influence of pavement condition and paint type on skid friction. Tice et al. (2019) highlighted the need for walk audits to include evaluations of the frequency of curb ramps and surface discontinuities. Kröyer (2021) concluded that infrastructure issues (e.g., inclement weather, gravel) should be addressed to improve safety by reducing the single-rider crashes. Maiti et al. (2020) and Gehrke et al. (2022) proposed better planning and infrastructure enhancement to reduce stress and crowding in traffic facilities.

Urban planners and transport administrators can also put effort to reduce MMV crashes from a policy and legislation-making perspective. Folco et al. (2022) proposed a new tool for optimizing for new micromobility track generation, travel demand, and riding safety. Models for evaluating MMV safety efficiency of urban areas were proposed by Prencipe et al. (2022) for identifying infrastructural improvements and the needs for stricter speed limits. Bai et al. (2022) proposed a shared responsibility framework including the public, city government, and private licensees, with the ability to use crowdsourced feedback to identify issues (e.g., park-related violations), adjust regulations, and modify user instructions. Shin et al. (2022) suggested using speed bumps, rumble strips, and traffic calming measures in highly dense areas to reduce MMV-pedestrian crashes.

In discussions among EU countries, a pan-European benchmark for e-scooter regulation was suggested. Areas to be harmonized could include technical requirements, safety elements, and sustainability. A joint EU framework should address the responsibilities of commercial e-scooter operators, particularly concerning issues like collisions and reckless parking [Sokolowski, 2020]. Yang et al. (2020) stressed the importance of mandatory helmet use;

innovative solutions are needed, since existing ones (e.g., embedded helmet box, helmet selfie) do not prevent helmetless users from riding shared MMVs [Serra et al., 2021]. Tian et al. (2022) addressed the need for public education, rider training, and stricter traffic violation sanctions. Reduced or adaptive (e.g., spatial, temporal) speed limits have also been also discussed [Tice et al., 2019; Kröyer, 2021].

MMV engineers and manufacturers should address the mechanical characteristics and performance of e-scooters (including acceleration, braking, and vibration) before introducing new products onto the market [della Mura et al., 2022; Das et al., 2023]. The crash risk could be reduced by increasing the visibility of MMVs, perhaps with appropriate lights and reflective parts. Reliable braking systems and adequate tires for MMVs also play important roles [Kröyer, 2021]. Further, communication between MMVs and motorized vehicles using vehicle-to-everything (V2X) technology could be a good investment for providers of shared MMVs [Baqer et al., 2022]; the technology could effectively prevent and right-angle collisions.

1.2.4. Advanced driver assistance systems (ADAS) and autonomous driving (AD)

The development of car ADAS and AD systems also plays an essential role in preventing MMV-to-car crashes. ADAS and AD systems aim to increase road safety efficiently by preventing crashes with cars and mitigating the injuries. Threat assessment is a sub-system in ADAS/AD that evaluates potential threats to aid the car in collision avoidance. Threat assessment algorithms are implemented to perceive and analyze the surrounding environment and inform the decision-making strategy, which dictates the vehicle’s response (such as a braking or steering-control intervention). Such systems measure risks through factors like distance, speed, and acceleration relative to the surrounding environment. If certain conditions are violated, the car will issue a warning to alert the driver and assist the driver in collision avoidance via overriding systems [Hamid et al., 2018].

Current threat assessment systems are classified as mainly physical model-based or data-driven (e.g., machine learning) based on the decision-making process. Physical model-based methods can be further divided into single-behavior threat metrics (e.g., time-to-collision, required acceleration), optimization-based, formal, and probabilistic approaches [Dahl et al., 2018]. These methods are often computationally inexpensive but may lack robustness and long-term accuracy due to simplification in the dynamic models. On the other hand, data-driven methods have attracted interest for the development of ADAS and AD systems, particularly for image segmentation. Much research in AD has been conducted on the detection and classification of pedestrians and bicyclists, utilizing the combination of deep learning and computer vision-based methods, such combination demonstrated relatively good performance [Apurv et al., 2021; Gilroy et al., 2022]. However, the detection of e-scooter riders has been largely overlooked. Moreover, these algorithms always require rich, large training data sets, and pose challenges related to computational power and memory allocation for real-time deployment. In addition, their applicability to core safety features requires further development, especially in the interpretability of the decision-making process [Dahl et al., 2018] and interference-resistance capability [Nassi et al., 2020].

Current threat assessment approaches in active safety systems face a trade-off between high performance and precision. Kinematic and dynamic models of other road users are key input for threat assessment systems. This input may be beneficial in predicting a nearby object’s trajectory and intention [Mohammadi et al., 2023] while reducing the probability of false alarms, which may also ease the high computational or training costs. Thus, by integrating new kinematics and dynamics models of novel MMVs into the ADAS and AD systems, as well as ADAS/AD's development process (e.g., simulation and virtual verification), the threat assessments may be further improved and thus the collisions between motorized vehicles and MMVs can be reduced.

One consumer rating program, the European New Car Assessment Programme (Euro NCAP), has been developing test criteria and scenarios for new car safety over the last two decades. As an advocate for safer cars, Euro NCAP has highlighted ADAS and AD technologies and raised awareness of their benefits in recent years [Roadmap 2025]. They will also react to the safety concerns brought by the emerging micromobility solutions [Roadmap 2030]. Thus, it is highly possible that novel MMVs will appear in the future test catalogue as distinct from traditional bicycles, inspiring the development of more comprehensive ADAS/AD systems in new cars.

Moreover, exploring the driving patterns and behaviors of individuals or groups is of great relevance in the development of ADAS and the evolution of AD systems from semi- to fully autonomous [Vilaca et al., 2017]. According to Michon et al. (1985), a driver's problem-solving tasks in traffic and transportation can be categorized into three behavioral levels: the strategic level (e.g., planning the goal, route, and transport modes of a trip), the tactical level (e.g., maneuvers of obstacle avoidance and overtaking), and the operational level (e.g., the basic control skills of accelerating, braking, and steering). We believe that understanding the tactical and operational behaviors of MMV users involved in traffic interactions can benefit car ADAS. In our study, we will not focus on the strategic level (planning).

1.2.5. Literature reviews

MMV safety is a novel research field which has witnessed the emergence of many studies. This section describes several literature reviews for interested readers to pursue further reading, especially for the aspects that are not focused on in this thesis, such as the history of MMVs, the development of sharing systems, the impact of MMVs on human travel behavior, etc.

Abduljabbar et al. (2021) conducted a systematic literature review (SLR) on micromobility, aiming to cover micromobility's history, challenges, barriers, and success factors using global case studies. The authors examined 328 publications from 2000 to 2020, providing insights into current trends and identifying future research directions that might overcome identified challenges and limitations.

Hossein Sabbaghian et al. (2023) conducted a comprehensive literature review to identify research gaps in safe micromobility infrastructure. The review includes 76 articles, with most studies conducted between 2020 and 2022 and e-scooters being the most researched mode. The review aims to inform micromobility designers and operators about safety considerations for different micro-vehicles on cycle paths, offering best practices to enhance safety. Şengül et al. (2021) reviewed 29 scientific articles after 2016 to analyze the impact of electric micromobility on travel behaviors, energy consumption, the environment, and safety regulations. The review also expects a significant increase in future studies within the relatively new field.

Orozco-Fontalvo et al. (2022) conducted a systematic review of electric micromobility (EM), particularly dockless shared electric scooters (DSES) and electric scooters for private use. The review includes 70 articles published since 2018. Various attributes were covered in the review, including e-scooter history, operation, user experiences, regulation, environmental impact, safety concerns, and pricing. The authors noted that research on e-scooters is relatively scarce due to their recent emergence. They also observed a shift in the nature of research, with more robust studies, including surveys and modeling approaches, being published after 2021.

Elmashhara et al. (2022) presented an overview of micromobility sharing system (MSS) users' (macroscopic) behavioral patterns by reviewing 203 academic research articles published between 2011 and 2020. The review identifies 25 key factors influencing MSS user behavior, categorized as temporal, spatial, weather-related, system-related, or user-related. Similarly, Liao et al. (2022) reviewed the literature on the usage patterns of MSS and the influential factors but also included electric car sharing.

Moran et al. (2020) conducted a literature review on the spatial arrangement and regulation of shared MMVs, exploring geofence tracking and spatial coverage analysis methods. Marques et al. (2022) presented a critical literature review on micromobility to evaluate its relationship with various research topics, including demanding populations, device manufacturing, infrastructure, safety, security, renewable energy sources, big data analysis, and mobility as a service (MaaS). The authors proposed a life-cycle thinking (LCT) approach to analyze micromobility.

1.2.6. Research gaps

Riding an e-scooter may lead to various types of crashes and injuries [Beck et al., 2020; Cicchino et al., 2021]. In fact, several studies have demonstrated that riding an e-scooter is riskier than riding a bicycle [Fearnley et al., 2020; Badeau et al., 2019]. Most research on MMV safety has primarily focused on analyzing crash reports that are gathered after the crashes occurred, typically by the police, hospitals, news, or insurance companies. Although these data provide information about the aftermath of a crash, they do not reveal the events that transpired immediately before or during the crash, meaning they may not offer insights into the causes of the crash. Additionally, these data often have limitations, such as underreporting and bias in the datasets [Kröyer; Yang; Bai; Maiti]. Studies on post-crash data have concluded that enhancing MMV design, infrastructure, and regulations is essential to accommodate these new modes of transportation. They have also proposed valuable recommendations and analytical tools for stakeholders. However, there is uncertainty regarding how these factors (i.e., vehicle dynamics and rider behaviors) may quantitatively impact MMV safety and the extent to which adaptations (i.e., in the vehicle design, infrastructure planning, and policy-making) should be described physically and mathematically.

A useful complement to post-crash data is the data collected in real-world settings, either through naturalistic observation [Dozza et al., 2014] or controlled experiments [Kovácsová et al., 2016]. Such data can complement the retroactively collected crash data and contribute to our understanding of why MMV crashes happen — and how they can be prevented [Dozza et al., 2022]. Naturalistic riding data provide a valuable opportunity for understanding riders' natural behavior due to its high ecological validity (e.g., the presence of various environmental factors such as road and light conditions [Ehsani et al. 2021]). However, naturalistic studies of riding MMVs are still very few, and the dataset is relatively small and lacks standards [I van Schagen et al., 2012]. On the other hand, field tests are conducted in a manner that is more controlled, thereby enabling the acquisition of a greater amount of data from pertinent scenarios. Even though field data collection could result in data with less variety and naturalness, it is still an efficient way in the early modeling stage to identify, extract, and study specific riding patterns, which may inform the standardization and contextualization for future data collection and analysis. Several field studies on e-scooter kinematics have helped us take the first step in modeling riding maneuvers (such as braking and slalom) of e-scooters from a top-down perspective [Garman, 2020; Klinger et al., 2022; Asperti et al., 2021; Vella, 2023]. However, these studies either based the modeling of MMVs on traditional bicycle models or experimented on a very small scale—in terms of participants, vehicle models, and riding maneuvers. These limitations make the models less effective for improving MMV safety, such as developing new threat assessment methods and planning safer infrastructure.

1.3. Aims and project outline

The primary research gaps in the field of MMV collision avoidance have been identified as follows: there is a lack of research concerning the dynamics of both the MMVs themselves and the behavior of the riders maneuvering them, and the interaction between these two components (e.g., how the rider controls the vehicle, and how the vehicle's response influence the rider's perception) as an interconnected system is still unknown.

To address these gaps, we formulated three main objectives of the overall Ph.D. studies:

1) Model behavior of MMV rider's longitudinal and lateral maneuvering in specific traffic scenarios from a top-down ("inductive") perspective. (Data are collected from field tests. Rider and vehicle are treated as an integrated system.)
2) Model e-scooter and rider-body dynamics in routine riding from a bottom-up ("deductive") perspective. (Data are collected from laboratory tests. The rider and the vehicle are treated as two standalone modules within in the rider-vehicle system.)
3) Develop a benchmark model that integrates both models derived from the studies on the first two objectives, utilize the models to create a simulation environment, summarize and verify the models and the simulation results, and validate with field test and naturalistic data.

