Collective Dynamics

Controlled Experiment Investigating Micromobility Traffic Flow Interactions: Setup, Implementation, and Preliminary Results

Yufei Yuan[1] · **Weiyi Zhang**[1] · **Sicong Zhu**[2] · **Qing Lan**[3] · **Winnie Daamen**[1]

[1]Delft University of Technology, Faculty of Civil Engineering and Geosciences,
Delft, The Netherlands
E-mail: Y.Yuan@tudelft.nl, wenyizhang003@gmail.com, W.Daamen@tudelft.nl
[2]Beijing Jiaotong University, Beijing, China and
Hebei Higher Institute of Transportation Infrastructure Research and Development Center
for Digital and Intelligent Technology Application
E-mail: sicongzhu@hotmail.com
[3]Hebei University of Water Resources and Electric Engineering,
College of Transportation Engineering, CangZhou, China and
Hebei Higher Institute of Transportation Infrastructure Research and Development Center
for Digital and Intelligent Technology Application
E-mail: QingLan@hbwe.edu.cn

Received: 2 February 2026 / Last revision received: 6 June 2026 / Accepted: 8 June 2026
DOI: 10.17815/CD.2026.192

Abstract Travel patterns and lifestyles in cities around the world have changed in recent years due to the strong growth of travel modes commonly referred to as micromobility, including e-bike, e-scooter, and e-moped. Understanding micromobility flow dynamics is essential for designing safer, more efficient, and better-integrated urban transport systems that accommodate the unique behaviors of these emerging modes. Micromobility flow research at the operational behavioral level is limited, mainly due to the lack of empirical data. To overcome this data shortage, we performed a controlled experiment to observe one-on-one interactive behaviors on a Chinese university campus. This paper describes the approach for setting up and implementing such an experiment, from the motivation of its design using a conceptual model describing interaction behavior to the adjustments required during the experiment. The main contribution is, therefore, to collect such a dataset and to serve as a reference for future experimental studies on micromobility flow. Moreover, we provide a qualitative description of experiences observed during the experiment. Preliminary insight into overtaking behavior between e-bike and e-scooter is further elaborated to unravel their unique operational movement and to demonstrate the data potential. Finally, we emphasize that the data potential also holds for future research into understanding and modeling other operational riding behaviors and the stability of micromobility users.

Keywords Micromobility · Controlled experiment · Operational behavior · Stability · Interactive maneuver

1 Introduction

Recent years have witnessed the rapid emergence and adoption of micromobility modes, which are reshaping urban travel behavior and traffic dynamics worldwide These vehicles, which facilitate personal mobility and augment the capabilities of pedestrians, encompass a broad spectrum of designs and functionalities, ranging from lightweight rollers and skis to more substantial options like two-wheeled self-balancing personal transporters [1]. Notably, both motorized and non-motorized varieties of these vehicles exist, offering flexible choices for individual users, owned whether privately or accessed through shared services.

Among the most popular types of micromobility vehicles are e-scooters, e-bikes, and e-mopeds. Their popularity has surged remarkably over the last few years. This surge can be attributed to several factors: the decreasing costs of purchasing these vehicles, improvements in the efficiency of their motors, and innovations leading to more lightweight and manageable designs. This trend also manifests in the broader metrics of transportation such as the increase in the total distance traveled and the number of trips undertaken by users. Furthermore, there is an increasing global emphasis on sustainability, which has propelled the adoption of these environmentally friendly transportation alternatives [2]. The integration of these vehicles into urban transport ecosystems represents a pivotal shift towards more sustainable urban mobility, promoting reduced reliance on traditional fuel-based vehicles and encouraging a more active, health-conscious urban populace. These trends are reshaping urban environments, making them more navigable and less congested, thus significantly enhancing the quality of urban life.

The notable rise in the number of micromobility vehicles is evidenced by the significant increases in both private ownership and participation in shared mobility programs. Specifically, the market for e-bikes has seen an exponential growth in recent years. For instance, electric bicycle sales in the European Union surged to approximately 5.3 million units in 2022, a stark contrast to the 854,000 units recorded in 2012 [3]. This surge is not uniformly distributed across Europe; Germany stands out as a particularly strong market, with over 2.2 million e-bikes sold in 2022 alone [4], making it the largest e-bike market in Europe for that year.

Moreover, the expansion of e-scooter and e-moped services further illustrates the growing appeal of micromobility. VOI, a Swedish e-scooter operator that launched in 2018, exemplifies this growth. Within a year, VOI expanded to 10 countries. By 2020, they recorded nearly 16 million rides [5], highlighting the rapid adoption of e-scooters as a viable urban transport mode and reflecting a broader shift in urban mobility preferences. E-mopeds offer a balance between the compact convenience of e-scooters and the speed of traditional mopeds, making them an attractive option for urban commuters. For example, the shared e-moped service Revel, which launched in New York City in 2018, expanded rapidly to other major U.S. cities, boasting over 600,000 rides within its first year [6]. This growth trajectory highlights a significant change in how people choose to navigate city environments, increasingly favoring smaller, more efficient forms of transportation that align with growing environmental consciousness and urban planning aimed at reducing traffic congestion and pollution.

The motorized features of micromobility vehicles place them in a unique position within urban traffic dynamics. On one hand, these features, such as better acceleration capability and higher top speeds than conventional bicycles, allow them to reach the maximum allowable speed of 25 km/h under EU standards (or 20 mph under US regulations), which is on average 2–9 km/h faster on urban roads, rural areas, or dedicated bike paths [7–10]. These performance advantages make micromobility vehicles attractive for users seeking convenient, time-efficient, and low-effort transportation options in increasingly congested urban environments. This feature, however, also makes riders more vulnerable to serious injuries in accidents. On the other hand, these same features pose risks to other vulnerable road users who share the same infrastructure (i.e., cycle paths or sidewalks), including pedestrians and traditional cyclists, due to the increased potential for collisions and high injury severity [11–16].

To ensure the effective integration of e-bikes, e-scooters and e-mopeds into urban environments, it is crucial to understand and account for the behavioral nuances of micromobility users, especially on shared cycling infrastructure. By addressing these behavioral patterns, there is a potential to significantly reduce the incidence of accidents and enhance safety for all road users. This approach necessitates the incorporation of such insights into safety regulations, urban infrastructure planning/design, and traffic management. Effective urban space design and smart traffic management must account for the growing prevalence of these micromobility modes to create a safe and inclusive environment for all forms of mobility.

Numerous studies have been conducted on strategic travel behavior, such as mode/route choice, ridership and usage patterns of micromobility users [17, 18]. However, existing studies on micromobility operational behavior remain fragmented, particularly regarding individual-level interactive maneuvers within micromobility modes. Recent research has begun to address this gap through empirical data collection. For example, semi-controlled campus experiments [19] have been used to extract micromobility trajectories and validate camera-based measurement techniques for pedestrians, cyclists, and e-scooter users. Other studies have examined micromobility behavior in specific infrastructural contexts, such as mini-roundabouts [20], highlighting differences in speed profiles and lane positioning between bicycles and e-scooters. In addition, controlled experiments have recently provided the first empirical measurements of micromobility users' reaction times, revealing substantial variability across vehicle types and user characteristics [21]. Despite these advances, existing empirical studies typically focus on isolated behavioral variables, specific infrastructures, or single interaction contexts, and therefore do not yet provide a systematic operational-level understanding of micromobility interactions. In particular, empirical evidence on basic interactive maneuvers, such as overtaking across different micromobility modes and mode combinations remains limited.

This work aims to address this gap by investigating the behavior and movement dynamics of micromobility users during their one-on-one interactions with conventional bicycles and among themselves through empirical data collection and analysis. Depending on how the data are collected, there are controlled experiments and real-world observations [19, 20, 22, 23]. Both methods offer distinct advantages and challenges. Real-world observations allow participants to behave naturally in their usual environments, providing data that accurately reflects daily behaviors [20, 24]. However, such settings also introduce variables that are difficult to control, including varying environmental conditions and the unpredictable nature of human behavior. This variability can obscure the specific impacts of external factors and the inherent diversity within the population. Moreover, the complexity of real-world settings can necessitate prolonged observation periods to gather sufficient data across various scenarios. Alternatively, controlled laboratory studies offer a more structured environment where external conditions are eliminated, and variables can be tightly controlled. This consistency ensures that observations are repeatable and attributable to specific behaviors or conditions, facilitating the observation of one-on-one interactive behaviors and the extrapolation of outcomes to real-world scenarios.

This paper describes the approach for setting up and implementing such a data collection experiment with the participation of N=42 users riding various micromobility modes. These steps may be used as a reference in future experimental data collections and for future analyses using the data. It describes the collected dataset and elaborates on its potential uses. The contribution of the work is, therefore, threefold: (i) delineating the process to set up a controlled experiment on micromobility flow interactions (including e-bike, e-scooter, e-moped, and conventional bicycle); (ii) describing the implementation and performance of the experiment; and (iii) presenting a large database of micromobility user trajectories and some preliminary insights on a specific overtaking maneuver.

The remainder of the manuscript is organized into six sections. Sec. 2 presents the related work on micromobility traffic flow interactions, including the definitions of various interactive movements and the determinants on impacting these movement, which leads to presenting a conceptual framework describing micromobility flow interactions. Sec. 3 further justifies the objectives on data collection and potential data applications. Sec. 4 describes the development of the data collection plan, and Sec. 5 elaborates its implementation. Finally, Sec. 6 presents preliminary insights into the data of one specific interactive maneuver, followed by an outlook of future research in Sec. 7.

2 Conceptual foundations on micromobility flow interaction

This section summarizes key findings from the literature on interactive micromobility movements and the determinants influencing these behaviors. Rather than providing an exhaustive review, the aim is to extract the most relevant insights needed to construct a conceptual framework of micromobility flow interactions and to motivate the research objectives.

2.1 Various interactive movements

Operational riding behavior on an individual level can be represented by decisions regarding the use of the provided infrastructure while riding and the interaction with other traffic participants [23]. This behavior operates on two levels: the mental layer involves choosing intermediate destinations and build a path within the route while interacting with other traffic users and with the infrastructure, while the physical layer involves the actual controls exercised by riders, such as steering, pedaling [25]. At this operational level, the base motion cases that can trigger interactions between riders include a wide range of movement behaviors. Inspired by the work by Duives et al. [26] on pedestrian flows, we can distinguish interactions between uni-directional and multi-directional flows. The targeted interaction movements in this study include four major types, as illustrated in Fig. 1:

1. Overtaking at uni-directional riding: Includes a micromobility flow passing over (overtake) a static obstacle, and over a micromobility mode of lower speed.
2. Merging at bottlenecks: Includes a micromobility flow entering and exiting a narrow bottleneck (lane-drop or on-ramp case), to accept gap to proceed or adjust speed.
3. Yielding at crossings: Includes a micromobility flow yielding to pedestrians at zebra lines, and yielding between two micromobility flows at a 90-degree intersection.
4. Meeting at bi-directional riding: A 180-degree encounter between two micromobility flows, to avoid head-on collision.

While there are relatively limited studies on the overtaking behavior of micromobility users, some significant research has highlighted critical aspects of these dynamics. Wang et al. [27] focused on the overtaking behavior in mixed micromobility flows (bicycle, e-bike, tricycle) in Hefei, China, utilizing drone aerial photography and roadside cameras to observe that the average speed of these vehicles is 5.56 m/s with considerable individual variance. Their findings suggest that gender significantly influences overtaking decisions, with males more likely to overtake. Similarly, Khan and Raksuntorn [28] investigated the overtaking and meeting maneuvers on a dedicated bicycle path in Denver, Colorado. This study found that overtaking bicycles typically traveled at higher speeds than those they overtook, with a maintained speed difference rather than a constant speed, and that the lateral positioning narrowed during the maneuver. In Shanghai, Lin et al. [29] analyzed moped-bicycle overtaking on shared lanes, finding differences between complete and incomplete passes and correlating these with speed differences and lateral spacing. Mohammed, Bigazzi, and Sayed [30] utilized a multivariate finite mixture model to cluster cyclist behaviors during overtaking on New York City's Brooklyn Bridge, identifying different states such as initiation, merging, and post-overtaking, which help in understanding the dynamics crucial for developing traffic microscopic simulation models. However, these studies mainly focused on conventional bicycles. Similarly, steering maneuvers of bi-directional cyclists on collision course have been studied by Yuan et al. [22], revealing the difference in gender group and passing side, but the interaction with other directions or with other modes is yet unknown.

