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E-scooters and bicycles: A behavior comparison based on analysis of microscopic trajectory data☆

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A R T I C L E I N F O

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Safety

A B S T R A C T

Background: Recently, safety issues related to e-scooters have attracted attention. The behavior of e-scooter riders – such as using pedestrian infrastructures and wrong-way riding as well as their interactions with pedestrians, have raised concerns among people. The safety of e-scooters can be evaluated by comparing them to bicycles. Hence, the aim of the presented study is to reveal the differences between e-scooters and bicycles in terms of infrastructure usage, wrong-way behavior, and interactions with other road users.
Method: To compare the microscopic trajectories of e-scooters and bicycles, traffic was observed for three days at three locations in Berlin. Using image recognition technology, road users were identified, and their positions, as well as kinematic data such as speed and acceleration, were extracted.
Results: At all three locations, e-scooter riders (straight road: 16.3%, intersection: 50.7%, shared space: 67.7%) used pedestrian infrastructures (pedestrian paths and pedestrian crossings) more frequently than cyclists (straight road: 9.5%, intersection: 20.5%, shared space: 46.3%). Additionally, e-scooter riders (18.9%) rode more frequently in the wrong direction in comparison to cyclists (14.4%). With regard to the comparison of interactions with pedestrians, in head-on interactions on pedestrian crossings, e-scooter riders showed riskier behavior (higher speed and lower TTC) than cyclists. In crossing interactions, there was little difference between e-scooter riders and cyclists.
Discussion: The study discusses the impact of user characteristics on the illegal use of pedestrian infrastructure, wrong-way riding, and risky head-on interactions with pedestrians. In terms of practical applications, the effective guidance for users was suggested.
Conclusion: In this study, riding behavior of e-scooters and bicycles was compared based on the analysis of microscopic trajectory data. E-scooter riders exceeded cyclists in the illegal use of pedestrian infrastructure, wrong-way riding, and risky head-on interaction with pedestrians, suggesting a higher potential risk. The results of the study aim to inspire future research and safety policies.

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1. Introduction

Electric scooters (e-scooters) are electrically powered vehicles with a handlebar, deck, and wheels (Bozzi & Aguilera, 2021). As one micro-mobility solution, e-scooters are designed to address the last-mile problem in a low-carbon and cost-effective way. In recent years, e-scooters have become a trend in Germany (Hobusch et al., 2021). However, concerns about the safety of e-scooter riders, their influence on pedestrians, and parking issues are growing as well. In 2020, 2155 e-scooter-related personal injury accidents were recorded in Germany. The number increased more than 1.5 times to 5502 in 2021, while bicycle-related personal injury accidents in the same period decreased by 8.8 % (Statistisches Bundesamt, 2021). Some previous studies on e-scooter associated injuries (English et al., 2020; Kobayashi et al., 2019; Namiri et al., 2020; Störmann et al., 2020) suggested that the risky behavior of e-scooter riders should be given attention. One argument is that current infrastructure and regulations have not considered the emergence of these electrically powered two-wheeled vehicles, leading to relatively high-risk levels. Thus, understanding the riding behavior and preferences of e-scooter riders and distinguishing them from cyclists could help improve road planning and the development of corresponding infrastructure and regulations.

1.1. Risky behavior

The risks associated with e-scooters are a subject of ongoing discussion (Bozzi & Aguilera, 2021). A review identified several primary risky riding behaviors of these electric micro-mobility devices: illegal use of motor vehicle lanes, riding at excessive speeds, running red lights, and illegal tandem riding and wrong-way riding (Ma et al., 2019). Surveys and traffic observations have revealed that e-scooter riders prefer using bicycle lanes that are separated from the roadway (Pazzini et al., 2022; Siebert et al., 2021), aligning with current regulations in many countries, including Germany. When bicycle lanes are not separated from the roadway, e-scooter riders often opt for footpaths. However, this practice is not permitted under current German traffic regulations, which require e-scooters to operate only on bicycle lanes or roadways. E-scooters have also been reported to frequently travel in the opposite direction of the roadway (Bai et al., 2014). In Germany, during 2023, there were 9296 instances of personal injuries involving e-scooters that were due to improper riding. The most frequent violation, representing 19.4 % of these cases, involved the incorrect use of roadways or footpaths (Statistisches Bundesamt, 2024). However, Haworth et al. (2021) found that in Brisbane, Australia, the rate of actual conflicts between pedestrians and e-scooters on footpaths ranged only from 0 to 1.5 %. Speed limits may have played a role in this low incidence. A review reported that injuries on footpaths accounted for between 3.3 % and 46.2 % of incidents (Janikian et al., 2024). The risks associated with e-scooters on footpaths can therefore vary greatly.