The overall structure of the Ph.D. project, as depicted in Figure 1, includes several dynamic and behavioral models that tackle the aforementioned objectives. In this licentiate thesis, PAPERS I and II address the first objective by developing kinematic models for MMV-rider systems during braking and steering maneuvers and compares the models of bicycles, different e-scooters, and a Segway balance scooter. PAPERS III and IV, which are part of the future work from the licentiate to the Ph.D., will tackle Objectives 2 and 3. PAPERS I and II present kinematic models of the MMV motion of specific maneuvers within a limited timeframe on the tactical level, showcasing how e-scooters differ from bicycles in maneuverability. A proposal follows for the re-examination of MMV design, infrastructure planning, policy making, and active safety system development. PAPERS III and IV may shift the focus to the MMVs and their riders' operational-level behaviors (i.e., dynamics and control), as well as the interconnected rider-vehicle system in generic riding maneuvers. PAPERS I and II were developed within the project DICE, funded by Toyota Motor Europe. PAPERS III and IV will be within the project e-Model, which Chalmers University of Technology funds through the cooperation of the Vehicle Safety and the Vehicle Engineering and Autonomous Systems divisions.

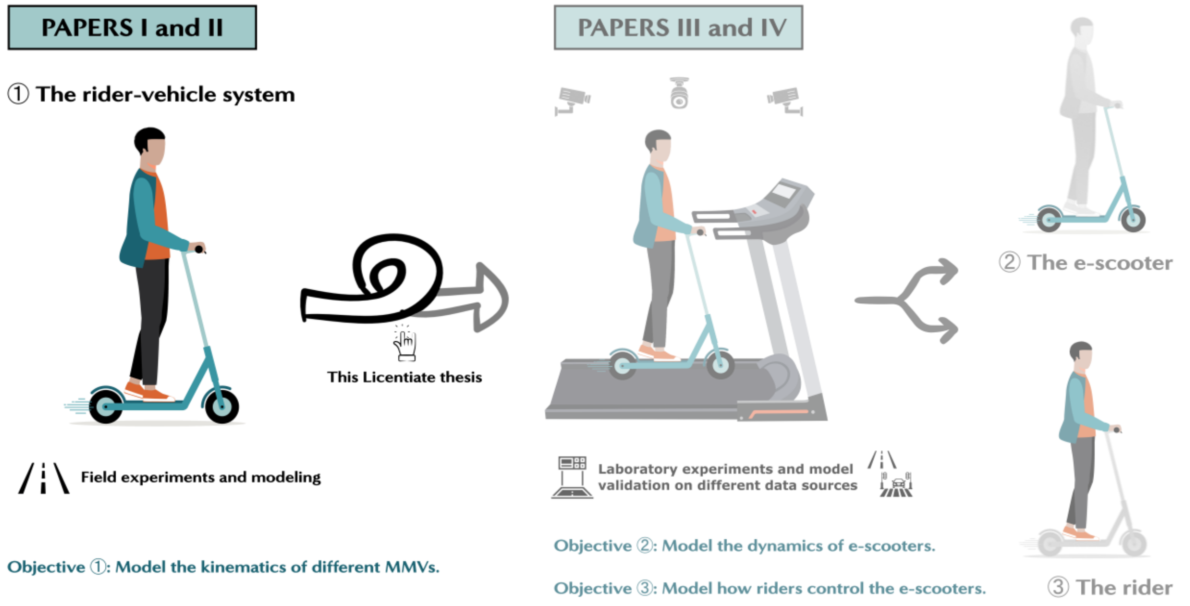

Figure 1. The overall framework of the Ph.D. studies. Four papers are planned, which will address the three objectives. Papers III and IV are future work for the second part of the Ph.D. project. In the first part of the project (Objective ①) we treat each rider and each of the vehicles as one system and model the kinematics of the MMVs in longitudinal and lateral manoeuvres. Then, we will modularize the system and study the two modules, respectively. We will, study 1) the e-scooters themselves from a vehicle dynamic perspective (Objective ②), and 2) the rider's body motion and control while riding the e-scooters (Objective ③).

In this licentiate thesis, we aim to delve into the first research objective with the help of field data. Since field data are collected in a controlled manner, we are able to efficiently derive quantitative kinematic models for specific scenarios (e.g., braking, overtaking, turning) in the data analysis phase. The models, after further validation, may inform the countermeasures for MMV crashes and shed light on:

1) The development of safer MMVs.
2) The development of ADAS/AD (i.e., to reduce uncertainties in threat assessment by improving accuracy of trajectory prediction).
3) The planning of the infrastructure (i.e., to optimize the width, pavement, curvature, and visibility of the road).
4) The making of policies (i.e., lower speed limits, requirements for helmet use and rider education).
5) The rating programs (i.e., assist the design of test scenarios for car-to-MMV crash avoidance).

2. METHODOLOGY

This thesis includes two field experiments conducted in Gothenburg, Sweden, to study rider control of MMVs from a top-down perspective. This chapter introduces the general methodology, the design of the experiments, data collection, data analysis, and the mathematical models used to describe MMVs' longitudinal and lateral control.

2.1. Methodology overview

As mentioned above, we addressed the research questions using data collected in field experiments on a test track. Field data are collected in a real-world setting, often according to an experimental protocol that constrains the parameters and variables such as riding maneuvers, velocities, and road surfaces [Mullen et al., 2011]. Field data are usually collected at a dedicated site (e.g., a closed test track), using vehicles instrumented with sensors [Boda, Dozza, et al., 2018; R. Kiefer et al., 2003; Najm and D. L. Smith, 2004]. Laboratory experiments (using driving/riding simulators) and naturalistic studies are two other common approaches in transportation research. The former are conducted in artificial settings where the researchers rule out as many extraneous variables as possible, resulting in high internal validity, and the possibility to study behaviors that are unsafe to study on real roads [Shinar, 2017; Boyle, 2020]. On the other hand, naturalistic studies allow the collection of vast amounts of data in the real world without constraining the variables: the riders perform their usual daily activities, often without being aware of the ongoing experiment [Shinar, 2017]. Naturalistic data has the highest ecological validity of the real human behaviors and may support the virtual safety assessment (e.g., a counterfactual simulation that virtually compares the performance of collision avoidance with/without a specific active safety system, which usually includes mathematical models of the driver and vehicle [Bärgman, et al., 2017]) of new active safety systems. Generally, field experiments offer a higher ecological validity than laboratory experiments since the experimental setting is highly realistic, and the tasks are usually contextual and similar to the participants' natural behavior (outside the experiments). Compared to naturalistic studies, field experiments also guarantee an easier manipulation of related variables and the control of the extraneous ones.

However, there are also challenges in field experiments. Firstly, the selection criteria for participants, vehicles, and test scenarios create biases in the data (and an inevitable poorer generalizability of the results). Sometimes, the participants may not behave naturally since a field test is still experimental, and the setting may not be fully realistic [Green, 2000; Hoffman et al., 2002]. They may act in a way they think the researchers expect or be unconsciously affected by the potential learning effect. Even though field experiments ensure a high control over the variables, they may still be interrupted by certain uncontrollable extraneous ones, such as weather conditions. Comprehensive preparation well in advance of the experiments is needed to address some of the challenges. These preparations include, but are not limited to, the design and installation of a robust data logging system, a prudently designed experimental protocol validated in a pilot phase, an ethical approval by an ethics review board, and countermeasures for potential risks (e.g., insurance that covers any possible injuries).

Our ethical application No. 2022-00314-01 was reviewed and approved by the Swedish Ethical Review Authority (Etikprövningsmyndigheten, referred to as "the Authority") well before the field tests began. The major ethical concern identified by the Authority was: 1) The research is carried out according to a method that may affect the research subject physically or psychologically, or the research involves an obvious risk of harming the research subject. In other words, the participants might fall off the vehicle and hurt themselves, and on some occasions, they might feel uncomfortable performing the given tasks (e.g., to not brake/steer until the researchers give a signal). In practice, before the field tests started, we explicitly explained the potential risks and gave the participants enough time and training to feel comfortable with the equipment. We also offered protective gear and let them read the terms of the pre-purchased commercial insurance. The participants had the right to abort the experiments at any time. In addition, we did not accept people who had previously been in serious traffic crashes, to avoid potential psychological harm. Another concern of the Authority was: 2) The research will collect sensitive personal data and make exclusion criteria based on certain biometric information (e.g., height, weight). When participants sign up for the experiments, we would ask them to provide health and biometric data. Such data could make one able to uniquely identify a person; the data are thus sensitive and should be handled in a highly confidential manner. Before requesting these data from the participants, we indicated that the participants have the right (informed consent) to not provide them; all the data are collected only on a hard copy (handed to the participants), which will be physically locked up in the Chalmers facility and are accessible only to the experimenter(s). As for the exclusion criteria, we would exclude a participant only if his/her height and weight exceed the minimum/maximum safety limits of the equipment. However, we must admit such limitations that only the "average" humans within certain height, weight, and age ranges, are studied. Future study must adapt in the design, equipment, and protocol to include the "minority" in the data collection and analysis, but not to ignore them.

To summarize, this licentiate thesis presents two field experiments within the DICE project. The experiments employed similar protocols but studied different MMVs and riding behaviors in different maneuvers and used different fitting models in the data analysis. Future Ph.D. work could also employ laboratory and naturalistic studies. In the following Section 2.2, the field experiments will be presented in detail.

2.2. DICE field experiments

2.2.1. Vehicles and instrumentation

Table 1 shows the specifications of the vehicles used in the experiments. In Study 1, we used the MONARK bike (the same one bicycle used in both assisted/unassisted modes), the small personal e-scooter (hereafter s-scooter), and the Segway balance scooter (Segway). Study 2 used the MONARK bike, the s-scooter, and the larger public-sharing e-scooter (l-scooter).

On each vehicle, we installed several sensors controlled by a single-board computer. Figure 2 shows the configurations for the tested MMVs. A Raspberry Pi 3 model B gathered all the inputs from IMUs (PhidgetSpatial 3/3/3 1044_B, sampling rate 125Hz) and a potentiometer that measures the steering angle if the vehicle has a center column. The signal from the potentiometer was converted by an analog-to-digital converter (ADC) module.

Table 1. Specifications of the vehicles used in the experiments.

	Bike	**E-bike**	**S-scooter**	**L-scooter***	**Segway****
Model	MONARK Karin 3-VXL		Segway Ninebot ES2	Segway Max Plus X	Segway Ninebot S
Weight [kg]	17.8	21.8	11.3	31.5	12.8
Power	N/A	250W Front motor	300W Front motor	400W Rear motor	2 x 400W Transverse
Drive mode	Pedaling	Front wheel assisted pedaling	Pure electric FWD	Pure electric RWD	Pure electric AWD (2WD)
Max. speed [km/h]	N/A	25	25	25	16
Braking system	Front disc Rear coaster		Front electric Rear fender	Front electric + drum Rear electric + drum	Electric
Wheels	28’’ Pneumatic tires		8’’ Front 7.5’’ Rear Solid rubber tires	11.5’’ Front 10’’ Rear Rubber + gel filled tires	10.5’’ Tubeless tires

* The L-scooter was only used in Study 2.
** The Segway was only used in Study 1.