Research examining micromobility users' yielding behavior (to pedestrians) is scarce. However, insights may be drawn from studies on drivers' yielding behaviors. Zafri et al. [31] found that drivers were more likely to yield to pedestrians who were female, part of a group, carrying baggage, not using a mobile device, gesturing, or using a rolling gap strategy to cross. Similarly, Schneider et al. [32] observed that drivers were more inclined to yield to pedestrians who were white, positioned in the street, or displayed assertive behavior. However, it is unclear to what extent this yielding decision can lead to maneuver adjustment at the operational level, especially when considering the case of micromobility.

In summary, although previous studies have examined isolated aspects of micromobility interactions, and certain behaviors may be partially inferred from conventional bicycle or vehicular traffic research, a systematic, operational-level understanding of interactive micromobility behavior, particularly across different modes and maneuver types, remains largely unexplored.

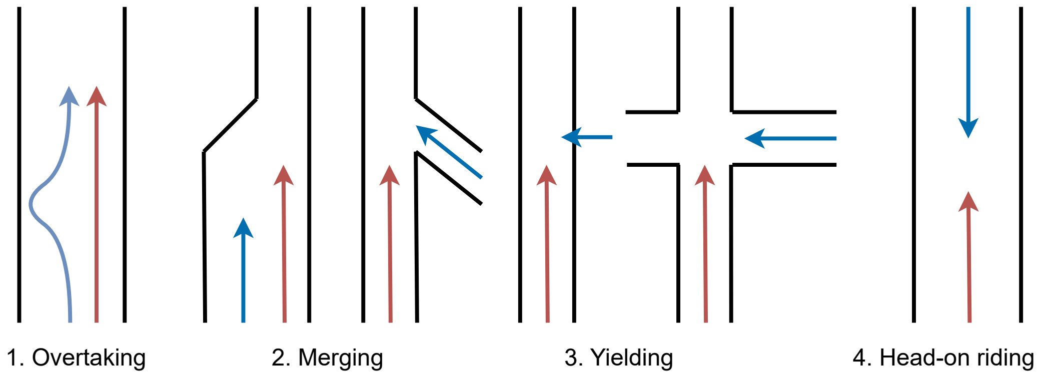


Figure 1 Four interaction movements considered in this work.

2.2 Determinants on interactive riding behavior

2.2.1 Micromobility vehicle types

To identify the determinants that influence micromobility interaction movements, we first examine vehicle-related factors that shape operational behavior across e-bikes, e-scooters, bicycles, and e-mopeds. Studies comparing e-bikes, e-scooters, and bicycles highlight several factors and their unique features influencing rider behavior, particularly in terms of safety, performance, and speed. Billstein and Svernlöv [33] found that e-bikes and e-scooters offer good rider comfort and stability, although e-scooters have poor braking performance. Dozza et al. [24] similarly reported inferior braking capabilities in e-scooters and Segways compared to bicycles, which are generally more stable and safer. E-bikes and e-scooters also exhibit better acceleration and higher speeds than bicycles, with e-bikes reaching higher average and maximum speeds as noted by [7,34]. Almannaa et al. [16] and Pazzini et al. [35] provide mixed results on the average travel speeds of e-scooters versus bicycles, respectively. The rapid acceleration of e-scooters can reduce reaction time to avoid hazards, as found in [36,37]. Higher speeds, however, increase risk, with Dozza et al. [10] observing more conflicts between e-bikes and motorized vehicles. Appearance and acceleration capabilities also influence pedestrian behavior, with e-bike riders more likely to overtake others, as noted by Wang et al. [27]. In addition to these findings, studies on e-mopeds show that they often have higher speeds and greater stability than e-scooters and e-bikes, but they also present unique safety challenges due to their increased weight and acceleration capabilities. ERSO [38] found that e-mopeds, while more stable at high speeds, require longer stopping distances, increasing the potential for collisions in urban environments.

Overall, these differences in design, speed, braking, and maneuverability illustrate why vehicle type is a critical determinant of micromobility interaction behavior. By synthesizing existing findings, we also identify which measurable variables, such as speed, acceleration, braking capability, spacing, or stability, are most relevant for capturing behavioral changes and interactive maneuvers in controlled or real-world settings.

2.2.2 Demographics and experience

It is hypothesized that micromobility riding behavior is influenced by rider's demographic factors such as gender and age, as well as their experience and skills. This assumption can be extrapolated from studies on cyclists. Research by Gulino et al. [34] indicates that female cyclists tend to ride with lower acceleration and speed, while male cyclists exhibit higher rates of violations and are more likely to overtake due to their aggressive behavior [27, 39]. Age also plays a role, with younger riders overtaking more frequently and older e-bike users, especially those over 60, facing balance issues due to the bike's weight [39, 40]. Experience and skills further impact behavior; experienced cyclists tend to commit fewer violations, and frequent users may engage in risky behaviors like using smartphones while riding [39, 41]. In addition, the interactive behavior might be further influenced by the characteristics of modes to be interacted with, such as pedestrians [32].

2.2.3 Cycling infrastructure

The configuration and dimensions of bicycle lanes significantly impact cyclists' behaviors, particularly in overtaking and meeting maneuvers. Wang et al. [27] found that wider cycling lanes increase the probability of overtaking compared to narrower lanes. Garcia et al. [42] showed that cyclists' clearance during head-on encountering increases with track width and decreases when obstacles are present, causing more cautious reactions on narrower and obstructed tracks. A study by Fonseca-Cabrera et al. [43] explored different types of bicycle tracks, revealing that physical or vegetated curbs reduce clearance distances, whereas tracks without edge elements offer more freedom for riders. Meeting and overtaking maneuvers, both requiring side-by-side positioning, are influenced by lane width, topology, and boundaries, with obstacles at handlebar height causing cyclists to ride closer to the center line and brake more frequently [42–44].

2.2.4 Traffic conditions and external factors

Traffic conditions, such as traffic volume and speed, are critical attributes influencing rider behavior and safety on shared cycling lanes. Lin et al. [29] found that low traffic density allows for more stable and less disturbed overtaking maneuvers, such as mopeds passing bicycles, while high traffic density complicates these maneuvers, leading to increased interactions and potential conflicts. Speed also plays a critical role; Dozza et al. [10] noted that higher travel speeds correlate with more critical events and dangerous situations. Cicchino et al. [45] found that e-scooter riders on roads are more likely to sustain severe injuries due to higher speeds, which reduce reaction times and increase collision impacts. Niska et al. [46] and Schepers et al. [47] identified high speed as a frequent cause of crashes, emphasizing the risk of reduced maneuverability at higher speeds. Khan et al. [28] explored how the behavior of cyclists during passing or meeting maneuvers on dedicated bike lanes is affected by speed. The findings indicated that the speeds of both interactive parties play crucial roles in this process: higher speeds can complicate these maneuvers, making them more risky and likely to result in close passes or collisions.

Besides, the external factors, such as weather or lighting conditions are assumed to influence this behavior as well [23]. All the aforementioned attributes influencing conventional bicycle (and/or e-mode) riders are assumed to potentially affect the interactive movement decisions of micromobility riders. Although most of existing studies focus on conventional bicycles, it is reasonable to extrapolate that similar attributes impact micromobility riders, which share the same travel environments on cycling infrastructure. However, this assumption necessitates further empirical validation to determine its extent and level of impact.

2.3 Conceptual framework on micromobility flow interaction

Summarizing all these possible attributes and the above base motion cases, the conceptual model to investigate interactive behavior of micromobility riders as inspired by [25] has been developed in Fig. 2. We have identified five attribute categories: micromobility

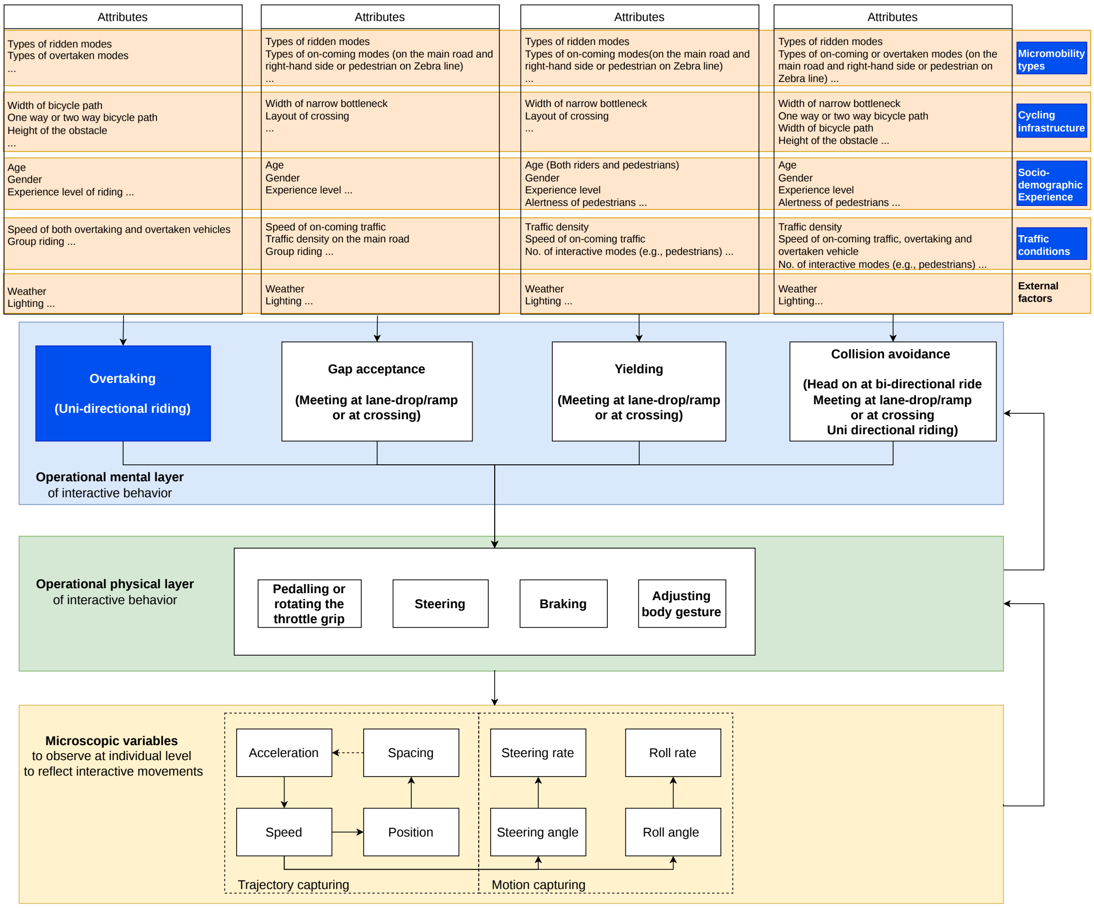


Figure 2 Conceptual framework describing two operational layers of interactive behavior, with 5 main attribute categories and microscopic variables linked to the corresponding decisions. It represents the overall conceptual structure of micromobility interactive behavior, whereas only one specific interaction movement, overtaking, is further explored empirically in Sec. 6 through hypothesis testing and statistical validation (summarized in Fig. 8).

types, cycling infrastructure, socio-demographics and experience, traffic conditions, and external factors. The specific attributes are linked to the corresponding interactive mental-layer decisions, namely overtaking, yielding, gap acceptance, and collision avoidance, at various base motion cases. These decisions are manifested through microscopic variables that describe the traffic state resulting from individual behaviors. Next to speed, acceleration and spacing, variables such as steering angle (rate) and roll angle (rate) offer valuable insights into the rider's control actions during the interactive process, namely steering the handlebar and adjusting their body gesture. The extent of these control actions have been used in many studies to represent stability [33, 48, 49], thus integrating stability as an integral component of individual behavior. These variables reflect physical-layer decisions during interactive movements, such as pedaling (or rotating the throttle grip), steering, braking, and adjusting body gesture. This conceptual framework offers valuable insights into the behavioral attributes and traffic variables that potentially influence micromobility users' interactions with each other and with other road users. However, further validation with empirical data is necessary, underscoring the need to collect such datasets.