Subjectively, there is a discrepancy between how e-scooter riders perceive themselves and how other road users view them. E-scooter riders have been perceived as exhibiting higher rates of risky behaviors compared to cyclists (Bieliński and Ważna (2020) and Useche et al. (2022)). A recent survey also highlights a perceptual gap: while non-riders tend to view e-scooter use as relatively unsafe, e-scooter users themselves largely believe that their riding does not pose a risk to other road users (Drimlová et al., 2024). Utilizing wearable devices, a study showed that 60 % of pedestrians who encountered an e-scooter experienced an increased heart rate (Maiti et al., 2022), suggesting a high perceived risk and uncertainty. This may be related to the current riding behavior and infrastructure usage of e-scooters. E-scooters move faster in open spaces and on streets than on footpaths or when encountering others (Pazzini et al., 2022). Due to their similar characteristics, e-scooters and bicycles are often considered comparable research subjects in studies (Gehrke et al., 2021; Hardinghaus & Oostendorp, 2022). The riding speeds of both vehicles are below the speed limit (Dibaj et al., 2021). A field study showed only a slight difference in speed between bicycles and e-scooters (Pazzini et al., 2022). Nevertheless, another field study revealed that e-scooters are more maneuverable in steering, while bicycles could stop faster, implying differences in avoidance maneuvers (Dozza et al., 2022). In a recent field experiment, Jafari & Liu (2024) measured the dissatisfaction of pedestrians interacting with e-scooters, with microscopic trajectory data playing a crucial role in quantifying their objective risks.

Both the number of e-scooter accidents and bicycle accidents has increased in recent years, with the severity of injuries being similarly high for both modes of transport. However, head injuries are more common in e-scooter accidents (James et al., 2023). In addition, e-scooter riders are more often under the influence of alcohol and wear helmets less frequently (Murros et al., 2022; Yannis et al., 2024). The risk of requiring medical treatment after an accident is similar for e-scooters and e-bikes, but higher than for regular bicycles. E-scooter accidents are more often single-vehicle incidents (falls, collisions with fixed objects), while e-bikes and bicycles are more frequently involved in crashes with other road users (Yannis et al., 2024).

1.2. Methodological approach and study aim

Microscopic trajectory data, defined as “a trace generated by a moving object in geographical spaces” (Zheng, 2015, p. 29), has greatly contributed to transportation research. Real trajectory data is typically acquired through mobile sensors (e.g., those mounted on vehicles) or fixed sensors (e.g., on infrastructure or drones). The advantages of sensor-based trajectory data collection lie in the ability to collect data at scale and ensure objectivity and avoid subjective biases from manual measurements. As a result, trajectory data is often used to develop or validate traffic behavior models. For instance, in terms of vehicle interactions, car-following models and lane-changing models have been developed based on trajectory data (Kesting & Treiber, 2008; Thiemann et al., 2008). In the context of interactions involving vulnerable road users, trajectory data has been employed to develop social force models (Zeng et al., 2014). Thanks to sensor-based trajectory data collection approaches and automated scenario mining processes, the scale of the data and the accuracy of quantification have both been enhanced compared to manual observation. However, interactions involving e-scooters at the trajectory level have rarely been investigated. Even fewer studies have compared e-scooters to bicycles.

Therefore, the aim of the presented study is to compare e-scooters and bicycles in terms of infrastructure usage and at the micro-level in specific interaction scenarios, using trajectory data. For this purpose, real-world data in the form of trajectories of e-scooters and bicycles, as perceived by video observation and image recognition techniques, is analyzed. At the methodological level, this study's approach demonstrates the potential of microscopic trajectory data for analyzing the riding behavior and preferences of e-scooters riders and micro-mobility in general. Our findings will aid in enhancing the traffic system during the ongoing transformation of urban mobility.