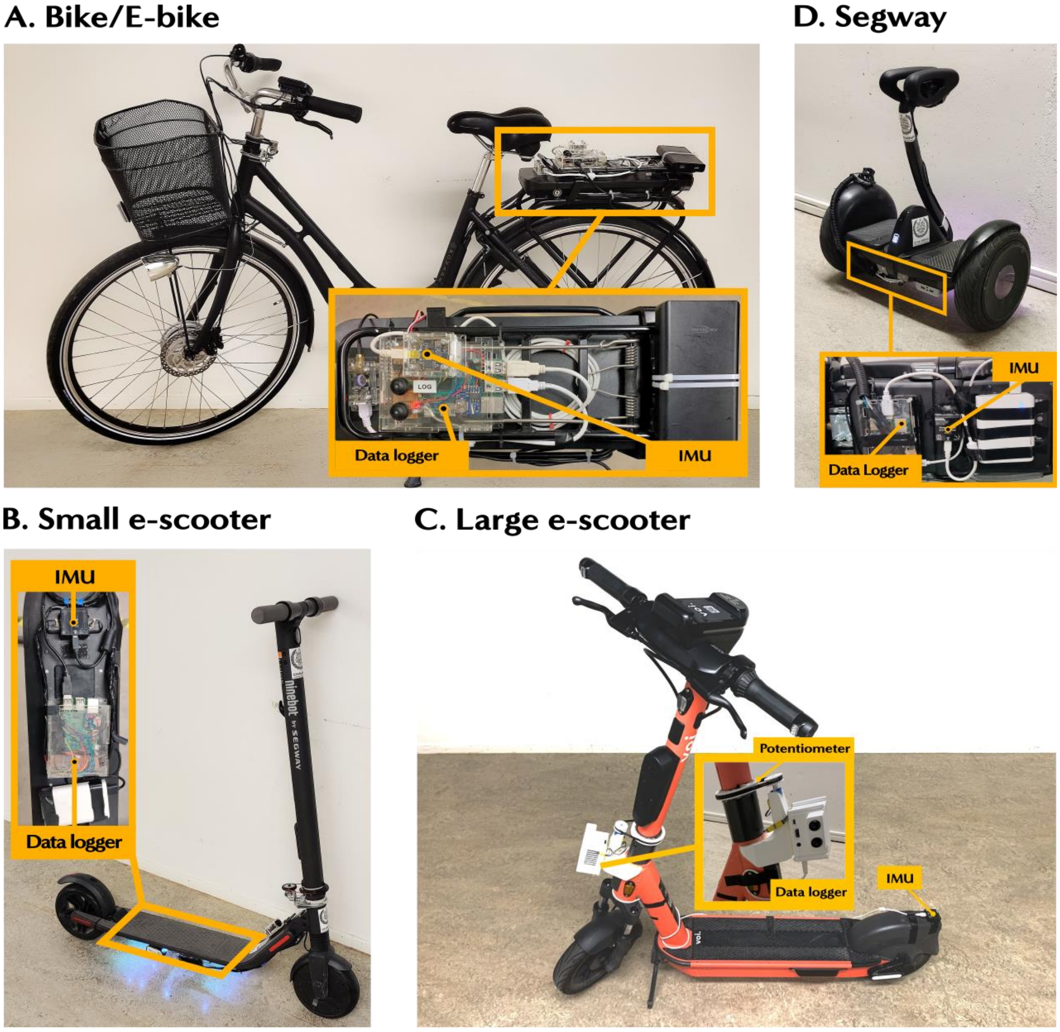

Figure 2. Data loggers installed on the four vehicles used in two experiments.

2.2.2. Test environment

In both experiments, the participants were asked to ride different types of MMVs and perform specific riding tasks on a test track. Sensors used for data collection were installed on the vehicles (i.e., IMUs: inertial measurement units and potentiometers) or placed by the side of the test area (i.e., LIDAR: light detection and ranging sensor and a camera).

The LIDAR with a camera sensor was placed at a fixed position by the side of the test area. A LIDAR measures distances and detects objects by transmitting laser pulses and measuring their return time. In our experiments, a HOKUYO UXM 30LAH EWA single thread LIDAR was placed by the right side of and facing the test track (Figure 3). The distance between the LIDAR and the center of the test track is 5m in Study 1 and 3m in Study 2. A camera sensor was attached to the LIDAR to record image data.

Figure 3. Photo of the test area.

2.2.3. Experimental protocol

Both experiments took place on a straight paved road that was long and flat enough to ride MMVs comfortably, with little to no traffic nearby. In both experiments, the participants were asked to complete specific maneuvers with two levels of urgency, planned comfortable and harsh. In planned comfortable maneuvers, the rider performs a riding task such as accelerating, braking, or steering as comfortably as possible. In the planned harsh maneuvers, the rider was asked to take action as late as possible without endangering themselves by crashing or falling off. Specifically for Study 1, a third urgency level, "unplanned harsh", was included. In the unplanned harsh maneuvers, the experimenter would give out an auditory signal at random time and the participant was asked to respond by braking as hard as possible.

Study 1: Longitudinal control

The first study was a continuation of the data analysis from the master's thesis [Billstein et al., 2021] "Evaluating the Safety and Performance of Electric Micro-Mobility Vehicles Comparing E-bike, E-scooter and Segway Based on Objective and Subjective Data from a Field Experiment." Figure 4 shows the riding tasks in Study 1. Each participant was asked to perform the three braking tasks (two planned and one unplanned) on each of the four vehicles configurations (12 tasks in total). In every task the participant was asked to firstly accelerate the vehicle to a speed of 17-20km/h (the speed was visible to the participant via a screen on the vehicle) and try to keep the speed as constant as possible. For the planned braking maneuvers, a line was marked on the ground; the participant was asked to stop the vehicle by braking before the line, however whether he/she stopped before or after the line at last did not matter. The distance between the position where the participant stopped and the where the line would be extracted and analyzed later as an indicator for the braking performance. The order of the vehicles and tasks was balanced for each participant, and we revealed the next task after the participant had finished the previous one. All trials were completed for each vehicle before the rider rode a different vehicle.

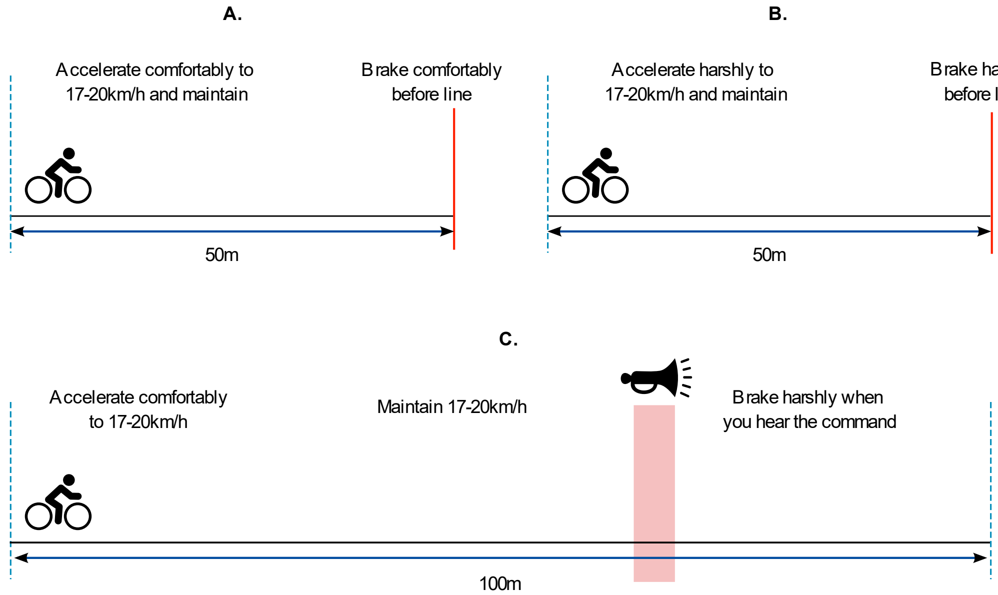

Figure 4. Experimental protocol in Study 1. Panel A: accelerating and braking comfortably. Panel B: accelerating and braking harshly. Panel C: braking harshly in response to a command from the experimenter; in this condition, the ridden distance was greater than in the other conditions (100 m vs 50 m) to increase the variability of the braking command time.

Study 2: longitudinal and lateral control

The four vehicles tested in Study 2 were the bicycle (with/without electrical assistance), the l-scooter and the s-scooter. The second experiment modified the protocol proposed in Study 1:

- An obstacle made of cardboard and wrapped with an image of the back of a car was placed 15m before the end of the test track. This fake car obstacle was soft and would not hurt a rider if a collision happened. However, if a rider crashed into the obstacle, we would ask them to repeat the riding task until they could either safely stop in front of it or overtake it.
- In all the trials, the rider was asked to accelerate to a speed over 15km/h and keep the speed as constant as possible before performing the maneuvers. The riders could see the speed on the vehicle display.
- Two lateral overtaking maneuvers, differing in level of urgency (whether the steering was comfortable or harsh), were added to the task list. The rider was asked to perform the steering maneuver without using the brake and to overtake the cardboard car on the left side.
- In addition to the four normal maneuvers (i.e., comfortable/harsh, braking/steering, each was performed once), each participant was asked to perform one task thrice (comfortable braking/steering on non-assisted bike or l-scooter) at the beginning, middle, and end of their experiment session to record a potential learning effect.

Figure 5. shows the proposed experimental protocol in Study 2.

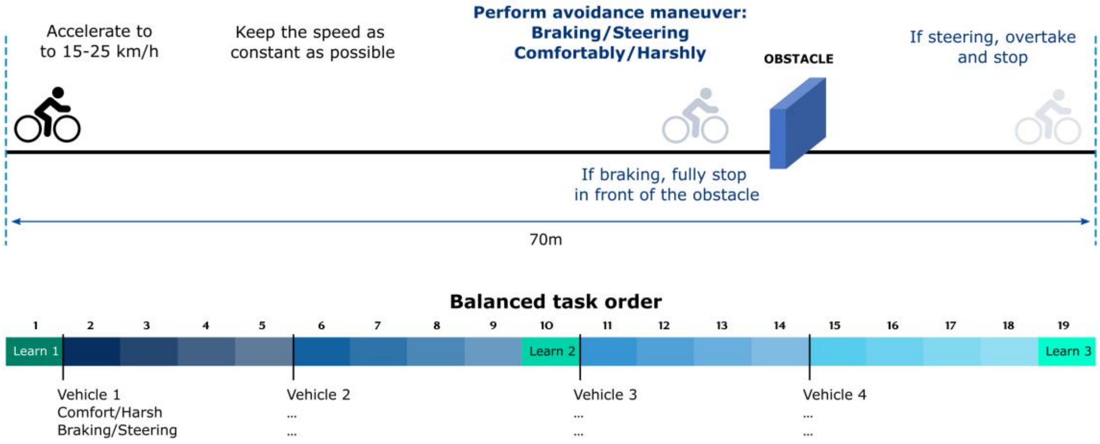

Figure 5. Experimental protocol in Study 2. For each vehicle, the four tasks, comfortable and harsh braking and steering, were shuffled for every participant. Each participant performed 19 trials in total. The 1st (Learn 1), 10th (Learn 2), and 19th (Learn 3) trials, equal for each participant, were used to control for a learning effect.

2.3. Field data analysis

The data was preprocessed before further analysis. The times of the on-vehicle sensors and the LIDAR were synchronized by removing the difference in time between the flag events (i.e., the recorded button-press events when the experimenter tried to press the buttons on the vehicle-logger and the LIDAR-logger at the same time, with one hand for each of the buttons). There was a loss of accuracy due to the asynchronous hand actions and a discrepancy between the logging-systems' response times, but the deviation was less than 0.5s. Calibrations between the frames of reference for the IMU and potentiometer and that of the vehicle were applied to the signals, to remove the offset at the zero point. A rotational transformation was also applied to eliminate the effect of gravitational acceleration components acting on the longitudinal and lateral directions due to pitch (mainly the Segway) and roll.