3 Research objectives

Based on the given literature overview, it can be concluded that the research effort to observe and understand micromobility operational behavior is limited, since most existing studies focused on conventional bicycles. The most essential gap seems to be studying operational movements of micromobility flow, as well as mode-to-mode interactions at designated cycling infrastructure. To address these gaps, we focus on micromobility flows in the absence of conventional motorized transport modes (cars or trucks), and on examining the impact of different micromobility types/modes (e-bike, e-scooter, or e-moped) and individual characteristics on interactive behaviors. Our objective is to collect a novel dataset that captures micromobility flows and where overtaking, yielding, merging and meeting interactions take place, including their gap acceptance and collision avoidance. The aim of this dataset will therefore be to retrieve the characteristics and determinants (e.g., ridden types/modes, individual characteristics) on influencing these interactions amongst micromobility users. Moreover, the dataset will be used to investigate the attributes that best explain the decisions to overtake, yield, and merge, and the extent of differences in such decisions that exist amongst e-bike, e-scooter, and e-moped riders compared with conventional bicycles. Note that in this paper, we further apply the collected dataset to test a few behavioral related hypotheses on one specific interactive movement: overtaking.

4 Development of data collection plan

The research steps to set up the data collection plan are described. First, the data requirements are identified, followed by the motivation of the choice for the data collection approach and equipment. A controlled experiment is selected and its setup is presented, covering the design of the track, the selection of participants and vehicles needed, the scenarios and the duration required for each scenario, and the tasks for participants.

4.1 Data requirements

The purpose of this study is to investigate the influence of individual factors and different combinations of micromobility modes on the operational riding behavior during interactive movements. These operational behaviors can be observed through a number of microscopic variables presented in Fig. 2. To ensure valid and reliable behavioral analysis, the following data requirements must be met. First, high-resolution trajectory data is required, as it forms the foundation for analyzing individual micromobility behavior. Trajectory data describe the vehicle's position on a two-dimensional plane over time and are used to derive essential microscopic variables such as speed, speed differences, and longitudinal and lateral spacing between interacting vehicles. To guarantee accurate derivation of these variables, the trajectory data should have a spatial precision of at least 10 cm [23]. Second, vehicle stability indicators must also be recorded. In particular, steering angle and roll angle data are required to capture subtle variations in rider balance and steering behavior during interactive maneuvers, serving as important measures of micromobility stability.

Furthermore, since this study involves different types of micromobility combinations, it is necessary to ensure the controllability of the vehicle combinations and to make sure that the targeted interaction movement takes place.

4.2 Data collection approach and equipment

The ability to isolate specific behaviors or conditions in laboratory settings enables the replication of precise traffic scenarios, including various combinations of interactive maneuvers amongst e-bikes, e-scooters, e-mopeds, and conventional bicycles. This control is particularly advantageous for studying interactions that are infrequent or necessitate specific conditions, considering the wide range of possible vehicle combinations. A controlled experiment is designed to collect data on riders' behavior.

However, a notable drawback of using controlled experiments is that as the experiment progresses, participants may become more familiar with the tasks and the behavior of the other opponents, potentially leading to changes in their behavior. Additionally, physical and psychological fatigue might influence their performance, although physical fatigue is less likely to be an issue for powered vehicles. This phenomenon, known as the learning effect, can alter the behaviors exhibited from the beginning to the end of the experiment. To mitigate the learning effect, it is crucial to minimize riding time, provide adequate rest periods, and ensure that participants engage in a variety of tasks throughout the experiment.

In this experiment, a video extraction technique is used to extract the participants' trajectory data. Based on the trajectory data, key variables can be further extrapolated. There are several reasons for choosing cameras to collect data. First, we need to derive trajectory data with an accuracy of approximately 10 cm as discussed in the previous section. The two most common methods for collecting trajectory data are video extraction and GPS. Achieving this level of accuracy with GPS requires high-precision GPS systems, which use a combination of fixed base stations and mobile receivers [50]. These systems are sophisticated and significantly more expensive than video extraction. Additionally, capturing the trajectory of multiple vehicles on the track simultaneously would require multiple high-precision GPS devices. In contrast, image-processing-enhanced cameras provide high-accuracy trajectory data at a lower cost, making them a more economical and practical choice.

Overhead video cameras are selected to place above the experiment site, and the cameras with advanced software can track participants movements with as little occlusion as possible, and continuously in time. To be able to automate the extraction of trajectories from the video images, each participant wears a red cap to facilitate the tracking of participants' head positions. This is because red is the color easiest to recognize under a wide range of lighting conditions [51]. The caps are assigned a unique identification code, which enables linking individual characteristics to the identified trajectory.

The Inertial Measurement Unit (IMU) is employed to measure the roll angle of e-bikes, and e-scooters, providing insights into the stability of these micromobility vehicles. Studies by Violin [48], Billstein and Svernlöv [33] used several stability indicators such as steer angle, steer rate, roll angle, and roll rate. While the steering angle and rate were measured using potentiometers, which often require the addition of devices to the steering rod (beyond the expertise of the researchers) the roll angle and roll rate were effectively captured using an IMU. The IMU's high integration and ease of installation, requiring only tie-wraps without further modifications and directly outputting data, made it the preferred choice for this study [52].

4.3 Track design

In designing the cycling track on experimental site, several critical factors are considered to ensure the successful completion of interactive maneuvers, including straight riding, overtaking, merging, yielding, and head-on riding.

First, riders should maintain a speed as close as possible to their normal speed and behave as they would in reality (no or less speed change). To ensure the riding continuity, continuous riding routes are designed for participants under specific riding maneuvers, so that they can run laps along these lines in the field (see red, blue, green lines as in Fig. 3).

The main track needs to be sufficiently long to accommodate interactive process, particularly for the overtaking process. Assuming the speed of the overtaken mode at a higher bound of 4 m/s and the speed of the overtaking mode at a lower bound of 5 m/s, and considering 5 m safe distance before and after the overtaking process (10 m in total), the minimal track length should be 50 meters, based on the basic physical law (speed $\times$ distance / speed difference = $5 \times 10/(5-4)$ m). This setting is in line with our previous configuration used in controlled experiments on bicycle interactions [22]. Consequently, a main track measuring 60 meters in length is designed to provide extra space to accommodate interactions occurring. This track includes two-way bike lanes, each lane being 1.8 meters wide (totaling 3.6 meters), with a buffer distance of ten meters on both the left and right sides. This buffer is intended to accommodate any necessary acceleration or deceleration. The layout is detailed in Fig. 3. The main reference for the 1.8 m width of the lanes is based on a study of field measurements of two-way bicycle lanes in the Netherlands [53], which is approximately 3.7 m, including the width of the markings in the middle of the road. To accommodate yielding maneuver, a zebra line and an intersection need to be placed perpendicular to the main track. Regarding merging, a 45-degree on-ramp is designed to connect the main track, additionally two-way bike lanes can be dropped to one lane to trigger merging. The lane drop can be realized by adding the temporary line (using ground tapes).

Therefore, overtaking can be realized by requesting participants riding on the red and blue lines in the track; yielding can happen at the intersection when participants riding on the red and green loops, respectively, and toward pedestrians at the zebra line; merging

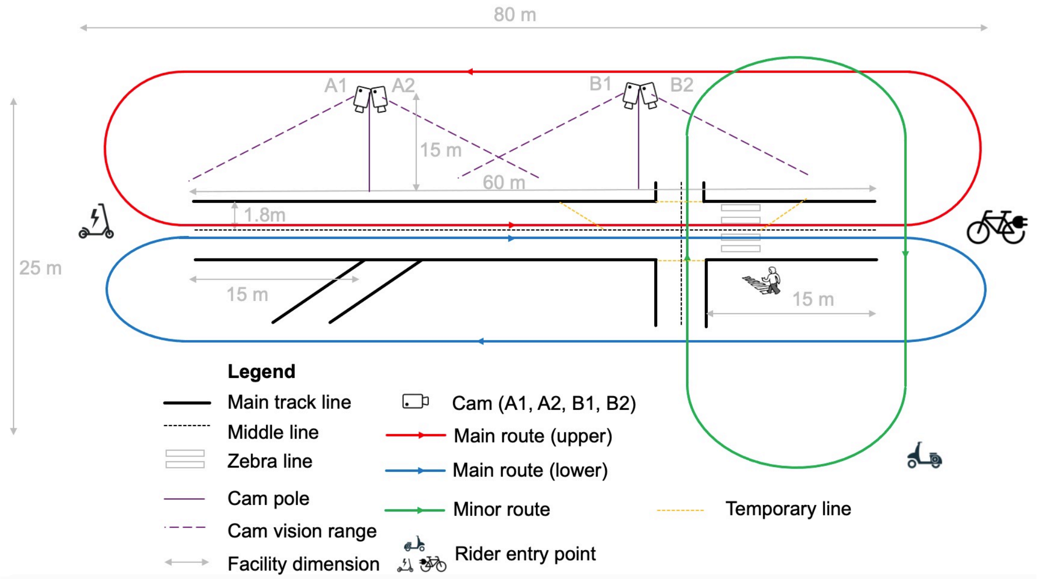


Figure 3 Track layout showing elements activated for distinct interactive scenarios.

can take place when participants entering the main track from the on-ramp or a lane drop segment is created on the main track; and head-on meeting can be realized by two flows riding toward two ends of the main track, as indicated in Fig. 3.

4.4 Vehicle and participant selection

The first step of the scenario design is to select the specific models of e-scooter, e-bikes and e-mopeds that to be investigated in this study. In selecting the travel modes, the following three factors are taken into consideration:

1. Popularity in the market.
2. Easiness of learning to use these e-mode vehicles - the need to avoid vehicles that participants could not learn to ride in a short period of time.
3. The maximum speed of the vehicle should be kept below 25 km/h to prevent potential safety issues during the experiment.

To consider the heterogeneity among participants, each scenario should include at least 30 combinations (as a rule of thumb), where one combination involves a rider with the designated mode performing the requested maneuver. The rider should be proficient in operating the specified mode. Ideally, the rider population should encompass a broad range of ages and genders. Considering the trade-off between time, financial budget, and feasibility, 12 combinations were ultimately selected. Consequently, 12 riders can be recruited per mode. And 4 repetitions/runs per combinations of participants (in total 48 runs per scenario) are performed to get statistically significant results.

4.5 Scenario design, duration and scheduling

The aim is to investigate the effect of the two main attributes of Fig. 2 on interactive behavior: namely the micromobility modes, and characteristics of participants. The latter one has been addressed in the previous section. For the former, in each type of interactive maneuvers, 3 intra-modal interactions are identified: e-scooter (ES) vs. ES, e-bike (EB) vs. EB, e-moped (EM) vs. EM; and 3 inter-modal interactions are included: ES vs. EB, ES vs. EM, and EB vs. EM – so 2 scenarios per inter-modal case. When involving conventional bicycles (B) or pedestrians (P) in interaction scenarios, 6 additional combinations are considered. The planned scenario runs and their properties are summarized in Tab. 1.

The estimation of the duration needed for each scenario is based on the requirement to have enough observations (i.e., 48 runs) to draw statistically significant findings. For the time taken to complete a lap, considering that the average speed of the e-bike, e-scooter, e-moped is around 4 m/s (as the lower bound) and the maximum distance to complete a full lap is roughly 150 m , it will take around 37.5 s to complete a lap, but taking into account the starting time, the probability of slowing down when turning, yielding, merging, etc., a lap of 1 min is taken (as the upper bound). Each experimental participant needs to run four laps to collect four valid interactive actions. The expected duration for each scenario is presented in Tab. 1, the actual duration might be less due to the fact that participant's riding would be scheduled in a consecutive order when conditions allow.