In Germany, and thus in the measurement data, e-scooters may be used by individuals aged 14 and older without a driver's license. They are permitted to travel at a maximum speed of 20 km/h. E-scooters must use the bicycle lane where available; if not, they are required to use the street (Elektrokleinstfahrzeuge-Verordnung [eKFV], 2019).

The aim of the present study is to compare the behavior of e-scooter and bicycle riders with regard to their usage of infrastructure and interactions in micro-level scenarios, particularly with pedestrians, by utilizing trajectory data. In the Methods section, we detail the process of data collection and analysis. Real-world trajectory data of e-scooters and bicycles was acquired through video observation and image recognition techniques (Section 2.1). These trajectories were then processed and analyzed (Sections 2.2 and 2.3) to derive relevant movement characteristics and behavioral metrics. The Results section presents findings in two key areas: infrastructure usage (Section 3.1) and interaction with pedestrians (Section 3.2). For the latter, we report comparative metrics such as average speed (3.2.1), minimum distance (3.2.2), and minimum time to collision (TTC) (3.2.3) between e-scooters and bicycles. In the Discussion (Section 4), we interpret these findings in light of behavioral tendencies and risk profiles of the observed modes. Finally, the Conclusion (Section 5) emphasizes the methodological contribution of this study—showcasing the potential of microscopic trajectory data to evaluate riding behavior and user preferences of e-scooters riders and micro-mobility modes. These insights are intended to support the development of safer and more efficient urban traffic systems amid ongoing mobility transformations.

2. Methods

As part of the project 'Micro-mobility on pedestrian paths and cycle paths – Conflicts of use and effects on traffic (MMoNK)', the normal riding behavior and the behavior during interactions of e-scooter riders and cyclists were recorded and analyzed.

2.1. Traffic observation

2.1.1. Data acquisition

In order to capture as many e-scooters involved in road safety related interactions as possible, a preliminary survey was conducted at multiple accident hotspots for e-scooters in Berlin (Hardinghaus et al., 2022). Considering the diversity of infrastructures and official permits, we selected three locations in the urban area of Berlin (see Fig. 1b–g). Based on their main characteristics, these three locations are referred to as STR (straight road), INT (intersection), and SHA (shared space), respectively (see Table 1). Because there are no separate bicycle lanes at any of the three locations, cyclists and e-scooter riders have to use the roadway.

Traffic observations were conducted over three working days, each lasting eight hours from 8:00 am to 4:00 pm. Regarding weather conditions, the first and third day were clear, while it rained in the afternoon on the second day. This period did not include any public holidays.

A research vehicle equipped with two cameras was applied to record the traffic (see Fig. 1a). The vehicle was positioned on the