2.3.1. Vehicle data

The vehicle data were processed in four steps:

1) Low-pass filtering on all the signals.
2) Segmentations in terms of time were applied based on specific thresholds for velocity, acceleration, and lateral offset, in order to identify and extract braking and steering maneuvers.
3) Mean correction of the steering angle.
4) A Madgwick filter with IMU measurements was used to estimate orientation.

Velocity and position data were derived by integrating the measurements of the IMUs. This approach worked for our data across a relatively short time span (i.e., a few seconds for each maneuver), before the accuracy dropped significantly as the errors accumulated.

2.3.2. LIDAR data

The LIDAR data consist of 2D point clouds. The field of view was limited to ±50m in the longitudinal direction of the test track and [2m, 9m] in the lateral direction, to avoid potential "noise" clusters from the environment. A DBSCAN algorithm [Ester et al., 1996], which clusters point-cloud data based on density, was tuned and used to cluster the LIDAR data. The center of the identified rider-vehicle cluster was used to represent the MMV. Velocity, acceleration, and jerk data were calculated by deriving the center's position.

2.3.3. Kalman filtering with Rauch-Tung-Striebel (RTS) smoother

Combining vehicle and LIDAR data allowed the trajectories to be reconstructed more accurately than they would be with only one data source. A Kalman filter with RTS smoother was used to reconstruct the trajectories. This filter is an iterative algorithm that approximates the current condition of a dynamic system by merging predictions from a system model and sensor measurements. It incorporates a noise covariance matrix to accommodate uncertainty in both the process (system) and measurement models. The RTS smoother is a continuation of the Kalman filter that operates after the filtering process. It enhances state approximations by considering previous and future measurements, resulting in a more refined, precise estimation of the complete states over time [Rauch et al., 1965]. In essence, the Kalman filter focuses on the present, while the RTS smoother enriches it with hindsight and foresight to generate a smoother state approximation. For the longitudinal maneuvers (i.e., accelerating and braking), a one-dimensional (distance) prediction model was used in RTS, while for lateral maneuvers, a two-dimensional model was used.

2.3.4. Fitting models and generalized linear mixed-effect (GLME) analysis

Study 1: Linear models

We followed previous research [Kovácsová et al., 2016; Lee et al., 2020] that used linear regressions to characterize the acceleration and deceleration maneuvers (i.e., constant acceleration assumptions) in the five tasks (readers can refer to Figures 3 and 4 in the appended Paper I for more details). The goodness of fit of the linear models was assessed by calculating the coefficient of determination (R^2). The maneuver segments with the linear models applied were defined as follows:

1) Braking: starting when the vehicle speed falls below 16 km/h (12 km/h for the Segway) and ending when it drops below 2.5 km/h.
2) Acceleration: starting when the vehicle speed exceeds 2.5 km/h and ending when it exceeds 16 km/h (12 km/h for the Segway).

Additionally, the distance traveled to achieve a complete stop during braking maneuvers was logged. The deviation between the marked line and the actual stopping position of the participants was also analyzed, to evaluate their ability to estimate their braking distance accurately. Furthermore, the response time for the unexpected braking task was computed, to investigate whether the type of vehicle influenced the time it took for the participants to initiate deceleration after receiving the stop command. The reaction time in the unexpected braking maneuver was defined as the period starting when the experimenter issued the stop command and ending when the speed had decreased by 1 km/h.

Study 2: Arctangent models

Several studies have shown that jerk, the change rate of acceleration, is widely used in threat assessment of cars and motorcycles, aggressive driver identification, and optimal trajectory planning in automated vehicles and robots [Galvani, 2013; Piprek, 2020]. To further explore the accuracy and naturalness of the kinematic MMV models, in Study 2 we explored the maximum achievable jerk as a parameter of the rider's control during braking and steering maneuvers. We compared the linear model with an arctangent model to determine which better described the kinetics.

Like the linear models, the braking and steering maneuvers were segmented based on velocity thresholds. Additionally, two thresholds (for acceleration and jerk) were added, since we no longer assumed that the acceleration was constant, or the jerk was zero.

We could efficiently compute the maximum instant acceleration and jerk by fitting the trajectory and velocity profiles with arctangent functions. We also explored the four coefficients of the arctangent models.

Generalized linear mixed-effect (GLME) analysis

Several GLME models were created to ascertain the outcomes' significance in the comparisons. These models incorporated participant ID as a random effect and considered age, sex, vehicle type, and emergency level as fixed factors. We also created GLME models to study a potential learning effect based on the three extra trials performed by each participant. Whenever a factor with more than two categories displayed significance, post-hoc tests were conducted on the model's outcomes. The threshold for statistical significance was set at $\alpha = 0.05$, adjusted using the Bonferroni correction to manage multiple tests across diverse analyses with uncorrelated measures.

Subjective data

Upon completing all tasks, participants were asked to respond to a questionnaire. The questionnaire sought to obtain two types of information: (1) the participants' demographic details and their level of previous experience with the MMVs used in the experiment, and (2) their evaluations of the MMVs' performance throughout the experiment. For the second part, participants were asked to rank the four vehicle configurations on a 7-point Likert scale [Dawes, 2008], with 1 indicating "very poor" performance and 7 indicating "exceptional." Six performance categories were assessed: mounting and dismounting, maintaining balance, sustaining a constant speed, braking capability, steering capability, and acceleration from a standstill. Furthermore, participants were asked to assign a score, using the same Likert scale, to each vehicle configuration based on their perceptions of its overall comfort, maneuverability, stability, and safety.

3. SUMMARY OF APPENDED PAPERS

The rise of novel micromobility vehicles (MMVs) like electric kick scooters (e-scooters) is reshaping city travel, offering potential solutions to congestion and pollution. However, safety concerns arise as e-scooters pose a higher crash risk than bicycles, leading to different types of injuries. Existing safety studies rely mostly on post-crash data, which offer limited insights into why these accidents happen. Field data through controlled field experiments could help us understand the causes behind crashes, since the data can be used to quantitatively model both MMVs and rider behavior.

Understanding the unique kinematics of MMVs is crucial for the safety of all road users. Advanced Driving Assistance Systems (ADAS) have been effective in reducing road fatalities, but to enhance road safety further they need a better grasp of MMV users' behavior. Current ADAS models do not account for MMVs, since the latter have evolved quickly and there is still a lack of research in this area. To address this gap, it is crucial to develop a method to model and compare the braking and steering controls of novel MMVs and bicycles, in order to obtain crucial insights for ADAS threat assessment and, in turn, improve road safety.

3.1. Paper I: How do different micromobility vehicles affect longitudinal control? Results from a field experiment

This study compares longitudinal control among different MMVs, focusing on improving threat assessment of active safety systems and understanding how novel MMVs differ from bicycles. A field experiment was designed to investigate how riders perform longitudinal control (i.e., acceleration and braking) in different urgencies on different MMVs, and to create a potentially appropriate model to describe and predict MMV trajectory mathematically.

Thirty-four participants took part in a controlled field experiment, repeatedly performing five maneuvers on a closed test track: comfortable and harsh acceleration and comfortable, planned harsh, and unplanned harsh braking. They rode four different vehicle setups: a bicycle in either human-powered or electrical-assisted mode, a light personal e-scooter, and a Segway balance scooter. The participants were asked to fill in a questionnaire to record their qualitative feedback (e.g., perceived safety, controllability).

The analysis of the collected data shows that the performance of acceleration and deceleration varies among the vehicles; the e-scooter and the Segway have less efficient braking capability than bicycles. The electrical assisted (the e-bike) or powered (the e-scooter and Segway) vehicles demonstrated greater acceleration from a standstill in both comfortable and harsh acceleration maneuvers than the non-assisted bicycle. In the experimental emergency situation (the unplanned, harsh braking condition), riders could perform braking maneuvers at approximately twice the deceleration rate of their comfortable maneuvers, for all vehicles. The bicycle (in either mode) was perceived as safer, more stable, and more maneuverable than the Segway or the e-scooter. Finally, the linear regression models assuming constant acceleration for acceleration and braking could accurately describe the MMVs' kinematics during those maneuvers.

This study highlights how different MMVs influence rider behavior and vehicle control. We also found that the participants performed poorly on the Segway in the field experiment, implying the need for adequate training before novice users ride in traffic. The linear acceleration and braking models are sufficiently accurate for use in predicting trajectories for safety systems like automated emergency braking (AEB). These models could also help consumer rating programs, such as Euro NCAP, design test protocols for crash avoidance systems. This study emphasizes the growing need to model human behavior as novel MMVs enter the increasingly automated and connected transport systems nowadays. Future research should also investigate the role of infrastructure design and regulations in improving the safety of MMV riders and other road users.

3.2. Paper II: Modeling collision avoidance maneuvers for micromobility vehicles

Braking may not be the optimal collision-avoidance strategy for some novel MMVs (e.g., e-scooters); under certain circumstances, lateral maneuvers could be a better option. This study extends the study in Paper I by adding a lateral maneuver (steering), with the aim of refining the linear kinematic models by considering both longitudinal and lateral jerk as key indicators for threat assessment. This study also includes a large, public-sharing e-scooter, as the e-scooter sharing system has seen significant growth in recent years, and these models are very different from personal e-scooters.

Following the methodology in the prior investigation, we conducted a comparative analysis of a large e-scooter and a small e-scooter in relation to a bicycle (in both assisted and non-assisted modes) during field trials in a rear-end collision scenario. The aim was to ascertain whether e-scooters exhibit distinct limitations in maneuverability when attempting to avoid a rear-end collision through braking or steering. Thirty-six participants were recruited for the experiment, during which they were asked to repeatedly perform controlled braking and steering maneuvers, both comfortably and harshly, on each of the four vehicles. Additionally, a questionnaire was distributed to gather qualitative feedback from each participant.

The results show that the braking capabilities of the various vehicle types differ in terms of deceleration and jerk. Bicycles exhibit better braking performance than both e-scooters, and the larger e-scooter demonstrated better braking performance than the smaller one. However, there was no statistically significant difference in the vehicles' steering performance. Both e-scooters were perceived as less stable, maneuverable, and safe than bicycles. Moreover, this study introduces arctangent kinematic models (for both braking and steering).

The findings of this research indicate that the maneuverability features of the new MMV solutions deviate considerably from those of bicycles. In a near-rear-end collision situation, steering may be a more effective strategy to avoid crashes than braking for an e-scooter. Importantly, educating e-scooter riders to adapt their behavior accordingly (steering away rather than braking) could improve their safety. Furthermore, it is suggested that the arctangent models can be implemented in ADAS to prevent collisions between cars and MMV users by anticipating the trajectories of MMVs. Understanding these differences could provide valuable insights for designing infrastructure and formulating traffic regulations. Finally, further research is needed to determine if jerk is an appropriate parameter for modeling MMV rider behavior and improving threat assessment engineering. Future studies should also focus on improving the models of the vehicles' inherent dynamics and developing interconnected vehicle-rider systems.

4. DISCUSSION

4.1. Methodology for field data collection

In Studies 1 and 2, we employed a consistent approach to vehicle instrumentation, field data collection, and data processing [see Lee, et al., 2020; Billstein & Svernlöv, 2020]. The selection of vehicles for the field test experiment was based on factors such as popularity, availability, maintainability, ease of sensor installation, and rideability. The chosen vehicles represented the most common micromobility transportation modes, including those that can be privately owned and those available in public sharing systems. However, the electric-assisted bicycle in human-powered mode (with the electric motor turned off) is different than a "real" non-assisted bicycle in terms of sitting position, load distribution, and braking. These differences could affect the dynamics of the riding maneuvers.

Overall, the logging system demonstrated a relatively high accuracy, robustness, and adaptability to different vehicle configurations. Future improvements should include assuring higher availability of the data. Methods to achieve valid time synchronization between the vehicle and the stationary LIDAR should be explored, as these components were the primary cause of data loss (some data had to be discarded due to synchronization failure).