4.6 General instruction and task design

On the straight main track, participants are asked to slow down 5 m before the endpoint (there was a road marker) to facilitate the turning. Prior to conducting the interactive maneuver experiment, it is important to obtain the reference values in key variables. We first conduct an unhindered scenario where the rider maintains a normal/desired speed, decelerates to standstill, and then accelerates back to the normal speed without any interruptions. This step is primarily aimed at understanding the rider's speed and acceleration/deceleration behavior under normal riding conditions.

The main tasks for participants are to perform various interactive maneuvers: overtaking, merging, yielding, head-on meeting. The overtaking maneuver, consisted of two types of riders, in which some participants were instructed to ride at low speeds on the designed bike lanes as overtaken riders, and the other part of participants would overtake the low-speed vehicles from the left side in a safe manner as overtaking riders. The speedometer dashboard was available for e-scooter, the speed was bounded to be around 10 km/h under the cruise control mode. For the e-bikes or e-mopeds, their speeds were not strictly limited due to the absence of dashboards and cruise control functions. The

Table 1 Scenario design and expected duration. Note, ES: e-scooter, EB: e-bike, EM: e-moped, B: conventional bicycle, P: pedestrian. Column ”Revision” contains the information for scenario adjustment when implementing experiment.

Sce No.	Sce Name	Participating mode					Exp. duration	Revision
		ES	EB	EM	B	P	(min)	
1	Overtaking-intra1	✓	-	-	-	-	12 x 4	
2	Overtaking-intra2	-	✓	-	-	-	12 x 4	
3	Overtaking-intra3	-	-	✓	-	-	12 x 4	
4	Overtaking-inter1	✓	✓	-	-	-	12 x 4 x 2	
5	Overtaking-inter2	✓	-	✓	-	-	12 x 4 x 2	
6	Overtaking-inter3	-	✓	✓	-	-	12 x 4 x 2	
7	Overtaking-bike1	✓	-	-	✓	-	12 x 4	
8	Overtaking-bike2	-	✓	-	✓	-	12 x 4	
9	Overtaking-bike3	-	-	✓	✓	-	12 x 4	
10	Bypassing-obstacle1	✓	-	-	-	-	12 x 4	
11	Bypassing-obstacle2	-	✓	-	-	-	12 x 4	
12	Bypassing-obstacle3	-	-	✓	-	-	12 x 4	
13	Yielding-pedestrian1	✓	-	-	-	✓	12 x 4	
14	Yielding-pedestrian2	-	✓	-	-	✓	12 x 4	
15	Yielding-pedestrian3	-	-	✓	-	✓	12 x 4	
16	Yielding at crossing1	✓	-	-	-	-	12 x 4	removed
17	Yielding at crossing2	-	✓	-	-	-	12 x 4	removed
18	Yielding at crossing3	-	-	✓	-	-	12 x 4	EM to EM
19	Yielding at crossing4	✓	✓	-	-	-	12 x 4	ES to EB
20	Yielding at crossing5	✓	-	✓	-	-	12 x 4	ES to EM
21	Yielding at crossing6	-	✓	✓	-	-	12 x 4	EB to EM
22	Yielding at crossing7	✓	-	-	✓	-	12 x 4	
23	Yielding at crossing8	-	✓	-	✓	-	12 x 4	
24	Yielding at crossing9	-	-	✓	✓	-	12 x 4	
25	Merging at ramp1	✓	✓	-	-	-	12 x 4 x 2	removed
26	Merging at ramp2	✓	-	✓	-	-	12 x 4 x 2	removed
27	Merging at ramp3	-	✓	✓	-	-	12 x 4 x 2	removed
28	Merging at lane-drop1	✓	-	-	-	-	2 x 4	removed
29	Merging at lane-drop2	-	✓	-	-	-	2 x 4	Combined B
30	Merging at lane-drop3	-	-	✓	-	-	2 x 4	
31	Head-on meeting1.	✓	-	-	-	-	12 x 2	
32	Head-on meeting2.	-	✓	-	-	-	12 x 2	
33	Head-on meeting3.	-	-	✓	-	-	12 x 2	

overtaken riders were asked to ride at a low speed that does not interfere with their control of balance (e.g., requiring additional control maneuvers such as a large wiggle of the steering grip or adjustment of body position). Overtaking riders were merely asked to follow their habits and methods when overtaking low-speed vehicles without colliding.

In situations involving yielding to pedestrians at crosswalks or to traffic approaching from the right, riders without the right of way were instructed to behave as they would in reality, i.e., continuing to ride, stopping, or yielding, as long as safety is guaranteed (i.e., no collision occurred). In cases involving bi-directional encounters, participants must prioritize their riding behavior to prevent head-on collisions or ensure safety.

5 Implementation of experiment design

Having set the requirements and the experiment design, the implementation follows and is divided into the selection of the location, the recruitment of participants and vehicles, and the setup of the measuring and tracking equipment. The experiment execution and adjustment is presented. Lastly, the video processing procedure is briefly described.

5.1 Location selection

The experimental site is a square area located at the Hebei University of Water Resources and Electric Engineering in Cangzhou, China, as shown in the red rectangle part of Fig. 4. The dimensions of this square are about 25 m in width and 80 m in length, which fulfills the track design requirements. In the actual experiment, the track in Fig. 3 was created using ground tape (of 48 mm in width). The boundary lines of the road were marked with yellow and black tape, as this color combination is most visible to participants, while the dotted line in the middle of the road was made using white ground tape. Note that the width of these tapes closely aligns with the preferred lane marking width (50 mm) specified in the pavement marking manual [54].

This site is an outdoor environment. The external attributes such as weather and light cannot be controlled, but we try to keep the circumstances constant during the whole experiment. In this experiment, video recognition techniques are used to extract the trajectory data of micromobility riders. The video extraction technique requires the camera to be set up in a high place, to this end, the aerial work platforms are used to mount the cameras. In order to ensure that the data obtained by the video extraction technique is accurate and consistent, two groups of cameras are used. Before the experiment started, the position of the two aerial trucks, as well as the exact height of the lift, were adjusted to achieve the preferred position based on the real-time output from the camera. Figure 4 shows the position of the two aerial trucks and thus the camera groups, as well as the track on the ground. This area is covered with standard granite square tiles of size 60 x 60 cm, it is regularly used by pedestrians, bicycles, and motor vehicles within the campus. Therefore, the surface type resembles real-world riding/cycling conditions.

5.2 Participant recruitment and vehicle usage

Since the experiment site is in a campus, recruitment was carried out via the campus intranet, on a strictly voluntary basis, with reasonable monetary compensation. During the recruitment process, only the participants' heights, and genders were collected, no

Figure 4 Top view of experimental site. Red rectangle part denotes the site.

personal identifiable information was recorded. Finally, 42 participants are recruited: 12 for e-bikes, 12 for e-scooters, 12 for e-mopeds, and 6 for conventional bicycles.

For practical reasons, we ended up obtaining three e-scooters (Nitebot E9 model), four e-bikes (two regular - brand Phoenix, one fat e-bike, and one foldable e-bike), and 12 e-mopeds (similar models of brand AIMA). This implies that the variety within the same e-modes (particularly e-bikes) should be critically considered when analyzing the data.

Regarding rider personal characteristics, combined with the actual recruitment of the experimental participants, a broad coverage in age, and the equal level in gender and riding experience were difficult to realize because the participants were mainly university students, with very little difference in age. Most of them had similar experience in using e-scooter, e-bike, and/or e-mopeds, but varying in familiarity level. Two days prior to the experiment, participants attended a briefing session where they were informed about the riding procedures for the experiment days, and informed consent materials were collected. After the briefing, participants were allowed to voluntarily choose the type of micromobility vehicle they wanted to ride. The participants who have more experience in certain modes had the priority of using the corresponding mode in the experiment. Finally, the the male/female ratios are 9/3, 8/4, and 9/3 for e-scooter, e-bike, and e-moped, respectively. Although it is not perfectly balanced (50/50), potential effects of rider gender on micromobility interactions can still be examined. Once the groups were formed, each participant was assigned a micromobility vehicle based on their height order. This measure was taken because the limited number of e-bikes or e-scooters required three or four people to share one vehicle, and similar heights ensured that they did not need to adjust the seat height throughout the experiment. Additionally, the sitting or standing heights of each participant were measured.

After completing group assignment, participants familiarized themselves with and test drove the vehicles they would use during the experiment, ensuring they were qualified as riders of the assigned modes, despite varying levels of user experience and familiarity. According to Rasmussen [55], riding a bicycle involves a combination of tasks executed based on rules for performing maneuvers and automatic actions for split-second control of the bicycle. We posit that a similar operational process of actions and reactions applies to micromobility traffic. By providing participants with the opportunity and sufficient time to familiarize themselves with riding the vehicles (particularly e-scooters and e-bikes), their riding and interactive maneuvers are expected to reflect their natural behavior under split-second decision-making conditions.

5.3 Data collection equipment setup

5.3.1 Camera setup

The experiment employed four high-resolution cameras (Dahua), which were divided into two sets to cover the whole range of the main track with overlapping area for trajectory stitching purposes, see Fig. 3. An asymmetric setup of the two cameras was used, that means one camera would cover most of the interactive area, the other one would cover the central area plus a further area in the riding direction. Before the start of the experiment, the camera was secured to the railing of the aerial platform. The offset angle and focal length of the camera, as well as the position of the aerial work truck and the final operating height (about 15 m), were all adjusted repeatedly according to the output picture of the camera, which was accomplished after achieving the effect of clear video effect and reasonable coverage. The final four cameras all output video in 1920×1080, 20 fps format.

A top view at the locations for scenarios of unhindered riding, overtaking, bypassing, merging, yielding, and head-on meeting, can be seen in Fig. 5. From this view the trajectories can be extracted by tracking the red cap of each rider.

5.3.2 IMU setup

Due to the limited availability of IMU devices, only one e-scooter and one e-bike were instrumented throughout the experiment, with the sensors mounted on the e-scooter's steering stem and the e-bike's backseat, respectively. Sensor BNO-055 [56] has a built-in Kalman filter algorithm that directly outputs roll angle, yaw angle, and pitch angle. The devices did not need to be dismounted or recalibrated, allowing consistent and continuous data recording. The instrumented e-scooter was used by four riders with four runs each, resulting in 16 IMU samples, whereas the instrumented e-bike was used by three riders with four runs each, resulting in 12 IMU samples in each scenario. Although this setup ensured consistency in the measurements, the resulting stability-related findings should be interpreted as exploratory rather than fully representative of the broader population of micromobility users.

(a) Cam A2: unhindered (ES: normal riding) (b) Cam B1: unhindered (ES: decelerate to stop)

(c) Cam A2: overtaking (ES-B) (d) Cam A1: bypassing obstacles (EB)

(e) Cam B2: yielding to pedestrians (EB-P) (f) Cam B1: yielding (ES-EM)

(g) Cam B1: merging at lane-drop (EM) (h) Cam A2: head-on meeting (ES-ES)

Figure 5 Camera snapshots, including examples for various unhindered and interactive scenarios (a-h)

5.4 Experiment execution and adjustment

The original plan was to conduct the experiment on the weekend of May 25-26, 2024. However, due to rain, the experiment scheduled for Saturday was canceled. This resulted in a condensed experimental schedule on Sunday, requiring adjustments to scenario selection and timing to ensure completion within a single day, and underscoring the importance of contingency planning for outdoor experiments. Finally, the experiment was conducted on Sunday, a sunny day. The lighting remained relatively constant across different scenarios over the daytime. Each participant wore a red cap for automated video tracking and a white T-shirt to prevent interference with the red cap's visibility in camera images. A unique identification code, consisting of a specific shape and a Roman numeral, was assigned to each participant. The size of the code on the cap brim was designed and tested to be sufficiently large for visibility from the camera.