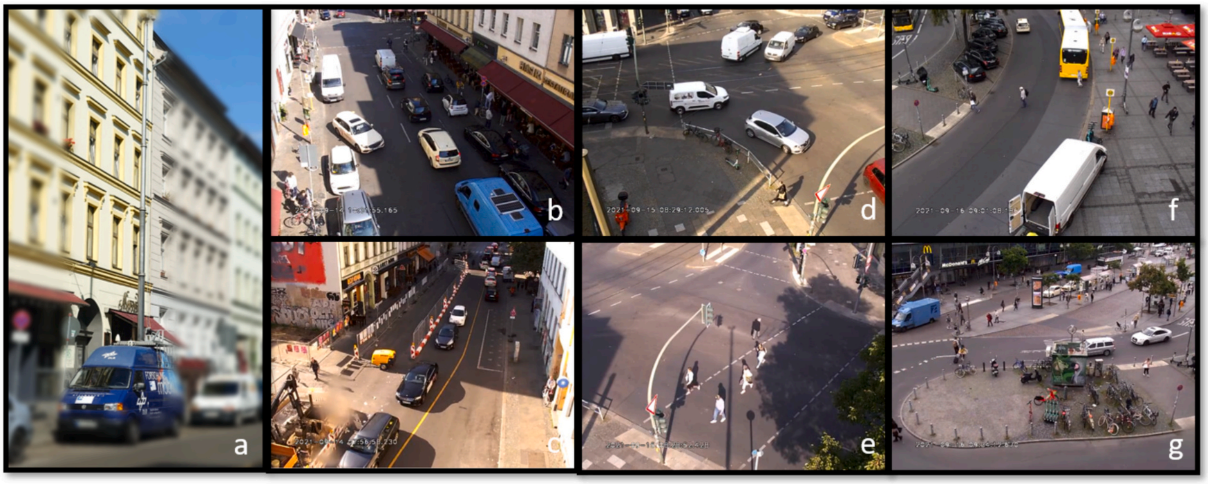

Fig. 1. (a) The research vehicle equipped with two cameras. (b, c) Screenshots of the camera views at Adalbertstr.; (d and e) at the intersecton of Torstr. and Friedrichstr.; (f, g) at Hardenbergplatz.

Table 1
The traffic observation locations and their characteristics. E-scooter riders and cyclists are required to ride on the street at all locations (STR: straight road, INT: intersection, and SHA: shared space).

Abbreviation	Locations	Characteristics
STR	Adalbertstr.	- a straight road approaching an intersection - one motor vehicle lane in each direction - speed limit of 30 km/h - no bicycle lanes - a narrow pedestrian pathE-scooter riders and cyclists must ride on the street.
INT	Torstr./Friedrichstr.	- an intersection with traffic lights - two or three motor vehicle lanes in each direction - tram tracks - speed limit of 50 km/h - no bicycle lanes E-scooter riders and cyclists must ride on the street.
SHA	Hardenbergplatz	- a shared space - large pedestrian paths - one-way street - speed limit of 20 km/h - bus stationsE-scooter riders and cyclists must ride on the street. - no bicycle lanes

roadside or pedestrian path without obstructing traffic flow. Although the camera mast might have attracted occasional glances from road users, the impact on their behavior is expected to be negligible in terms of the analysis. The cameras were mounted on a 12-meter-high mast, facing in different directions. The observation equipment was also used in previous studies (Grigoropoulos et al., 2022; Saul et al., 2016). The videos were recorded at a reduced resolution (0.3 megapixels) so that neither faces nor license plates could be recognized. A frame rate of 15 frames per second was applied in order to have trajectory data with a high frequency.

2.1.2. Image data processing

Using image processing technology, road users in the video were identified and categorized. A multi-object tracking pipeline with an AI-based object detection system was applied. Objects of interest visible in the scenes were detected by a Faster-RCNN-based object detector (Ren et al., 2015). The acquired detections were first fed to a multi-object tracker, which associates and filters the detected bounding boxes as image patches in the image domain. The tracking method applied here is Simple Online and Realtime tracking (Bewley et al., 2016).

From this first iteration of tracking, only the associations between object hypotheses and detections were used in a second tracking step. Because each measurement is now associated with only one object hypothesis, the multi-object tracking problem collapses to single-object tracking problem. The coordinates of the image patches were transformed into world coordinates on an assumed ground plane by applying a Perspective-n-Point (Marchand et al., 2016) method. Each list of associated, transformed measurements was filtered using an Unscented Kalman Filter (Julier, 2002), which estimated positions and velocities of the objects. Acceleration was derived in a post-processing step as the derivative of velocity. Images from each training video were annotated and used for training. Initially, only a few images were annotated, but pseudo-labels were then generated and manually corrected to further improve the training data. As a result, the neural network for image processing is no longer generalizable to other datasets, but it performed very well on our dataset. During processing, we always ran a test dataset in parallel to ensure that sensitivity and specificity were sufficient. However, the quantitative results for this are no longer available.

During the original detection step, the objects were classified into different categories (e.g., pedestrian, car, truck, and e-scooter). However, due to the limited recognition granularity of the employed model, the 'bike' category may encompass both conventional bicycles and electric bicycles (e-bikes). More fine-grained classifications, such as whether an e-scooter is part of a rental fleet or private use, as well as the rider's gender or helmet usage, were not detected and are beyond the scope of this study. The basic classification follows the technical delivery specifications for roadside stations established by the German Federal Highway and Transport Research Institute (BASt) with $5 + 1$ classes, with additional categories for e-scooters and parked e-scooters as our objects of interest (BASt, n.d.).