The experimental protocols for the field tests were solid and comprehensive, demonstrating good repeatability and suitability for future data collection. The protocols covered different maneuvers and urgency levels, representing several common scenarios (i.e., accelerating, braking, and steering) in MMVs' general riding and collision avoidance activities. As expected, both studies identified statistically significant distinctions in the collision avoidance performance during different riding activities on different MMVs: the e-scooters demonstrated statistically significantly poorer braking performance compared with the bikes but no statistically significant difference in steering. The e-scooters were also perceived as statistically significantly less stable and maneuverable than the bikes.

In Study 1, we could easily extract accelerating and braking maneuvers and make comparisons. The linear models in Study 1 achieved high accuracy and succeeded in describing the longitudinal maneuvers with short computation time due to its simplicity (i.e., riders accelerate and brake with constant acceleration). The models could be used to predict stopping distance and estimate whether a rider can brake and stop in time to avoid a collision.

In Study 2, modifications and expansions were made to the experimental protocol and modeling approach from Study 1. A lateral maneuver (steering to avoid a frontal collision) was introduced, in addition to a new publicly shared e-scooter model for the field test. This additional testing provided evidence that steering may be a safer option than braking for e-scooter riders when it comes to collision avoidance, as e-scooters demonstrated poor braking performance. Furthermore, the inclusion of jerk (the third derivative of position) in this study resulted in another descriptive model (the arctangent model) for collision avoidance maneuvers.

The coefficients of the models in Study 2 offer the potential to predict even more information (i.e., higher derivatives such as jerk) than the linear models used in Study 1 without introducing too much extra computational expense.

Questionnaires were used in both studies to collect qualitative feedback regarding perceived safety, stability, comfort, maneuverability, and performance. The subjective data obtained from the questionnaires demonstrate that riders perceive that e-scooters and Segways are less stable and secure than bicycles. As anticipated, the l-scooter received significantly higher scores than the s-scooter did. This difference could be attributed to the more advanced suspension, braking, and propulsion systems of the l-scooter. Furthermore, the riders also scored both e-scooters lower in steering, braking, and maintaining balance; these results were statistically significant. They demonstrate the significant differences perceived by the riders in the operation of e-scooters. Thus, rider education, e.g., how to operate novel MMVs, may be needed.

4.2. The use of MMV models for threat assessment in ADAS and AD systems

In Study 1, linear models were developed that were able to describe the longitudinal maneuvers of accelerating and braking. The predictable nature of accelerative and braking maneuvers on MMVs, owing to constant accelerations, means that these models could prove valuable for ADAS and AD systems and automated vehicles. The linear coefficients can anticipate stopping distance, allowing the systems to estimate whether a rider can brake and yield in time to prevent a collision. The investigation further highlighted the importance of vehicle classification in achieving accurate predictions, as braking and acceleration performances differ significantly across various MMVs. Furthermore, it was revealed that riders can accelerate and brake more rapidly (i.e., they can decelerate at approximately twice the deceleration than when braking comfortably) when prioritizing urgency over comfort. Braking capabilities were comparable for the bicycle in both assisted and unassisted states, but inferior for both l- and s- scooters and Segways. ADAS systems can use the deceleration data along with other MMV-recognition technologies to assess maneuvering responses and the risk of crashing in real time with relatively high accuracy.

Study 2 demonstrates a rapid method for calculating the minimum required deceleration, jerk, and the maximum lateral offset as well as the steering jerk in order to model the braking and steering maneuvers of MMVs. Using an arctangent function to fit the velocity curve, instead of a constant acceleration or a constant jerk model, provides a more natural description of the braking process. The arctangent function is especially suited for low-speed scenarios. Compared with the linear models that identify a maneuver based on thresholds, the arctangent models can achieve a broader prediction horizon in a threat assessment algorithm (e.g., before or after a braking maneuver when a vehicle coasts without pedaling, so that we can study when the rider start preparing for braking). The arctangent models' coefficients can be used to rapidly compute maximum braking and steering acceleration and MMV trajectories, as shown in Table 2.

It is worth noting that the linear and arctangent models both lack ecological validity and robustness, as they are deterministic and do not account for road user variability or uncertainty (unlike, e.g., Bayesian [Huang & Abdel-Aty, 2010] and deep learning [Zhu et al., 2022] modeling approaches using large naturalistic databases). However, their simplicity and low computational complexity make them suitable for the implementation in ADAS to anticipate the behavior of MMVs. Moreover, the models might improve the communication among road users and the infrastructure in extensive V2X road networks. For example, MMVs in a local V2X network might broadcast their kinematic models, as well as basic kinematic information such as speed and heading angle, in a VRU-awareness message (VAM, [SAE, 2017; ETSI, 2020]) [Lusvarghi et al. 2023]. The additional information can help car ADASs assess the threat of collisions with MMVs individually—compensating for the inaccuracies of GPS, on-board units (OBUs), and infrastructure sensors [Baqer et al., 2021; Denk et al., 2022]. Microscopic traffic simulations [Krajzewicz, 2010] used in traffic research and planning may also benefit from including kinematic models of MMVs to create realistic paths and movement predictions; for example, bicycle interactions could be simulated by considering bicycle dynamics using the social force paradigm [Schmidt et al., 2023].

Table 2. Comparison between coefficients of the arctangent model and linear model. Kinematic parameters are calculated with the coefficients and their combinations.

Arctangent model			**Linear model**	
$y = a_a \operatorname{atan}(b_a x + c_a) + d_a$			$y = a_l x + b_l$	
-1.69 ± 0.55	$a_a \cdot b_a$	**Min. deceleration $[m/s^2]$**	a_l	-1.80 ± 0.31
5.66 ± 0.62	$2 \cdot d_a$	**Initial speed $[m/s]$**	b_l	5.70 ± 2.50
-0.99 ± 0.80	$-3\sqrt{3}/8 \cdot \lvert a_a \cdot {b_a}^2 \rvert$	**Min. jerk $[m/s^3]$**	N/A	-
4.79 ± 1.42	$-2 \cdot c_a/b_a$	**Duration $[s]$**	$-b_l/a_l$	3.25 ± 0.63

As stated in the Introduction section, multiple approaches are being developed and employed in ADAS systems for threat assessment. Our studies have produced kinematic models that could be utilized to enhance threat assessment systems, particularly those use a physical model-based method (as classified by [Dahl et al., 2018]). These methods rely on precise dynamic and kinematic models of both the host vehicle and the surrounding road users to enhance threat assessment. For instance, when an e-scooter approaches an intersection, an ADAS or AD system equipped with an accurate, dynamic e-scooter model can anticipate the rider's actions by considering the model's parameters, such as velocity, acceleration, steering capabilities, and minimum required jerk [Viviani & Flash, 1995]. Consequently, the system can predict the e-scooter's trajectory, evaluate potential collision risks with the host vehicle, and adjust the host vehicle's path or velocity to minimize risk. The ADAS and AD systems' more precise threat assessments can lead to improved decision-making and enhanced road safety. Integrating these methods establishes a resilient framework for mitigating potential risks and safeguarding the well-being of all road users.

While this research focused on physical model-based methods, the kinematic models based on data-driven methods could also be fed into the model pretraining process and improve the performance of the machine-learning-based threat assessment networks by transferring prior knowledge [Ayachi et al., 2020]. Combining both physical model-based and data-driven methods can improve the ADAS's threat assessment and collision avoidance strategies, making ADAS more effective [Dahl et al., 2018].

4.3. Implications for traffic safety

In addition to informing the development of ADAS systems, our top-down kinematic models of MMV maneuvers can benefit traffic safety in many other ways. Including parameters such as maximum braking deceleration and minimum turning radius in addition to weight, top speed, and peak power in a more comprehensive classification and taxonomy of MMVs can facilitate better MMV design, infrastructure, and regulations. Moreover, qualitative factors such as the perceived safety of the MMVs by drivers, pedestrians, and MMV users themselves can also be included [Tice et al., 2019] .

The proposed MMV kinematic models can inform consumer rating programs such as Euro NCAP in creating appropriate test scenarios. According to Euro NCAP Vision 2030, test situations for new crash opponents, including powered-two-wheelers (PTWs), specifically powered-standing-scooters (PSS, e.g., the e-scooters we have studied), will be developed. Euro NCAP has been reviewing injury patterns, test methods, and criteria for MMVs and crashes at lower speeds, and will be adding new tests in 2026 (approximated). Current testing includes the following car-to-bicyclist (adult) scenarios: dooring (CBDA), nearside/farside collision (CBNA/CBFA), nearside collision obstructed (CBNAO), longitudinal collision (CBLA), and “right hook” turning (CBTA). Various test protocols and assessment criteria were developed; time-to-collision (TTC) and impact velocity are major indicators for an ADAS system. In several car-to-pedestrian and car-to-bicyclist scenarios, a warning (e.g., FCW) should be issued or an intervention (e.g., AEB, door retention, emergency-steering-support) should be triggered before or at a TTC of 1.7s, to attempt to avoid a collision. However, according to our findings, novel MMVs may achieve higher acceleration and speed than traditional bicycles, albeit with poorer braking capability, which suggests that the current TTC may be inappropriate. In particular, in the CBNA/CBFA and CBDA scenarios, 1.7s may not be enough time for the driver to react to the warning, because of the more substantial negative relative velocity due to the MMV's greater maximum velocity. On the other hand, a TTC of 1.7s may be too long—and more likely to result in a false alarm—in a CBLA scenario, since the relative velocity between the car and the rider is lower (greater MMV velocity), which also reduces slower when an MMV brakes (MMV's poorer braking performance). The findings of this thesis may support the development of new test protocols and criteria with a more accurate model for predicting MMV behaviors. Another application of the model could be planning the speed and trajectory of a robot MMV in these new scenarios as an opponent road user, to make the scenarios more realistic.

In addition, these findings may lead to new requirements in infrastructure design. Our field experiments have also shown that e-scooters are perceived as less stable and maneuverable, and steering may be more effective than braking for e-scooter riders to avoid collisions. Thus, an infrastructure designer might increase a bicycle lane's width and curve angle to provide more room for avoidance maneuvers. It is also essential to ensure improved road visibility, lighting, lane marking, and road signage to accommodate new MMVs with poorer maneuverability (e.g., e-scooters and Segways). Other examples of infrastructure improvements that would improve safety include allocating the bicycle lane more properly (e.g., to minimize the exposure where the MMVs have to share the road with motorized vehicles and pedestrians) and lowering the curb height at points where the bicycle lane has been interrupted to reduce falling crashes [Knight & Charlton, 2022; Jensen et al., 2008].

Policy-making may also benefit from our results; current policy addresses MMV safety based on general, static requirements. Integrating MMV kinematics and maneuverability into behavioral models could lead to more comprehensive, systematic regulations tailored to individual MMVs' capabilities and limitations. The collision-avoidance capabilities of e-scooters (i.e., maximum braking decelerations and lateral offsets) can be taken into account, with new speed limits or bans employed accordingly at certain areas (e.g., narrow lanes, sharp curves, long downhill stretches). Clear road signs could raise rider awareness of potential dangers. Additionally, as it is hard to use hand signals to indicate turning while riding an e-scooter, mandating the equipping and use of turning indicators may encourage safer interactions between MMVs and other road users.

Rider education is also crucial. As shown in a previous report [Austin Public Health, 2019], nearly one-third of e-scooter injuries occur during inexperienced riders' first journey. This statistic indicates that many crashes can be attributed to the riders' lack of experience or to their lack of awareness of the characteristics of new MMVs. Perhaps they are mindlessly assuming they can transfer the skills used with traditional bicycles to the new vehicles. According to the subjective data we collected, participants may interpret the braking system on the large e-scooter as similar to a bicycle's; however, although they may look alike, they function differently. Furthermore, understeering of e-scooters was reported by some participants, possibly due to their unfamiliarity with the body-leaning required to steer them. Clearly, inexperience may lead to mishandling of the vehicle and an increased risk of crashes. In our studies, the participants highly appreciated the training sessions before the formal experiment; inexperienced e-scooter riders learned to operate the vehicles and overcome their fears. A comprehensive program of rider education may reduce MMV crashes by raising rider awareness of the limitations of the vehicle.