For most of the design scenarios, we instructed participants to perform their riding task in a sequence order. That means one participant did not have to wait another participant to complete a lap before entering the track. This arrangement can expedite most of overtaking and bypassing scenarios.

Each scenario involves two interactive flows. It is essential to ensure sufficient interactive maneuvers are triggered during the experiment and captured by cameras in designated areas. Due to the loss of one experimental day and the limited number of e-scooters and e-bikes, scenarios requiring long running times were removed from the original schedule to avoid time constraints and long waiting times for other participants, which could potentially jeopardize their natural behavior. This decision was therefore primarily driven by practical and behavioral considerations, aiming to preserve participant attentiveness and maintain naturalistic riding behavior during the experiment. This applied to several scenarios: intramodal yielding scenarios for e-scooters (2 ES on the main upper route vs. 1 ES on the minor route) and e-bikes (2 EB on the main upper route vs. 2 EB on the minor route); intermodal yielding scenarios where e-scooters or e-bikes had to use the minor route; and all on-ramp merging scenarios. The final adjustments, shown in Tab. 1, allowed for a shorter expected duration for each scenario and enabled the completion of all scenarios within one day. Although some originally planned scenarios were excluded, the retained experiment design still captured the primary operational interaction behaviors of interest, particularly overtaking and yielding interactions across different micromobility mode combinations.

The cameras and IMU unit initiated recording simultaneously after the camera parameters were adjusted. Then, the researcher guided the participants about the appropriate time that they entered the designed track according to pre-defined schedule. After entering the track, they followed their designated path and performed their tasks.

5.5 Video processing procedure

We adopted and refined the automatic video procedure technique presented in [22, 57]: specifically, a) Processing video to identify and record pixel trajectories based on participants' head positions using a Moving Object Detection and Tracking (MODT) tool [58]; b) Filtering wrong trajectories using a software package developed at TU Delft, called TrajectoryViewer [57]; c) Orthorectification and lens correction, specifically a homography-based correction was derived from manually selected reference points and applied to all video frames (see example in Fig. 6); d) Ground-level projection of trajectories from tracked head positions to reflect ground positions; e) Time synchronization; f) Trajectory stitching across multiple cameras; g) Trajectory smoothing (using moving average method). The trajectory extraction process was fully video-based, and IMU data were not involved in the extraction or correction of trajectories. The expected trajectory precision (approximately 10 cm) is consistent with validation results reported in previous studies using the same methodology [23].

This method enabled automatically extract trajectories out of the images, stitch trajectories between consecutive cameras, and link to a participant number for all the conducted manoeuvres (overtaking, yielding, merging, head-on riding). At the time of writing, trajectories from all the overtaking scenarios for intra- and inter-modal interactions were derived, and will be elaborated in the next Section.

6 Exploratory Trajectory Analysis

This section presents an exploratory analysis of data processing and extracted trajectories for a representative interaction, namely overtaking behavior of micromobility riders (e-bikes and e-scooters). The results are intended to illustrate the analytical potential of the dataset rather than to provide a comprehensive behavioral assessment.

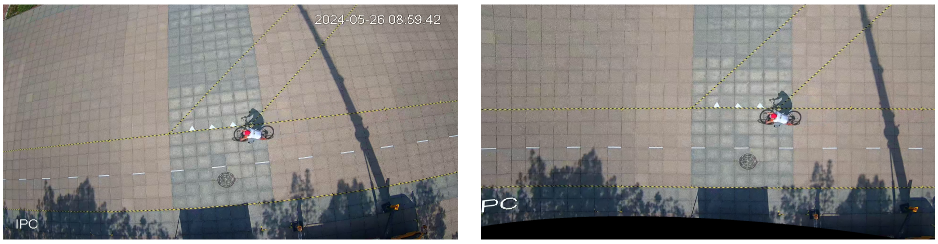
6.1 Trajectory derivation

Fig. 6 provides the original and orthorectified images (based a homography-based correction) from each camera to cover the whole main track. The orthorectification procedure was adopted to transform individual trajectories. Fig. 6(i) illustrates the combined view from the four cameras so that partial trajectories from cameras can be stitched to form continuous ones for data analysis. Fig. 7 shows an example of trajectories of three operational cameras from the overtaking scenarios (before stitching). These trajectories will be further stitched to derive speed, acceleration and distance variables, and their differences for overtaking and overtaken vehicles. Additionally, the trajectory data were synchronized with measurements from the IMU unit to ensure temporal alignment, enabling precise analysis of roll angle and stability variations during overtaking maneuvers.

6.2 Insights for behavioral analysis

First, three overtaking/passing phases are defined. The concept of ”passing phases” which is similar to previous study [28] was central to the data analysis. In this work, the overtaking process was primarily defined by the ”passing phase”, with additional phases identified before (”pre-”) and after (”post-”) this critical period. The passing phase was defined as the time period when the longitudinal distance between the front of the overtaking vehicle and the rear of the overtaken vehicle was within 2 m. The choice of a 2 m threshold for defining the passing phase was based on ensuring that this distance could adequately cover all possible combinations of vehicles involved in the experiment. This threshold corresponds to approximately half the combined length of the overtaking and overtaken

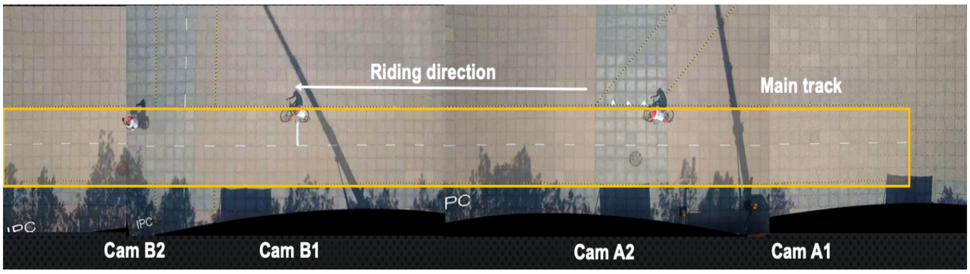
(a) Cam A1: raw image (b) Cam A1: orthorectified image



(c) Cam A2: raw image (d) Cam A2: orthorectified image

(e) Cam B1: raw image (f) Cam B1: orthorectified image

(g) Cam B2: raw image (h) Cam B2: orthorectified image



(i) Combined view of the four cameras

Figure 6 Combined view (i) from four cameras at the main track, based on the orthorectified images (b,d,f,h), derived from the raw images (a,c,e,g) of individual cameras.

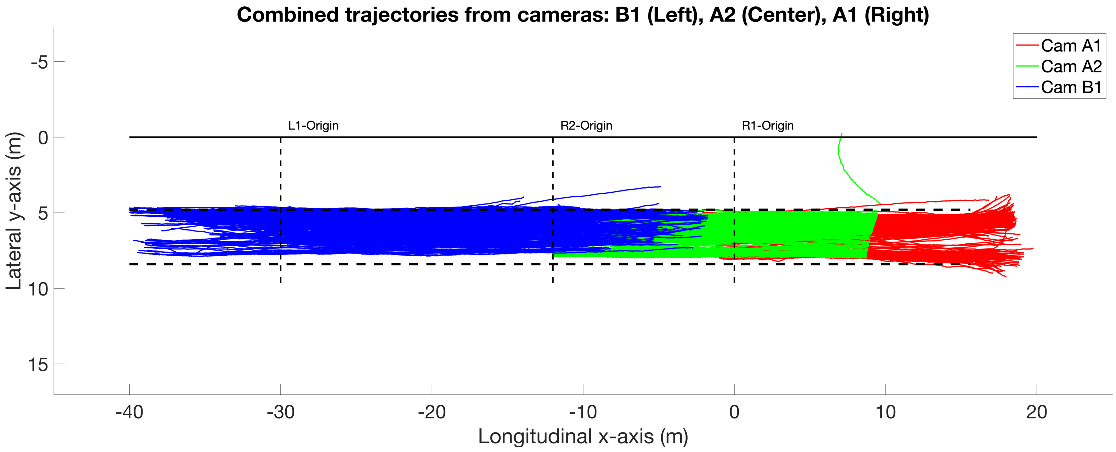


Figure 7 Stitched trajectory samples from three operation cameras for overtaking scenarios (Trajectories from Cam B2 were excluded from overtaking scenarios due to significant overlap with Cam B1).

vehicles. While this value is indeed subject to variation, given that riders on e-bikes or bikes may lean forward or change posture, and e-scooter riders can stand in different positions, the 2 m range provides a slight redundancy

The trajectory-based and stability-related variables can be used to test hypotheses regarding overtaking behavior between e-bikes and e-scooters. For instance, based on experimental observations, the conceptual framework, and the set of available measurable variables derived from trajectories, the following hypotheses are proposed.

1. There exist speed (H1a) and acceleration/deceleration (H1b) differences between e-bikes and e-scooters in non-interactive scenarios. And there exists a gender difference in speed variable (H1c).

2. E-bikes and e-scooters will maintain different lateral distance when overtaking each other (H2a). And there exists a gender difference in lateral distance during passing phase (H2b).

3. There is a difference in the overtaking starting position when the same micromobility riding type overtakes a different micromobility overtaken mode during (pre-) passing phase (H3a). And there exists a gender difference in overtaking starting position (H3b).

4. The speed different during overtaking will have a positive relationship with lateral overtaking position across different modes.

5. The speed difference during overtaking will vary based on the type of overtaking and overtaken vehicles.

6. The roll angle and roll rate of the overtaking vehicle will be influenced by both the overtaking phases (H6a) and the type of vehicles (H6b).

Based on these identified factors and hypotheses, the conceptual framework describing interactive behavior (Fig. 2) is further refined into a framework focusing specifically on overtaking maneuvers, incorporating all behavior-related hypotheses and their corresponding statistical outcomes (Fig. 8).

In total, there are 5 scenarios featuring the overtaking interaction amongst e-bike, e-scooter and conventional bicycle as provided in Tab. 1: namely Scenarios No.1 (ES-ES), No.2 (EB-EB), No.4 (EB vs. ES: two scenarios), No.7 (ES-B), No.8 (EB-B). To facilitate subsequent analysis, the scenarios were renumbered using Roman numerals, resulting in six scenarios: Scenario I. EB vs. B; Scenario II. EB vs. ES; Scenario III. EB vs. EB; Scenario IV. ES vs. B; Scenario V. ES vs. EB; Scenario VI. ES vs. ES. Using the collected trajectory data in these scenarios, we have tested these hypotheses. Note that all statistical analyses were performed using trajectory-level aggregated variables (e.g., average speed, maximum lateral distance, overtaking initiation location), rather than raw time-series observations sampled at 0.05 s intervals. Consequently, each sample used in the statistical tests corresponds to one complete trajectory or one interacting trajectory pair during a specific interaction phase, avoiding temporal autocorrelation effects. In addition, repeated observations from the same participant were temporally separated during the experiment. Therefore, the t-tests and ANOVA analyses were conducted based on independent observations. Although the dataset remains exploratory in nature, the main behavioral trends were consistently observed across multiple scenarios and variables, supporting the robustness of the reported findings. The related explanations are provided in the ensuing.

6.2.1 Speed and deceleration in non-interactive conditions

We began by comparing the overall traveling speeds of e-bikes and e-scooters. It can be observed that the average traveling speed of e-bikes is significantly higher than that of e-scooters (two-sample t-test, $|t| = 5.47$, $p < 0.001$). The average traveling speed of e-bikes was 19.95 km/h, while the average traveling speed of e-scooters was 17.86 km/h. This comparison confirms the hypothesis that there is a significant difference in speed between these two micromobility types (H1a). This finding is also consistent with the actual specifications of the experimental vehicles we selected. The e-scooter we chose has a maximum speed of only 20 km/h, while the e-bike has a speed limit of 25 km/h, even when using the pedaling mode.