Object dimensions in the world coordinate system were taken from a lookup table containing average values for each category.

Finally, the data of interest (trajectories) were stored in a plaintext file for further traffic behavior analysis.

2.2. Traffic analysis

The positional information of e-scooters and bicycles was calculated by referencing corresponding digital maps. Their use of roadways, pedestrian paths, and pedestrian crossings at the three locations was counted. The proportions across the three types of infrastructures were reported. Similarly, wrong-way riders were identified by comparing the direction of object movement with the designated direction of the road. The proportions of right- and wrong-way riding were reported for all three locations. Here, only instances where road users were moving in the wrong direction on the roadway were considered, as the direction of pedestrian infrastructure was not defined.

According to Markkula et al. (2020, p. 737), an interaction is defined as "a situation where the behavior of at least two road users can be interpreted as being influenced by the possibility that they are both intending to occupy the same region of space at the same time in the near future." Based on the definition, road users are facing the risk of "space-sharing conflicts" in interactions. Markkula et al. (2020) summarized five typical interactions in urban traffic: obstructed path, merging paths, crossing paths, unconstrained head-on paths, and constrained head-on paths. This generalization of interactions provides the basis for an analysis of microscopic trajectory data. In the present study, the interaction behavior of e-scooter riders and cyclists with pedestrians was investigated. The common interactions in urban traffic, as suggested by Markkula et al. (2020) were simplified into three types:

- Obstructed interactions, where pedestrians are on the paths of e-scooters or bicycles.
- Head-on interactions, where e-scooters or bicycles and pedestrians are moving in opposite directions.
- Crossing interactions, where the paths of e-scooters or bicycles and pedestrians intersect.

We extracted obstructed interactions with pedestrians on the pedestrian path at location STR, head-on interactions with pedestrians on the pedestrian crossing at the INT, and crossing interactions with pedestrians on the roadway at location SHA (see Fig. 2). Here, time-to-collision (TTC) (Jafari & Liu, 2024; Minderhoud & Bovy, 2001), a well-established surrogate measure of safety, was employed. TTC represents the time remaining before a potential collision would occur if two entities continue on their current trajectories and speeds. When no collision is expected, TTC reflects the temporal gap at the point of closest approach. A smaller TTC indicates a shorter temporal distance between road users, thereby requiring quicker reactions to maintain a safe distance. According to Rasouli and Tsotsos (2020) review, pedestrians generally accept gaps in the range of 3–7 s. Based on this, we defined a TTC threshold of less than 5 s to indicate the presence of an interaction. In our context, TTC was used to filter interactive scenarios, which may include both regulated encounters and potential conflicts between road users.

The valid range of an interaction was defined in post-processing, beginning when the TTC between the two parties first fell below 5 s and ending at their point of minimum distance. During this interval, the interaction angle, the minimum distance, the minimum TTC as well as the average speed were calculated. The angle between the paths of the two interaction partners was used as a basis for determining the type of interaction. It is defined as an obstructed interaction if the magnitude of the angle is less than 30 degrees, while a head-on interaction has an angle greater than 150 degrees and a crossing interaction has an angle between 30 and 150 degrees. With regard to the investigation of risky behavior, we compared the average speed during the interaction, minimum distance to pedestrians, and the minimum TTC to pedestrians between e-scooters and bicycles. In this context, the mean speed serves as an indicator of the potential severity of risk, while the minimum distance and minimum TTC represent spatial and temporal proximity to pedestrians, respectively. We used the center of the objects for the calculations. The average tracking error was smaller than the width of a bicycle handlebar, indicating that the smaller handlebar width of e-scooters compared to bicycles is of little significance.

2.3. Statistical analysis

We conducted a series of inferential statistical tests to examine whether there are differences between e-scooter and bicycle users in terms of their behavior during interactions with pedestrians. Specifically, three behavioral indicators were analyzed: average speed during the interaction, minimum distance to pedestrians, and minimum time to collision (TTC).