Finally, the models devised in this thesis have the potential to be applied in autonomous driving. Previous research has suggested that, compared to manually driven vehicles, autonomous vehicles may need a more cautious driving approach when encountering VRUs [Rasch, 2023]. To gain the driver's trust, autonomous vehicles should maintain longer distances to VRUs than those calculated by the AD systems as safe distances, similar to those maintained by human drivers, and aim for comparable speeds [Abe et al., 2017]. Our models can be employed to constrain the control units of the vehicle in order to achieve such careful behavior. Moreover, the models from this thesis can be useful for local V2X networks, as prior study has demonstrated that alerts generated through vehicle-to-micromobility communication could effectively prevent right-hook and right-angle collisions. The models could be rapidly implemented using a threshold of MMVs' minimum stopping sight distance [Baqer et al., 2021], a distance defined by a quadratic equation using the vehicle's speed [AASHTO, 1993]. Alerts incorporating the models from this thesis can be more individualized. For example, instead of one specific universal equation for all types of MMVs, new systems using these models can consider the kinematics and stopping distances of individual MMV types and models.

4.4. Limitations and future work

Both studies had limitations in data collection, the datasets, and data analysis.

In Study 1, only 25 out of 34 participants felt comfortable riding the Segway, while only 14 participants could provide reliable sensor data for modeling. Additionally, up to 20% of the data obtained from the other vehicles was lost because participants encountered challenges controlling their speed per the instructions. While such data loss is typical in field experiments, it is plausible that this loss resulted in a dataset that exhibits a bias toward the subset of participants who are particularly athletic or adventurous (especially regarding the Segway). These biases were lessened in Study 2 due to a more flexible speed requirement and the Segway's absence. However, not regulating the initial velocity has been identified as a major limitation of Study 2: the comparisons of the braking and steering capabilities of the various vehicles were less accurate and valid, since the initial speed parameter may influence braking and steering performance indicators, including braking distance, acceleration, and maximum steering rate. In future field data collections, these influences should be addressed by manually controlling the desired constant speed (e.g., limiting throttle positions) or giving clearer prompts when riders enter or exit the desired speed range.

While we have not encountered any other research project involving more participants in e-scooter field tests, it is important to note that our sample size of around 30 individuals might not accurately represent individuals of all sexes, ages, and geographical locations. Test scenarios in both studies were also simplified and idealized to represent only longitudinal collision situations without involving other road users or infrastructure. Future field data collections should widen the ranges of demographic and traffic scenarios, e.g., building real-world infrastructure and involving oncoming or approaching road users. Generally, future research should also focus on standardizing MMV data collection, and database maintenance, [Karpinski et al., 2022]. At the same time, researchers need to understand the context and limitations of data, choose risk metrics that align with specific research questions, and then try to improve database accessibility, quality, complexity, completeness, and comprehensiveness.

In Study 2, hardware failures happened to the button controlling the logging start/stop and the one synchronizing the on-vehicle and LIDAR data loggers (temporal synchronization should have been done by pressing the two buttons on the loggers as simultaneously as possible after logging has started). The failures, possibly due to the deterioration of the older data loggers on the bicycle and the small e-scooter, resulted in incomplete vehicle data and asynchronous signals from the vehicles and the LIDAR. Manually recovering the damaged data was impossible. Therefore, we disregarded the vehicle data and relied exclusively on the LIDAR data; sensor fusion in the data processing phase was thus not possible. In other words, the velocity, acceleration, and jerk were computed indirectly from the derivations of the position data collected by the LIDAR at a relatively low sampling rate (20Hz), which treated the vehicle-rider system as a central point within a clustered point cloud. As a result, the inaccuracies arising from the indirect method used to measure the kinematics of vehicles in data collection and analysis could not be corrected. In order to enhance the precision of the models, further research could incorporate additional direct measurements, such as wheel speed obtained using an optical encoder with a higher sampling rate. These measurements can then be fused with the LIDAR measurements to model and predict MMV trajectories more accurately. A better synchronization module, e.g., wireless communication, may be needed to control manual synchronization, which may induce some noise and errors. Additionally, the positioning of the LIDAR in Study 2 posed a minor limitation, because the LIDAR could not continuously track the riders' steering maneuvers after they had overtaken the cardboard car.

This issue could be resolved by placing the LIDAR to the left of the test track instead, so that the cardboard car does not interfere with the LIDAR’s line of sight.

The significant limitations in data validity, and the consequent indirect measuring approaches required, reduced the models’ accuracy. Future work should implement newer, more robust logging systems. Ideally, the logging system would enable sensor fusion and enrich the information in the data by creating redundancies in sensing and data transmission. One example is measuring vehicle speed: fusing the data from the LIDAR and the IMU can correct the error from each sensor (e.g., drift errors from the IMU and angular errors from the LIDAR). Additionally, use of wheel-speed sensing (e.g., an optical encoder) and throttle/brake lever position sensing in the vehicle speed measurements could further improve the accuracy by including information on energy transfer and wheel lock. Redundancy in data transmission (i.e., by using both wired and wireless communication) can reduce data loss when either system fails. In future work within the Ph.D. project, logging systems should be improved by using global control for temporal synchronization while creating redundancies in direct and indirect measuring approaches.

In the two field experiments presented in this thesis, ecological validity might have been constrained in several ways. First, the experiments took place on road stretches that did not represent a real, open-road environment. Not only were very few other road users and a wider-than-usual space for riding, but neither the cone marks nor the cardboard car was fully realistic. Second, there was bias in the selection of participants (the criteria were “average” persons whose height and weight were within certain ranges, and fewer female participants were recruited) and in the vehicles (recall that the participant needed to pretend to ride a non-assisted bicycle while on an e-bike with the motor off). Third, the riding tasks might also differ from what the participants would do in real life. For example, the auditory signal used in the unplanned braking task in Study 1 might demonstrate better ecological validity than asking the riders to brake as late as possible for anticipating riders’ response in emergency situations. However, using an auditory signal still predetermined the occurrence of such “emergencies” in the riders’ minds when the instruction of the experiment was given. Fourth and lastly, the information loss due to the measuring methods and tools also reduced the ecological validity. In general, higher validity would enable us to derive more accurate and robust results from the tests. One example of the benefit of higher an ecological validity could be the partially confirmed phenomenon that, in the tests of drivers’ hazard perception assessment (i.e., the process of detection, evaluation, and response to road hazards [Crundall et al., 2012]), increased ecological validity enhances the test’s sensitivity to variations in driving expertise [Malone & Brrünken, 2016].

Previous studies have shown significant differences between the types of crashes and injuries incurred by male and female riders on e-scooters [Tian et al., 2022; Yang et al., 2020]. However, we found no statistically significant differences between male and female riders in the longitudinal control (braking) of bicycles, e-bicycles, e-scooters, or Segways. Moreover, in Study 1, braking distances and response times were comparable regardless of gender, and the proportion of female participants who successfully completed the experiment with the Segway was similar to the proportions for the other vehicles. None of our findings support the prevailing notion that male riders exhibit more aggressive riding behavior or engage in riskier actions than female riders. This lack of significance between male and female riders’ behaviors may be due to the small number of female participants (9 out of 34 in Study 1 and 13 out of 36 in Study 2).

After this licentiate and up to the final Ph.D. thesis, the focus will shift to modeling MMVs from the vehicle dynamic and human rider's control perspectives in a bottom-up manner. The rider-vehicle system will be modularized, where the vehicle and the rider will be studied as two standalone modules. In the first step, we will develop dynamic models for the e-scooter, drawing inspiration from the concepts presented in the research by Meijaard et al. (2007) and Moore (2012). Instead of field trials, laboratory experiments are planned and will be conducted at Chalmers FUSE's Physiology lab using a treadmill and high-speed motion capture system. New experimental protocols will be designed in which participants riding e-scooters on the treadmill will perform routine riding maneuvers, such as balancing, leaning, and following a line. The main features we intend to incorporate into these models are the torque generated by the steering assembly and the adjustments to the center of gravity resulting from shifts in the driver's position. This work will heavily rely on geometric principles, measurable data, and parameters previously identified in existing literature and benchmark models, such as moments of inertia and tire stiffness. Kinematic data and riders' body movements will be captured at the same time. From these data, a new benchmark model dedicated to e-scooter dynamics will be developed and presented in the following papers. The next step will be to model the rider's body motions in the controlling of e-scooters. Various model architectures will be examined to find one that best strikes a balance between complexity, degrees of freedom (DOF), and bio-fidelity. These models (and those developed before this licentiate thesis) will be integrated into the benchmark e-scooter model and validated with naturalistic data.

We should conduct a parametric investigation into the vehicle characteristics to conduct a more profound comprehension and measurement of the factors that influence the performance of the e-scooter and its rider, proposing potential modifications to the design of e-scooters to improve safety. Voi (a shared e-scooter service provider) and Chalmers have been collecting naturalistic data since 2021, so a substantial dataset should be available for our studies. The intention is to select specific situations and compare the recorded kinematics to those predicted by our model. Finally, in addition to the dynamics, future studies may also consider variables encompassing implicit and explicit communication by the riders (e.g., head orientation, indicating whether they are planning to turn). This information is essential for predicting the interactions between riders and their surroundings from the riders' perspective, such as how they perceive and react to critical events (e.g., involving oncoming/lateral traffic).

5. CONCLUSIONS

This thesis represents an early-stage exploration of MMV safety research regarding methodology and MMV behavioral modeling at the operational and tactical levels. The significance of field data in ensuring the secure integration of micromobility into the transportation system is emphasized by the results of this thesis. The two field experiments highlight how the characteristics of different MMVs affect their kinematics and, as a consequence, rider behavior. The results suggest that e-scooter riders may be better off executing steering maneuvers instead of braking (as one example)—in contrast to cyclists, who rely more on braking maneuvers. Study 1 also reveals that Segways performed poorly in field tests, indicating the necessity of proper training for inexperienced users before riding in traffic. Moreover, it was also found that the linear accelerating and braking models, which demonstrate that riders maintain consistent accelerations and decelerations, can be employed to predict trajectories for safety systems such as automated emergency braking (AEB) as well as for automated driving.

The collision avoidance behaviors of braking and steering exhibited by bike and e-scooter riders were examined in Study 2. It was found that larger public-sharing e-scooters exhibit superior braking performance than smaller, privately owned ones. However, steering maneuvers were consistent across all types of vehicles. In order to enhance the effectiveness of ADAS systems and improve our understanding of e-scooter safety, Study 2 put forth an arctangent model that provides a more accurate representation of MMV kinematics. This model enables the calculation (and thus the prediction) of the maximum acceleration/deceleration and jerk, the lateral clearance achieved by the riders, and a more precise prediction of MMV trajectories. Both the linear and arctangent models demonstrated satisfying performance in describing short-term kinematics of MMVs, although the latter are perhaps best suited to describing comfortable maneuvers (which are less linear). Specifically, the linear model has two parameters and (usually) a time complexity of O(n); the arctangent model has four parameters, and the time complexity can vary significantly from O(n) to higher, depending on the fitting approach used. However, the arctangent model is still computationally efficient for most state-of-the-art computational units. Both models may prove useful to consumer rating programs like Euro NCAP, as they can help design test protocols and assessment criteria for threat assessment and crash avoidance systems.

To extend the ecological validity of the models, future research should compare other MMV models in diverse traffic scenarios, while considering additional road users. Furthermore, future research should focus on improving the models for e-scooter kinematics and rider behavior and validating the models with naturalistic data. In summary, the first research objective (i.e., modeling the behaviors of MMV riders' longitudinal and lateral maneuvering in specific traffic scenarios from a top-down perspective) of the Ph.D. project has been addressed and as results, two descriptive models of MMV collision avoidance maneuvers have been proposed. Lastly, this thesis may provide evidence for the necessity of rider education in MMV operation and regulations tailored for MMVs to enhance road safety.