The results revealed significant speed differences between e-bikes and e-scooters, with e-bikes traveling at notably higher speeds. However, no distinction was observed in their acceleration/deceleration behavior, thus rejecting H1b. Significant gender differences in travel speed were observed for both e-scooter and e-bike riders, with male riders consistently exhibiting higher speeds than female riders (e-scooters: 18.23 vs. 16.26 km/h, $|t| = 2.22$, $p = 0.0310$; e-bikes: 21.08 vs. 19.18 km/h, $|t| = 2.24$, $p = 0.0293$). Hence, we accept hypothesis H1c.

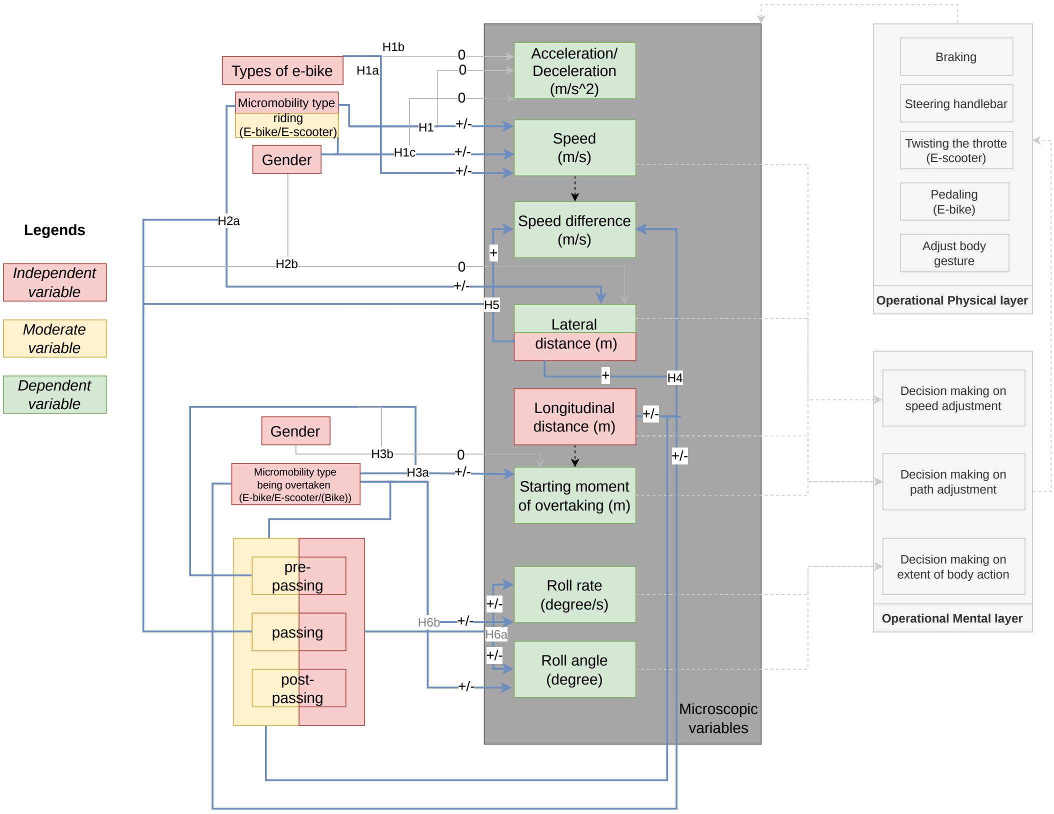


Figure 8 The corroborated conceptual model of behavioral related hypotheses including the results of the statistical tests, regarding the relations between influential factors and microscopic traffic variables that can reflect one specific interactive movement: overtaking. In the framework + represents a positive relation between the variables, and 0 represents no relation, while +/- indicates relationships whose sign depends on the specific definition or realization of the variable.

Table 2 Overview of longitudinal and lateral spacing variables in the six overtaking scenarios. dy_{ot}: overtaking lateral distance (m), dx_{ini}: overtaking initiation location (m).

Sce ID.	Overtaking(ot.) type	dx_{ini} (mean)	dx_{ini} (std)	dy_{ot} (mean)	dy_{ot} (std)
I	EB ot. B	6.63	2.87	1.32	0.23
II	EB ot. ES	6.75	3.91	1.31	0.18
III	EB ot. EB	8.15	5.22	1.37	0.34
IV	ES ot. B	5.80	4.18	1.08	0.45
V	ES ot. EB	7.21	3.11	1.07	0.40
VI	ES ot. ES	4.58	2.72	1.12	0.30

6.2.2 Overtaking lateral distance

In most cases, the maximum lateral distance occurs during the passing phase (within a 2 m range). However, we also observed instances where the maximum lateral distance occurred in the post-passing phase, indicating that the overtaking rider did not immediately return to the original path after passing the overtaken vehicle, but instead maintained the lateral offset for a longer distance before merging back. This behavior may reflect a cautious merging strategy or delayed path realignment to ensure sufficient clearance and stability after completing the overtaking maneuver.

Tab. 2 provides an overview of the longitudinal and lateral spacing variables across the six overtaking scenarios. Notably, when overtaking the same type of vehicles (i.e., e-bikes, e-scooters, and conventional bicycles), e-scooters maintain a significantly smaller average lateral distance compared to e-bikes (1.07 vs. 1.31 m for overtaking EB, $|t| = 3.47$, $p < 0.001$; 1.12 vs. 1.36 m for overtaking ES, $|t| = 3.44$, $p < 0.001$; 1.08 vs. 1.32 m for overtaking B, $|t| = 2.99$, $p = 0.0038$), with no significant gender influence observed (thus supporting H2a and rejecting H2b). This also suggests that the type of vehicle being overtaken does not significantly influence the lateral distance during overtaking, whereas the type of the overtaking vehicle does. In this case, e-scooter riders may perceive themselves as occupying less space and thus more maneuverable compared to e-bike riders, prompting them to feel more comfortable overtaking with a smaller lateral gap.

6.2.3 Overtaking initiation location

Using an analysis of the rate of change in the lateral position difference (by identifying deviations beyond a statistically defined threshold derived from non-overtaking phase), the study detected the initiation points (corresponding to the starting moments) for overtaking maneuvers in e-bikes overtaking e-scooters, e-bikes, and conventional bicycles. Generally, both e-bikes and e-scooters initiate overtaking from a greater longitudinal distance when passing e-bikes than when passing e-scooters or conventional bicycles (8.15 m vs. 6.75 m or 6.63 m for e-bike riders; 7.21 m vs. 4.58 m or 5.80 m for e-scooter riders), with no significant gender influence observed (thus supporting H3a and rejecting H3b). This behavior may be explained by the perception that e-bikes typically travel faster than e-scooters or conventional bicycles, prompting overtaking riders to initiate the maneuver earlier to ensure a smooth and safe pass. Additionally, overtaking another e-bike may require more anticipation due to similar acceleration profiles and greater space requirements.

In addition, e-scooters initiate overtaking e-bikes (7.21 m) or other e-scooters (4.58 m) from a shorter longitudinal distance compared to e-bikes overtaking e-bikes (8.15 m) or e-scooters (6.75 m). Although it may appear counterintuitive, the shorter longitudinal distance observed for e-scooter users when initiating overtaking compared to e-bike riders, may be attributed to the smaller physical footprint and higher perceived maneuverability of e-scooters (as e-scooter users may visually resemble standing pedestrians). Additionally, e-scooter users may be more reactive and less anticipatory in their riding style, initiating overtaking later in proximity to the leading vehicle.

6.2.4 Speed difference

We observed significant differences in speed between overtaking and overtaken riders across the three passing phases via an ANOVA analysis (in all six scenarios, $p < 0.001$). A multiple linear regression analysis was conducted to assess the relationship between speed difference and position differences (both lateral and longitudinal), as well as vehicle type across scenarios. The analysis results indicate that there was a consistent positive (+) correlation between relative speed difference and lateral distance, with higher speeds associated with larger lateral distances during overtaking. This indicates that riders adapt their lateral space for safety based on speed differences. So H4 is accepted.

The hypothesis H5 was supported by the data, demonstrating that the speed difference during overtaking phase varies based on the type of overtaking and overtaken vehicles. In general, when overtaking the same type of vehicles (i.e., e-bikes, e-scooters, and conventional bicycles), the average speed difference between the overtaking and overtaken modes is the largest when the overtaken vehicle is a conventional bicycle (exceeding 11 km/h), whereas it remains below 10 km/h when the overtaken vehicle is an e-scooter or an e-bike. This pattern can be explained by the generally lower speeds of conventional bicycles, which create a larger speed gap when overtaken by ”faster” micromobility vehicles such as e-bikes and e-scooters.

In addition, speed change of the overtaken riders was analyzed at the start moment of being overtaken (corresponds to the end of pre-passing phase - that these riders noticed that they were being overtaken), compared with the moment at the beginning of the pre-passing phase. It is interesting to observe that when riders (conventional bicycles, e-bikes, or e-scooters) were overtaken by e-bikes, they exhibited a slight speed increase (less than 1 km/h) at the end of the pre-passing phase, whereas when overtaken by e-scooters, they showed a slight speed decrease. Among all six scenarios, this effect was most pronounced when e-bikes were overtaken by e-scooters ($|t| = 2.18$, $p = 0.0332$), with a significant average speed reduction of 1.32 km/h. This behavior may be explained by the perception that e-bikes typically travel faster than e-scooters, prompting the ”faster” mode to adjust its speed to allow the ”slower” mode to complete the overtaking maneuver. In the study by [59], 38.3% of cyclists were observed to accelerate when being overtaken. Similarly, studies on car-following behavior highlight that people adapt their speed in response to surrounding vehicles [60], a behavior that can be similarly applied to micromobility riders in close interactions. Considering that e-bikes and e-scooters are either pedal-assisted or fully electric, it is reasonable that they readily adjust their speed in response to surrounding traffic conditions. This adjustment can be seen as a natural reaction to being overtaken, that riders alter their speed as a form of defensive or adaptive behavior when interacting with others in close proximity, facilitated by the stronger acceleration capabilities of these vehicles. This behavior helps maintain safety and comfort, especially in dynamic environments.

6.2.5 Roll rate and roll angle

The roll rate and roll angle were consistently higher during the overtaking phase than other (pre-/post-) phases across scenarios, suggesting more aggressive maneuvers during this period (partially supporting H6a, with H6a shown in grey in Fig. 8 due to limited representativeness). During overtaking, riders need to change position to avoid collisions with the overtaken vehicle, inevitably leading to larger angle changes. This is because completing an overtaking maneuver within a limited lane width requires riders to perform more abrupt and pronounced steering actions. However, because only one e-bike and one e-scooter were instrumented, the IMU results can indicate phase-related changes in roll angle and roll rate within the observed runs, but should not be generalized as population-level differences across vehicle types or riders.

In comparing e-bikes overtaking e-scooters (Scenario II) and e-bikes overtaking other e-bikes (Scenario III), Scenario III exhibited higher roll angles and lateral angle change rates during the pre-passing phase (4.48° vs. 4.04°; 30.41°/s vs. 26.17°/s). This behavior may be attributed to the larger physical volume of the overtaken e-bikes compared to e-scooters (which often resemble standing pedestrians), prompting e-bike overtakers to adopt greater roll angles and roll rates for safer overtaking maneuvers. While these observations are consistent with H6b, the limited IMU sample size prevents strong statistical generalization, and the hypothesis should therefore be considered only preliminarily supported (with H6b indicated in grey in Fig. 8). Note that the IMU data for Scenarios V and VI were incomplete and therefore not included in the analysis.

6.2.6 Overall findings and implications

Combining the findings on overtaking starting position with the maximum lateral distance difference for different modes, an overview of e-bike and e-scooter overtaking patterns can be illustrated in Fig. 9. Overall, e-scooter riders exhibit closer and later overtaking behavior compared to e-bike riders, maintaining smaller lateral distances and initiating overtaking from shorter longitudinal distances. Both e-bikes and e-scooters begin overtaking earlier when passing e-bikes than when passing e-scooters or conventional bicycles, with no significant gender effect observed.