In conclusion, this thesis sheds light on future research directions and knowledge gaps in the field of MMV safety. The significantly poorer braking capability demonstrated by the e-scooters in the field tests emphasize the need for advancement in the threat assessment process of active safety systems to better handle the car-MMV interaction in potential collisions. New evaluation criteria for car-to-MMV scenarios in consumer rating programs for new car safety may also be of interest to encourage car manufacturers in further reducing collisions with MMVs. A new taxonomy that classifies novel MMVs supported by knowledge of their kinematics and maneuverability could ensure that future infrastructure design and the policy-making lead to improved traffic safety. Our results in the distinctions between e-scooters and bicycles may align with the crash patterns presented in the statistics. More single falling crashes and misbehaviors due to fear and lack of experience and the potential design faults are frequently occurring, confirming that riding an e-scooter is riskier than riding a bicycle. Furthermore, even though steering maneuvers did not reveal significant differences in maneuverability across MMVs, they were still perceived differently. More knowledge about the interactions between the rider and the vehicle during steering maneuvers is needed, especially on an operational level. On the other hand, the proposed kinematic models are simplified and subject to specific longitudinal-control (Study 1) and collision-avoidance (Study 2) scenarios. Future work is needed to refine the models with knowledge about the vehicle dynamics and more diverse data modality (e.g., more sensing data such as the brake lever pressure, steering torque, and rider monitoring, etc.), in order to achieve better descriptions and predictions of MMV behaviors in a broader range of traffic scenarios.

REFERENCES

[1] Abduljabbar, R. L., Liyanage, S., & Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. Transportation research part D: transport and environment, 92, 102734.

[2] Abe, G., Sato, K., & Itoh, M. (2017). Driver trust in automated driving systems: The case of overtaking and passing. IEEE Transactions on Human-Machine Systems, 48(1), 85-94.

[3] Apurv, K., Tian, R., & Sherony, R. (2021). Detection of E-scooter Riders in Naturalistic Scenes. arXiv preprint arXiv:2111.14060.

[4] Asperti, M., Vignati, M., & Braghin, F. (2021). Modelling of the vertical dynamics of an electric kick scooter. IEEE Transactions on Intelligent Transportation Systems, 23(7), 9266-9274.

[5] Austin Public Health. (2019). Dockless electric scooter - related injuries study.

[6] Axelsson, A., & Stigson, H. (2019). Characteristics of bicycle crashes among children and the effect of bicycle helmets. Traffic injury prevention, 20(sup3), 21-26.

[7] Ayachi, R., Afif, M., Said, Y., & Abdelaali, A. B. (2020, September). Pedestrian detection for advanced driving assisting system: a transfer learning approach. In 2020 5th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP) (pp. 1-5). IEEE.

[8] Badeau, A., Carman, C., Newman, M., Steenblik, J., Carlson, M., & Madsen, T. (2019). Emergency department visits for electric scooter-related injuries after introduction of an urban rental program. The American journal of emergency medicine, 37(8), 1531-1533.

[9] Bai, S., & Jiao, J. (2022). From shared micro-mobility to shared responsibility: Using crowdsourcing to understand dockless vehicle violations in Austin, Texas. Journal of Urban Affairs, 44(9), 1341-1353.

[10] Baqer, M., Lowry, M., & Krings, A. (2022). Reliability of Vehicle-to-Micromobility Safety Communication. Journal of Transportation Engineering, Part A: Systems, 148(11), 04022102.

[11] Beck, S., Barker, L., Chan, A., & Stanbridge, S. (2020). Emergency department impact following the introduction of an electric scooter sharing service. Emergency Medicine Australasia, 32(3), 409-415.

[12] Billstein, L., & Svernlöv, C. (2021). Evaluating the Safety and Performance of Electric Micro-Mobility Vehicles: Comparing E-bike, E-scooter and Segway based on Objective and Subjective Data from a Field Experiment.

[13] Bloom, M. B., Noorzad, A., Lin, C., Little, M., Lee, E. Y., Margulies, D. R., & Torbati, S. S. (2021). Standing electric scooter injuries: Impact on a community. The American Journal of Surgery, 221(1), 227-232.

[14] Boda, C. N., Dozza, M., Bohman, K., Thalya, P., Larsson, A., & Lubbe, N. (2018). Modelling how drivers respond to a bicyclist crossing their path at an intersection: How do test track and driving simulator compare?. Accident Analysis & Prevention, 111, 238-250.

[15] Boufous, S., Rome, L. D., Senserrick, T., & Ivers, R. (2011). Cycling crashes in children, adolescents, and adults—a comparative analysis. Traffic injury prevention, 12(3), 244-250.

[16] Boyle, L. N. (2020). Techniques for Making Sense of Behavior in Complex Datasets. In Handbook of Human Factors for Automated, Connected, and Intelligent Vehicles (pp. 497-517). CRC Press.

[17] Bärgman, J., Boda, C. N., & Dozza, M. (2017). Counterfactual simulations applied to SHRP2 crashes: The effect of driver behavior models on safety benefit estimations of intelligent safety systems. Accident Analysis & Prevention, 102, 165-180.

[18] Cicchino, J. B., Kulie, P. E., & McCarthy, M. L. (2021). Severity of e-scooter rider injuries associated with trip characteristics. Journal of safety research, 76, 256-261.

[19] Crundall, D., Chapman, P., Trawley, S., Collins, L., Van Loon, E., Andrews, B., & Underwood, G. (2012). Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard. Accident Analysis & Prevention, 45, 600-609.

[20] Dahl, J., de Campos, G. R., Olsson, C., & Fredriksson, J. (2018). Collision avoidance: A literature review on threat-assessment techniques. IEEE Transactions on Intelligent Vehicles, 4(1), 101-113.
[21] Das, S., Hossain, A., Rahman, M. A., Sheykhfard, A., & Kutela, B. (2023). Case Study on the Traffic Collision Patterns of E-Scooter Riders. Transportation Research Record, 03611981231185770.
[22] Dawes, J. (2008). Do data characteristics change according to the number of scale points used? An experiment using 5-point, 7-point and 10-point scales. International journal of market research, 50(1), 61-104.
[23] della Mura, M., Failla, S., Gori, N., Micucci, A., & Paganelli, F. (2022). E-Scooter Presence in Urban Areas: Are Consistent Rules, Paying Attention and Smooth Infrastructure Enough for Safety?. Sustainability, 14(21), 14303.
[24] Denk, F., Brunner, P., Huber, W., Margreiter, M., Bogenberger, K., & Kates, R. (2022, October). Assessment of traffic safety interventions using virtual randomized controlled trials: potential of connected and automated driving including V2X for collision reduction at urban intersections. In 2022 IEEE 25th International Conference on Intelligent Transportation Systems (ITSC) (pp. 1183-1190). IEEE.
[25] 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. Journal of safety research, 84, 24-32.
[26] Dozza, M., Violin, A., & Rasch, A. (2022). A data-driven framework for the safe integration of micro-mobility into the transport system: Comparing bicycles and e-scooters in field trials. Journal of safety research, 81, 67-77.
[27] Dozza, M., & Werneke, J. (2014). Introducing naturalistic cycling data: What factors influence bicyclists' safety in the real world?. Transportation research part F: traffic psychology and behaviour, 24, 83-91.
[28] Eccarius, T., & Lu, C. C. (2020). Adoption intentions for micro-mobility–Insights from electric scooter sharing in Taiwan. Transportation research part D: transport and environment, 84, 102327.
[29] Ehsani, J. P., Michael, J. P., Duren, M. L., Mui, Y., & Porter, K. M. P. (2021). Mobility patterns before, during, and anticipated after the COVID-19 pandemic: an opportunity to nurture bicycling. American journal of preventive medicine, 60(6), e277-e279.
[30] Elmashhara, M. G., Silva, J., Sá, E., Carvalho, A., & Rezazadeh, A. (2022). Factors influencing user behaviour in micromobility sharing systems: A systematic literature review and research directions. Travel Behaviour and Society, 27, 1-25.
[31] Ester, M., Kriegel, H. P., Sander, J., & Xu, X. (1996, August). A density-based algorithm for discovering clusters in large spatial databases with noise. In kdd (Vol. 96, No. 34, pp. 226-231).
[32] ETSI TS 103 300. (2020). Intelligent Transport Systems (ITS); Vulnerable Road Users (VRU) awareness.
[33] Euro, N. C. A. P. Vision 2030: A safer future for mobility.
[34] Fang, K. (2022). Micromobility injury events: Motor vehicle crashes and other transportation systems factors. Transportation research interdisciplinary perspectives, 14, 100574.
[35] Fearnley, N., Berge, S. H., & Johnsson, E. (2020). Shared e-scooters in Oslo (No. 4783-4806).
[36] Folco, P., Gauvin, L., Tizzoni, M., & Szell, M. (2023). Data-driven micromobility network planning for demand and safety. Environment and Planning B: Urban Analytics and City Science, 50(8), 2087-2102.
[37] Galvani, M. (2013). Optimal-control-based ADAS for driver warning and autonomous intervention using manoeuvre jerks for risk assessment.
[38] Garman, C. M., Como, S. G., Campbell, I. C., Wishart, J., O'Brien, K., & McLean, S. (2020). Micro-mobility vehicle dynamics and rider kinematics during electric scooter riding (No. 2020-01-0935). SAE Technical Paper.

[39] Gehrke, S. R., Russo, B. J., Sadeghinasr, B., Riffle, K. R., Smaglik, E. J., & Reardon, T. G. (2022). Spatial interactions of shared e-scooter trip generation and vulnerable road user crash frequency. Journal of Transportation Safety & Security, 14(10), 1798-1814.
[40] Gilroy, S., Mullins, D., Jones, E., Parsi, A., & Glavin, M. (2022). E-Scooter Rider detection and classification in dense urban environments. Results in Engineering, 16, 100677.
[41] Glavić, D., Trpković, A., Milenković, M., & Jevremović, S. (2021). The e-scooter potential to change urban mobility—belgrade case study. Sustainability, 13(11), 5948.
[42] Green, M. (2000). " How long does it take to stop?" Methodological analysis of driver perception-brake times. Transportation human factors, 2(3), 195-216.
[43] Hamid, U. Z. A., Saito, Y., Zamzuri, H., Rahman, M. A. A., & Raksincharoensak, P. (2018). A review on threat assessment, path planning and path tracking strategies for collision avoidance systems of autonomous vehicles. International Journal of Vehicle Autonomous Systems, 14(2), 134-169.
[44] Hoffman, J. D., Lee, J. D., Brown, T. L., & McGehee, D. V. (2002). Comparison of driver braking responses in a high-fidelity simulator and on a test track. Transportation Research Record, 1803(1), 59-65.
[45] Hossein Sabbaghian, M., Llopis-Castelló, D., & García, A. (2023). A Safe Infrastructure for Micromobility: The Current State of Knowledge. Sustainability, 15(13), 10140.
[46] Hoye, A. (2018). Recommend or mandate? A systematic review and meta-analysis of the effects of mandatory bicycle helmet legislation. Accident Analysis & Prevention, 120, 239-249.
[47] Huang, H., & Abdel-Aty, M. (2010). Multilevel data and Bayesian analysis in traffic safety. Accident Analysis & Prevention, 42(6), 1556-1565.
[48] Isaksson-Hellman, I., & Lindman, M. (2012, October). The effect of a low-speed automatic brake system estimated from real life data. In Annals of Advances in Automotive Medicine/Annual Scientific Conference (Vol. 56, p. 231). Association for the Advancement of Automotive Medicine.
[49] Jensen, S. U. (2008, January). Bicycle tracks and lanes: A before-after study. In Transportation Research Board 87th Annual Meeting (Vol. 2095, p. 15). Transportation Research Board Washington DC, United States.
[50] Karpinski, E., Bayles, E., & Sanders, T. (2022). Safety analysis for micromobility: Recommendations on risk metrics and data collection. Transportation research record, 2676(12), 420-435.
[51] Kiefer, R. J., Cassar, M. T., Flannagan, C. A., LeBlanc, D. J., Palmer, M. D., Deering, R. K., & Shulman, M. A. (2003). Forward collision warning requirements project: refining the CAMP crash alert timing approach by examining" last second" braking and lane change maneuvers under various kinematic conditions (No. DOT HS 809 574). United States. Department of Transportation. National Highway Traffic Safety Administration.
[52] Klinger, F., Klinger, M., Edelmann, J., & Plöchl, M. (2021, August). Electric Scooter Dynamics–From a Vehicle Safety Perspective. In The IAVSD International Symposium on Dynamics of Vehicles on Roads and Tracks (pp. 1102-1112). Cham: Springer International Publishing.
[53] Knight, A., & Charlton, S. G. (2022). Protected and unprotected cycle lanes' effects on cyclists' behaviour. Accident Analysis & Prevention, 171, 106668.
[54] Kobayashi, L. M., Williams, E., Brown, C. V., Emigh, B. J., Bansal, V., Badiee, J., ... & Doucet, J. (2019). The e-merging e-pidemic of e-scooters. Trauma surgery & acute care open, 4(1).
[55] Kovacsova, N., de Winter, J. C., Schwab, A. L., Christoph, M., Twisk, D. A. M., & Hagenzieker, M. P. (2016). Riding performance on a conventional bicycle and a pedelec in low speed exercises: Objective and subjective evaluation of middle-aged and older persons. Transportation research part F: traffic psychology and behaviour, 42, 28-43.
[56] Krajzewicz, D. (2010). Traffic simulation with SUMO–simulation of urban mobility. Fundamentals of traffic simulation, 269-293.
[57] Kröyer, H. (2021). Bicycles, e-bikes and micromobility, a traffic safety overview.

[58] Li, T., Kovaceva, J., & Dozza, M. (2023). Modeling collision avoidance maneuvers for micromobility vehicles. Journal of safety research.

[59] Liao, F., & Correia, G. (2022). Electric carsharing and micromobility: A literature review on their usage pattern, demand, and potential impacts. International Journal of Sustainable Transportation, 16(3), 269-286.

[60] Liu, M., Seeder, S., & Li, H. (2019). Analysis of e-scooter trips and their temporal usage patterns. Institute of Transportation Engineers. ITE Journal, 89(6), 44-49.

[61] López-Molina, M., Llopis-Castelló, D., Pérez-Zuriaga, A. M., Alonso-Troyano, C., & García, A. (2022). Skid Resistance Analysis of Urban Bike Lane Pavements for Safe Micromobility. Sustainability, 15(1), 698.

[62] Maiti, A., Vinayaga-Sureshkanth, N., Jadliwala, M., Wijewickrama, R., & Griffin, G. (2022, March). Impact of e-scooters on pedestrian safety: A field study using pedestrian crowd-sensing. In 2022 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops) (pp. 799-805). IEEE.

[63] Malone, S., & Brünken, R. (2016). The role of ecological validity in hazard perception assessment. Transportation research part F: traffic psychology and behaviour, 40, 91-103.

[64] Marques, D. L., & Coelho, M. C. (2022). A Literature Review of Emerging Research Needs for Micromobility—Integration through a Life Cycle Thinking Approach. Future Transportation, 2(1), 135-164.

[65] Meijaard, J. P., Papadopoulos, J. M., Ruina, A., & Schwab, A. L. (2007). Linearized dynamics equations for the balance and steer of a bicycle: a benchmark and review. Proceedings of the Royal society A: mathematical, physical and engineering sciences, 463(2084), 1955-1982.

[66] Michon, J. A. (1985). A critical view of driver behavior models: what do we know, what should we do?. In Human behavior and traffic safety (pp. 485-524). Boston, MA: Springer US.

[67] Mohammadi, A. (2023). Computational interaction models for automated vehicles and cyclists (Doctoral dissertation, Chalmers Tekniska Hogskola (Sweden)).

[68] Moore, J. K. (2012). Human control of a bicycle. University of California, Davis.

[69] Moran, M. E., Laa, B., & Emberger, G. (2020). Six scooter operators, six maps: Spatial coverage and regulation of micromobility in Vienna, Austria. Case Studies on Transport Policy, 8(2), 658-671.

[70] Mullen, N., Charlton, J., Devlin, A., & Bedard, M. (2011). Simulator validity: Behaviors observed on the simulator and on the road.

[71] Najm, W. G., & Smith, D. L. (2004). Modeling driver response to lead vehicle decelerating (No. 2004-01-0171). SAE Technical Paper.

[72] Nassi, B., Mirsky, Y., Nassi, D., Ben-Netanel, R., Drokin, O., & Elovici, Y. (2020, October). Phantom of the adas: Securing advanced driver-assistance systems from split-second phantom attacks. In Proceedings of the 2020 ACM SIGSAC conference on computer and communications security (pp. 293-308).

[73] Lee, O., Rasch, A., Schwab, A. L., & Dozza, M. (2020). Modelling cyclists' comfort zones from obstacle avoidance manoeuvres. Accident Analysis & Prevention, 144, 105609.

[74] Lusvarghi, L., Grazia, C. A., Klapez, M., Casoni, M., & Merani, M. L. (2023). Awareness Messages by Vulnerable Road Users and Vehicles: Field Tests Via LTE-V2X. IEEE Transactions on Intelligent Vehicles.

[75] Orozco-Fontalvo, M., Llerena, L., & Cantillo, V. (2023). Dockless electric scooters: A review of a growing micromobility mode. International Journal of Sustainable Transportation, 17(4), 406-422.

[76] Piprek, P., Marb, M. M., Bhardwaj, P., & Holzapfel, F. (2020). Trajectory/path-following controller based on nonlinear jerk-level error dynamics. Applied Sciences, 10(23), 8760.

[77] Pokorny, P., Drescher, J., Pitera, K., & Jonsson, T. (2017). Accidents between freight vehicles and bicycles, with a focus on urban areas. Transportation research procedia, 25, 999-1007.

[78] Prencipe, L. P., Colovic, A., De Bartolomeo, S., Caggiani, L., & Ottomanelli, M. (2022, June). An efficiency indicator for micromobility safety assessment. In 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe) (pp. 1-6). IEEE.

[79] Rauch, H. E., Tung, F., & Striebel, C. T. (1965). Maximum likelihood estimates of linear dynamic systems. AIAA journal, 3(8), 1445-1450.

[80] Rasch, A. (2023). Drivers Overtaking Cyclists and Pedestrians: Modeling Road-User Behavior for Traffic Safety. Chalmers Tekniska Hogskola (Sweden).

[81] Reck, D. J., & Axhausen, K. W. (2021). Who uses shared micro-mobility services? Empirical evidence from Zurich, Switzerland. Transportation Research Part D: Transport and Environment, 94, 102803.

[82] Rogers, E. M., Singhal, A., & Quinlan, M. M. (2014). Diffusion of innovations. In An integrated approach to communication theory and research (pp. 432-448). Routledge.

[83] SAE J3194. (2019). Taxonomy and Classification of Powered Micromobility Vehicles

[84] SAE J2945. (2017). Vulnerable Road User Safety Message Minimum Performance Requirements.

[85] Santacreu, A., Yannis, G., de Saint Leon, O., & Crist, P. (2020). Safe micromobility.

[86] Schepers, P., Klein Wolt, K., & Fishman, E. (2018). The safety of e-bikes in The Netherlands. International Transport Forum Discussion Paper.

[87] Schmidt, C. M., Dabiri, A., Schulte, F., Happee, R., & Moore, J. K. (2023, April). Essential Bicycle Dynamics for Microscopic Traffic Simulation: An Example Using the Social Force Model. In The Evolving Scholar-BMD 2023, 5th Edition.

[88] Şengül, B., & Mostofi, H. (2021). Impacts of E-Micromobility on the sustainability of urban transportation—a systematic review. Applied Sciences, 11(13), 5851.

[89] Serra, G. F., Fernandes, F. A., Noronha, E., & de Sousa, R. J. A. (2021). Head protection in electric micromobility: A critical review, recommendations, and future trends. Accident Analysis & Prevention, 163, 106430.

[90] 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. Journal of safety research, 77, 217-228.

[91] Shin, S., & Choo, S. (2022). Influence of Built Environment on Micromobility–Pedestrian Accidents. Sustainability, 15(1), 582.

[92] Shinar, D. (2017). Traffic safety and human behavior. Emerald Publishing Limited.

[93] Sokolowski, M. M. (2020). Laws and policies on electric scooters in the european union: A ride to the micromobility directive?. European Energy and Environmental Law Review, 29(4).

[94] Stigson, H., Malakuti, I., & Klingegård, M. (2021). Electric scooters accidents: Analyses of two Swedish accident data sets. Accident Analysis & Prevention, 163, 106466.

[95] Tian, D., Ryan, A. D., Craig, C. M., Sievert, K., & Morris, N. L. (2022). Characteristics and risk factors for electric scooter-related crashes and injury crashes among scooter riders: A two-phase survey study. International journal of environmental research and public health, 19(16), 10129.

[96] Tice, P. C. (2019, November). Micromobility and the built environment. In Proceedings of the Human Factors and Ergonomics Society Annual Meeting (Vol. 63, No. 1, pp. 929-932). Sage CA: Los Angeles, CA: SAGE Publications.

[97] Transportation Officials. (1993). AASHTO Guide for Design of Pavement Structures, 1993 (Vol. 1). Aashto.

[98] Trivedi, T. K., Liu, C., Antonio, A. L. M., Wheaton, N., Kreger, V., Yap, A., ... & Elmore, J. G. (2019). Injuries associated with standing electric scooter use. JAMA network open, 2(1), e187381-e187381.

[99] van Schagen, I., & Sagberg, F. (2012). The potential benefits of naturalistic driving for road safety research: Theoretical and empirical considerations and challenges for the future. Procedia-social and behavioral sciences, 48, 692-701.

[100] Vella, A. D., Digo, E., & Vigliani, A. (2023, November). Experimental Analysis and Multibody Simulation of Electric Kick Scooter Braking Maneuver. In IFToMM World Congress on Mechanism and Machine Science (pp. 533-540). Cham: Springer Nature Switzerland.
[101] Vilaca, A., Cunha, P., & Ferreira, A. L. (2017, October). Systematic literature review on driving behavior. In 2017 IEEE 20th international conference on intelligent transportation systems (ITSC) (pp. 1-8). IEEE.
[102] Viviani, P., & Flash, T. (1995). Minimum-jerk, two-thirds power law, and isochrony: converging approaches to movement planning. Journal of Experimental Psychology: Human Perception and Performance, 21(1), 32.
[103] Wolfe, A. C. (1982). The concept of exposure to the risk of a road traffic accident and an overview of exposure data collection methods. Accident Analysis & Prevention, 14(5), 337-340.
[104] Yang, H., Ma, Q., Wang, Z., Cai, Q., Xie, K., & Yang, D. (2020). Safety of micro-mobility: Analysis of E-Scooter crashes by mining news reports. Accident Analysis & Prevention, 143, 105608.
[105] ZERO, I. P. O. V. (2017). Euro NCAP 2025 roadmap.
[106] Zhao, Y., Cao, J., Ma, Y., Mubarik, S., Bai, J., Yang, D., ... & Yu, C. (2022). Demographics of road injuries and micromobility injuries among China, India, Japan, and the United States population: evidence from an age-period-cohort analysis. BMC public health, 22(1), 760.
[107] Zhu, Z., Hu, Z., Dai, W., Chen, H., & Lv, Z. (2022). Deep learning for autonomous vehicle and pedestrian interaction safety. Safety science, 145, 105479.