This pattern is further corroborated by the phase-wise comparison of roll rates and roll angles' absolute values across different overtaking scenarios. Additionally, this comparison reveals a common motion characteristic: roll rates and roll angles reach their maximum values during the overtaking phase.

The findings from this research may have applications in guiding infrastructure design, informing traffic regulations, and enhancing the development of traffic simulation models, especially with the growing popularity of micromobility vehicles like e-bikes and e-scooters. Although the experiment was conducted primarily with university students, the study still provides valuable insights into fundamental interaction mechanisms among micromobility users, particularly within campus-like and shared urban cycling environments where such modes are commonly used. The quantitative findings should therefore be interpreted as reflecting behavioral patterns and variability within a relatively young

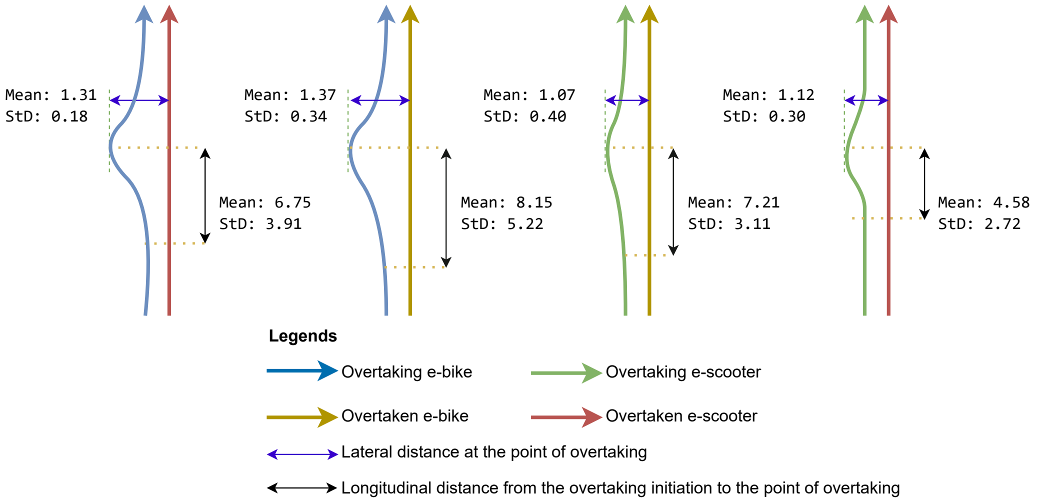


Figure 9 Overtaking pattern of e-bikes and e-scooters.

and homogeneous user group, rather than as population-wide estimates for all micromobility users. Nevertheless, the observed within-group variability and interaction patterns may be generalized to similar campus-like or young-user environments and can serve as a reference point for future studies involving more heterogeneous populations.

The study suggests that wider cycling lanes should be considered in urban planning to accommodate micromobility users, especially e-bike riders who maintain larger lateral distances when overtaking. Historically, the recommended width for two-way bicycle paths in the Netherlands was 2.0 m, based on the assumption of a minimum lateral spacing of 0.75 m between two bicycles [61]. However, our findings indicate that increasing the lane width to 2.3∼2.6 m would provide safer maneuverability and reduce collision risks in mixed-use traffic environments, as the observed average maximum lateral spacing during overtaking ranged from approximately 1.1∼1.4 m. This recommendation aligns with the 2022 update to the Dutch Design Manual for Bicycle Traffic by CROW (a Dutch knowledge platform for infrastructure challenges) [62], which raised the suggested lane width to 2.35 meters for improved safety, although CROW did not specifically cite micromobility as the reason for the change.

The analysis highlights the need for clearer, evidence-based guidelines on safe micromobility overtaking distances to support urban planners and infrastructure authorities in improving road safety. Differences in speed and acceleration among e-scooters, e-bikes, and conventional bicycles could inform traffic calming measures like tailored speed limits and designated overtaking zones to reduce conflicts and improve safety. Insights into overtaking behavior could also help improve the reproducibility of traffic simulation models, guiding the integration of e-bikes and e-scooters into urban transportation for safer and more efficient traffic systems. While the controlled nature of the experiment inevitably differs from fully naturalistic traffic conditions, participants were encouraged to ride naturally within a continuous mixed-traffic environment, allowing spontaneous interactions such as overtaking and speed adaptation to emerge (as indicated in Sec. 5.2). Moreover, operational riding behavior is largely intuitive and occurs at a relatively low cognitive level. As participants continuously rode and interacted with other users throughout the experiment, they were less likely to remain consciously aware of the experimental setting, thereby promoting more naturalistic behavior. Therefore, the experiment represents a compromise between behavioral realism and experimental controllability, providing a reproducible framework for studying operational micromobility interactions.

The findings underscore the need for micromobility targeted safety interventions and infrastructure improvements to mitigate risks associated with shared cycling spaces, ensuring safer coexistence of micromobility users and conventional cyclists in urban environments. Future work should further validate these findings using larger and more heterogeneous participant groups, additional infrastructure geometries, and naturalistic observational datasets collected under real-world traffic conditions.

7 Conclusions and Future Research with Collected Dataset

This paper described the setup of a controlled experiment on micromobility flow and elaborated the experimental design, implementation process, and the resulting empirical dataset capturing operational micromobility interactions. The primary contribution of this work lies in establishing a reproducible controlled experimental framework and providing a structured dataset for future research on micromobility behavior and interaction dynamics. Exploratory analysis of the overtaking movement (between e-bikes and e-scooters) has been provided as an illustrative example to demonstrate the potential of this dataset for validating several behavioral hypotheses, and for future research into understanding and modeling micromobility flow interactions.

The next research step is to process all the video data and IMU data, including overtaking (with e-moped), yielding, merging, and head-on riding. This rich dataset will be used to investigate behavior of different micromobility types and personal characteristics, and derive theoretical models that represent the decisions individual riders make while riding and interacting with other users, as well as models that describe the operationalization of these decisions. The dataset will also be used to calibrate and validate these models. Future work will further expand the empirical analysis beyond the preliminary overtaking investigation presented in this paper, enabling a more comprehensive understanding of operational micromobility interactions under mixed-traffic conditions.

Acknowledgements This research is supported by the cooperation research project between BJTU and TU Delft ”Active Mode Traffic Flow Behavioral Analysis and Modeling”, funded by BJTU. The authors would like to express many thanks to Dr. Dorine Duives from TU Delft, for her valuable suggestions on experiment design.

Ethics Statement As per international standard or university standard, experiment participants’ written consent has been collected and preserved by the author(s). The conduct of the controlled experiment received approval from the Human Research Ethics Committee (HREC) from the TU Delft.

Data Availability The video recordings and related experimental data generated during this study will be made available through the Urban Mobility Observatory (UMO) facility upon request. Access to the dataset will be managed by one of the coauthors Winnie Daamen, leader of the UMO project, in accordance with applicable data management, privacy, and research ethics regulations. Researchers interested in accessing the data for scientific purposes may contact the corresponding author or the UMO facility for further information regarding access conditions and usage agreements.

Author Contributions The authors confirm contribution to the paper as follows: study conception and design: Y. Yuan, S. Zhu, W. Zhang, and W. Daamen; data collection and experiment setup: Y. Yuan, W. Zhang, S. Zhu, and Q. Lan; analysis and interpretation of results: Y. Yuan, and W. Zhang; draft manuscript preparation: Y. Yuan, W. Zhang, and W. Daamen. All authors reviewed the results and approved the final version of the manuscript.

References

[1] Christoforou, Z., de Bortoli, A., Gioldasis, C., Seidowsky, R.: Who is using e-scooters and how? Evidence from Paris. Transportation Research Part D: Transport and Environment **92**, 102708 (2021). doi:10.1016/j.trd.2021.102708

[2] Gulino, M.S., Zonfrillo, G., Damaziak, K., Vangi, D.: Exploring performances of electric micro-mobility vehicles and behavioural patterns of riders for in-depth accident analysis. Designs **5**(4) (2021). doi:10.3390/designs5040066

[3] Rijwiel en Automobiel Industrie Vereniging: Number of electric bicycles sold in the European union (EU-28) from 2006 to 2022 (in 1,000 units). Statista (2023). Available at: https://www.statista.com/statistics/397765/electric-bicycle-sales-in-the-european-union-eu/ [Accessed Mar 2024]

[4] ZIV: E-bike sales volume in Germany from 2011 to 2022. Statista (2023). Available at: https://www.statista.com/statistics/1265760/e-bikes-sold-number-germany/ [Accessed Mar 2024]

[5] Oeschger, G., Carroll, P., Caulfield, B.: Micromobility and public transport integration: The current state of knowledge. Transportation Research Part D: Transport and Environment **89**, 102628 (2020). doi:10.1016/j.trd.2020.102628

[6] Hu, W.: Why revel shut down its moped service in New York. The New York Times (2023). Available at: https://www.nytimes.com/2023/11/18/nyregion/revel-mopeds-nyc-e-scooter.html [Accessed Jun 2024]

[7] Schleinitz, K., Petzoldt, T., Franke-Bartholdt, L., Krems, J., Gehlert, T.: The german naturalistic cycling study–comparing cycling speed of riders of different e-bikes and conventional bicycles. Safety Science **92**, 290–297 (2017). doi:10.1016/j.ssci.2015.07.027

[8] Twisk, D., Stelling, A., Van Gent, P., De Groot, J., Vlakveld, W.: Speed characteristics of speed pedelecs, pedelecs and conventional bicycles in naturalistic urban and rural traffic conditions. Accident Analysis & Prevention **150**, 105940 (2021). doi:10.1016/j.aap.2020.105940

[9] Baptista, P., Pina, A., Duarte, G., Rolim, C., Pereira, G., Silva, C., Farias, T.: From on-road trial evaluation of electric and conventional bicycles to comparison with other urban transport modes: Case study in the city of Lisbon, Portugal. Energy Conversion and Management **92**, 10–18 (2015). doi:10.1016/j.enconman.2014.12.043

[10] Dozza, M., Piccinini, G.F.B., Werneke, J.: Using naturalistic data to assess e-cyclist behavior. Transportation Research Part F: Traffic Psychology and Behaviour **41**, 217–226 (2016). doi:10.1016/j.trf.2015.04.003

[11] Statistisches-Bundesamt: Number of pedestrian, cycling and e-scooter traffic crash injuries in Germany from 2019 to 2022, by mode. Statista (2023). Available at: https://www.statista.com/statistics/1399153/active-and-micro-mobility-traffic-crash-injuries-germany-by-mode/ [Accessed Mar 2024]

[12] GITNUX: E-bike accident statistics (2024). Available at: https://gitnux.org/e-bike-accident-statistics/ [Accessed Mar 2024]

[13] Verstappen, E.M.J., Vy, D.T., Janzing, H.M., Janssen, L., Vos, R., Versteegen, M.G.J., Barten, D.G.: Bicycle-related injuries in the emergency department: a comparison between e-bikes and conventional bicycles: a prospective observational study. European Journal of Trauma and Emergency Surgery **47**(6), 1853–1860 (2021). doi:10.1007/s00068-020-01366-5

[14] Ma, Q., Yang, H., Mayhue, A., Sun, Y., Huang, Z., Ma, Y.: E-scooter safety: The riding risk analysis based on mobile sensing data. Accident Analysis & Prevention **151**, 105954 (2021). doi:10.1016/j.aap.2020.105954

[15] Mura, M., Failla, S., Gori, N., Micucci, A., Paganelli, F.: E-scooter presence in urban areas: Are consistent rules, paying attention and smooth infrastructure enough for safety? Sustainability **14**(21) (2022). doi:10.3390/su142114303

[16] Almannaa, M.H., Ashqar, H.I., Elhenawy, M., Masoud, M., Rakotonirainy, A., Rakha, H.: A comparative analysis of e-scooter and e-bike usage patterns: Findings from the city of Austin, TX. International Journal of Sustainable Transportation **15**(7), 571–579 (2021). doi:10.1080/15568318.2020.1833117

[17] Oeschger, G., Caulfield, B., Carroll, P.: Investigating the role of micromobility for first- and last-mile connections to public transport. Journal of Cycling and Micromobility Research **1**, 100001 (2023). `doi:10.1016/j.jcmr.2023.100001`

[18] Arias-Molinares, D., García-Palomares, J.C., Romanillos, G., Gutiérrez, J.: Uncovering spatiotemporal micromobility patterns through the lens of space–time cubes and gis tools. Journal of Geographical Systems **25**(3), 403–427 (2023)

[19] Christoforou, Z., Gioldasis, C., Valero, Y., Vasileiou-Voudouris, G.: Smart traffic data for the analysis of sustainable travel modes. Sustainability **14**(18), 11150 (2022). `doi:10.3390/su141811150`

[20] Distefano, N., Leonardi, S., Litrico, A.: Analysis of driving behavior of micromobility vehicle users at mini-roundabouts. Applied Sciences **14**(24), 11944 (2024). `doi:10.3390/app142411944`

[21] Chen, C., Christoforou, Z., Farhi, N.: Reaction times of micromobility users. Transportation Research Part F: Traffic Psychology and Behaviour **116**, 103441 (2026). `doi:10.1016/j.trf.2025.103441`

[22] Yuan, Y., Daamen, W., Goñi-Ros, B., Hoogendoorn, S.P.: Investigating cyclist interaction behavior through a controlled laboratory experiment. Journal of Transport and Land Use **11**(1), 833–847 (2018). `doi:10.5198/jtlu.2018.1155`

[23] Gavriilidou, A., Wierbos, M.J., Daamen, W., Yuan, Y., Knoop, V.L., Hoogendoorn, S.P.: Large-scale bicycle flow experiment: Setup and implementation. Transportation Research Record **2673**(5), 709–719 (2019). `doi:10.1177/0361198119839974`

[24] Dozza, M., Li, T., Billstein, L., Svernlöv, C., Rasch, A.: How do different micro-mobility vehicles affect longitudinal control? Results from a field experiment. Journal of Safety Research **84**, 24–32 (2023). `doi:10.1016/j.jsr.2022.10.005`

[25] Gavriilidou, A., Daamen, W., Yuan, Y., Hoogendoorn, S.: Modelling cyclist queue formation using a two-layer framework for operational cycling behaviour. Transportation Research Part C: Emerging Technologies **105**, 468–484 (2019). `doi:10.1016/j.trc.2019.06.012`

[26] Duives, D.C., Daamen, W., Hoogendoorn, S.P.: State-of-the-art crowd motion simulation models. Transportation Research Part C: Emerging Technologies **37**, 193–209 (2013). `doi:10.1016/j.trc.2013.02.005`

[27] Wang, C., Wei, L., Wang, K., Tang, H., Yang, B., Li, M.: Investigating the factors affecting rider's decision on overtaking behavior: A naturalistic riding research in china. Sustainability **14**(18), 11495 (2022). `doi:10.3390/su141811495`

[28] Khan, S.I., Raksuntorn, W.: Characteristics of passing and meeting maneuvers on exclusive bicycle paths. Transportation Research Record **1776**(1), 220–228 (2001). doi:10.3141/1776-28

[29] Lin, D., Chen, X., Lin, B., Li, L.: Phenomena and characteristics of moped-passing-bicycle on shared lanes. In: Proceedings of the TRB 93rd Annual Meeting Compendium of Papers. Transportation Research Board of the National Academies (2014)

[30] Mohammed, H., Bigazzi, A.Y., Sayed, T.: Characterization of bicycle following and overtaking maneuvers on cycling paths. Transportation Research Part C: Emerging Technologies **98**, 139–151 (2019). doi:10.1016/j.trc.2018.11.012

[31] Zafri, N.M., Tabassum, T., Himal, M.R.H., Sultana, R., Debnath, A.K.: Effect of pedestrian characteristics and their road crossing behaviors on driver yielding behavior at controlled intersections. Journal of Safety Research **81**, 1–8 (2022). doi:10.1016/j.jsr.2022.01.001

[32] Schneider, R.J., Sanatizadeh, A., Shaon, M.R.R., He, Z., Qin, X.: Exploratory analysis of driver yielding at low-speed, uncontrolled crosswalks in Milwaukee, Wisconsin. Transportation Research Record **2672**(35), 21–32 (2018). doi:10.1177/0361198118782251

[33] Billstein, L., Svernlöv, C.: 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. Master's thesis, Chalmers university of technology (2021)

[34] Gulino, M.S., Zonfrillo, G., Damaziak, K., Vangi, D.: Exploring performances of electric micro-mobility vehicles and behavioural patterns of riders for in-depth accident analysis. Designs **5**(4), 66 (2021). doi:10.3390/designs5040066

[35] Pazzini, M., Cameli, L., Lantieri, C., Vignali, V., Dondi, G., Jonsson, T.: New micromobility means of transport: An analysis of e-scooter users' behaviour in Trondheim. International Journal of Environmental Research and Public Health **19**(12) (2022). doi:10.3390/ijerph19127374

[36] FreeRide, F.: Electric scooter vs electric bike (Accessed January 2022). URL https://fluidfreeride.com/blogs/news/electric-scooter-vs-electric-bike#:~:text=the%20physical%20element.-,Speed%20%26%20Range,kph)%20than%20e%2Dbikes.

[37] Todd, J., Krauss, D., Zimmermann, J., Dunning, A.: Behavior of electric scooter operators in naturalistic environments. Tech. rep., SAE Technical Paper (2019)

[38] road safety observatory, E.: Traffic safety basic facts 2018 – motorcycles and mopeds. Tech. rep., ERSO (2018)

[39] Useche, S.A., Montoro, L., Tomas, J.M., Cendales, B.: Validation of the cycling behavior questionnaire: a tool for measuring cyclists' road behaviors. Transportation Research Part F: Traffic Psychology and Behaviour **58**, 1021–1030 (2018). `doi:10.1016/j.trf.2018.08.003`

[40] Haustein, S., Møller, M.: E-bike safety: Individual-level factors and incident characteristics. Journal of Transport & Health **3**(3), 386–394 (2016). `doi:10.1016/j.jth.2016.07.001`

[41] Gioldasis, C., Christoforou, Z., Seidowsky, R.: Risk-taking behaviors of e-scooter users: A survey in Paris. Accident Analysis & Prevention **163**, 106427 (2021). `doi:10.1016/j.aap.2021.106427`

[42] Garcia, A., Gomez, F.A., Llorca, C., Angel-Domenech, A.: Effect of width and boundary conditions on meeting maneuvers on two-way separated cycle tracks. Accident Analysis & Prevention **78**, 127–137 (2015). `doi:10.1016/j.aap.2015.02.019`

[43] Fonseca-Cabrera, A.S., Llopis-Castelló, D., Pérez-Zuriaga, A.M., Alonso-Troyano, C., García, A.: Micromobility users' behaviour and perceived risk during meeting manoeuvres. International Journal of Environmental Research and Public Health **18**(23) (2021). `doi:10.3390/ijerph182312465`

[44] Schepers, P., Theuwissen, E., Nuñez Velasco, P., Nabavi Niaki, M., van Boggelen, O., Daamen, W., Hagenzieker, M.: The relationship between cycle track width and the lateral position of cyclists, and implications for the required cycle track width. Journal of Safety Research **87**, 38–53 (2023). `doi:10.1016/j.jsr.2023.07.011`

[45] Cicchino, J.B., Kulie, P.E., McCarthy, M.L.: Severity of e-scooter rider injuries associated with trip characteristics. Journal of Safety Research **76**, 256–261 (2021). `doi:10.1016/j.jsr.2020.12.016`

[46] Niska, A., Eriksson, J.: Cycling accident statistics. background information to the common policy strategy for safe cycling (2013)

[47] Schepers, J., Fishman, E., Den Hertog, P., Wolt, K.K., Schwab, A.L.: The safety of electrically assisted bicycles compared to classic bicycles. Accident Analysis & Prevention **73**, 174–180 (2014). `doi:10.1016/j.aap.2014.09.010`

[48] Violin, A.: Development of an experimental protocol fortesting new electric personal mobility vehicles. Ph.D. thesis, Politecnico di Torino (2020)

[49] Garman, C., Como, S., Campbell, I., Wishart, J., O'Brien, K., McLean, S.: Micromobility vehicle dynamics and rider kinematics during electric scooter riding. In: SAE Technical Paper (2020). `doi:10.4271/2020-01-0935`

[50] Wikipedia contributors: Real-time kinematic positioning — Wikipedia, the free encyclopedia (2024). Available at: `https://en.wikipedia.org/wiki/Real-time_kinematic_positioning` [Accessed June 2024]

[51] Daamen, W., Hoogendoorn, S.P.: Experimental research of pedestrian walking behavior. Transportation Research Record **1828**(1), 20–30 (2003). `doi:10.3141/1828-03`

[52] Pérez-Zuriaga, A.M., Llopis-Castelló, D., Just-Martínez, V., Fonseca-Cabrera, A.S., Alonso-Troyano, C., García, A.: Implementation of a low-cost data acquisition system on an e-scooter for micromobility research. Sensors **22**(21), 8215 (2022). `doi:10.3390/s22218215`

[53] BicycleDutch: How wide is a Dutch cycle path (2021). Available at: `https://bicycledutch.wordpress.com/2011/06/30/how-wide-is-a-dutch-cycle-path/` [Accessed July 2024]

[54] TrafficEngineeringStandards: Pavement marking manual. Tech. rep., Department of infrastuture and transport - Government of South Australia (2025). Available at: `https://dit.sa.gov.au/__data/assets/pdf_file/0018/40257/Pavement_Marking_Manual.pdf` [Accessed Jan 2026]

[55] Rasmussen, J.: Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. IEEE Transactions on Systems, Man, and Cybernetics **SMC-13**(3), 257–266 (1983). `doi:10.1109/TSMC.1983.6313160`

[56] Townsend, K., LeBlanc-Williams, M., Ada, L., DiCola, T., Rembor, K., Nelson, C., Park, J., Herrada, E.: Adafruit bno055 absolute orientation sensor (2024). Available at: `https://learn.adafruit.com/adafruit-bno055-absolute-orientation-sensor/overview` [Accessed July 2024]

[57] Goñi-Ros, B., Yuan, Y., Daamen, W., Hoogendoorn, S.P.: Empirical analysis of the macroscopic characteristics of bicycle flow during the queue discharge process at a signalized intersection. Transportation Research Record **2672**(36), 51–62 (2018). `doi:10.1177/0361198118790637`

[58] Duives, D.C., Daamen, W., Hoogendoorn, S.: Trajectory analysis of pedestrian crowd movements at a Dutch music festival. In: Pedestrian and Evacuation Dynamics 2012, *Springer Books*, vol. None, pp. 151–166. Springer (2014)

[59] Li, Y., Liang, S., Liu, L., Shao, J., Wang, F.: Prediction of bicycle trajectory considering stressful avoidance behaviors. Journal of Transportation Systems Engineering and Information Technology **24**(2), 149 (2024). `doi:10.16097/j.cnki.1009-6744.2024.02.015`

[60] Aramrattana, M., Fu, J., Selpi: Behavioral adaptation of drivers when driving among automated vehicles. Journal of Intelligent and Connected Vehicles **5(3)**, 309–315 (2022). `doi:10.1108/JICV-07-2022-0031`

[61] C.R.O.W.: Sign up for the bike: Design manual for a cycle-friendly infrastructure. Tech. rep., Centre for Research CROW, Contract Standardization in Civil, and Traffic Engineering. (1994)

[62] Veroude, B., van Gurp, M., van Boggelen, O.: Geactualiseerde aanbevelingen voor de breedte van fietspaden 2022. Tech. rep., Centre for Research CROW, Contract Standardization in Civil, and Traffic Engineering. (2022)