According to the results of Shapiro-Wilk normality tests (Royston, 1982), the indicators in interactions with pedestrians were not normally distributed (average speed: $W = 0.94$, $p < 0.001$; minimum distance: $W = 0.89$, $p < 0.001$; minimum TTC: $W = 0.95$, $p < 0.001$). Thus, Wilcoxon tests (Hollander et al., 2013) were used to compare e-scooters and bicycles, and the results were converted and presented as standard score (Z-score). Additionally, for determining the effect size, the parameter r recommended by Rosenthal (1994) was used. Accordingly, the effect size is low if r is less than 0.1, medium if r is less than 0.3, and large if r is greater than 0.5. The significance level of $\alpha = 0.05$ was used for the tests.

Fig. 2. Screenshots of interaction with pedestrians: (a) an obstructed interaction with pedestrians on the pedestrian path of the STR; (b) a head-on interaction with pedestrians on the pedestrian crossing of the INT; (c) a crossing interaction with pedestrians on the roadway of the SHA.

3. Results

3.1. Usage of infrastructures

Infrastructures in this study involved three different types: roadway, pedestrian path and pedestrian crossing. In total, 858 e-scooters and 7700 bicycles were detected at the STR, 1039 e-scooters and 7927 bicycles at the INT, and 575 e-scooters and 664 bicycles at the SHA. Table 2 shows the usage of the infrastructures for e-scooters and bicycles. Both cyclists and e-scooter riders used all three types of infrastructures across the locations. Furthermore, the roadway was the most frequently used infrastructure for both e-scooter riders and cyclists. However, at the SHA, e-scooters were found on the pedestrian path more frequently than other types of infrastructures. With regard to the comparison of the usage of infrastructures between e-scooters and bicycles, at all three locations, e-scooter riders (STR: 16.3 %, INT: 50.7 %, SHA: 67.7 %) used pedestrian infrastructures more frequently than cyclists (STR: 9.5 %, INT: 20.5 %, SHA: 46.3 %). Furthermore, e-scooter riders (STR: 9.8 %, INT: 38.2 %, SHA: 18.0 %) were more likely to use pedestrian crossings than cyclists (STR: 5.4 %, INT: 7.0 %, SHA: 7.9 %).

Additionally, the direction of travel on roadways was investigated. No wrong-way riders were found at the INT and the SHA. At the STR (see Table 3), e-scooter riders and cyclists mostly moved in the right direction on the roadway. The results of a two-proportion z-test suggest that e-scooters exhibited a significantly higher rate of wrong-direction riding (18.9 %) compared to bicycles (14.4 %) ($X^2 = 2.78$, df = 1, $p < 0.05$). E-scooter riders (18.9 %) moved more frequently in the wrong direction compared to cyclists (14.4 %). As mentioned previously, the wrong-way riding is only considered on the roadway.

3.2. Interaction with pedestrians

The interaction behavior of e-scooter riders and cyclists with pedestrians was investigated. In total, 2 e-scooters and 24 bicycles were involved in obstructed interactions at the STR; 20 e-scooters and 171 bicycles in head-on interactions at the INT; and 17 e-scooters and 316 bicycles in crossing interactions at the SHA. It is worth mentioning that the low number of e-scooters involved in obstructed interactions (N = 2) may impact the representation of the results. These results should be interpreted with caution due to unbalanced sample sizes.

3.2.1. Average speed

According to the Wilcoxon rank sum test, in the obstructed interaction, average speed of the e-scooter riders (M = 2.19 m/s [7.88 km/h], SD = 0.46 m/s [1.66 km/h]) was slightly higher (Z = 1.69, p = 0.09, r = 0.33) than the speed of the cyclists (M = 1.26 m/s [4.54 km/h], SD = 0.94 m/s [3.38 km/h]). In the head-on interaction, the average speed of the e-scooter riders (M = 1.72 m/s [6.19 km/h], SD = 0.50 m/s [1.80 km/h]) was significantly higher (Z = 3.96, $p < 0.001$, r = 0.29) than the average speed of the cyclists (M = 1.26 m/s [4.54 km/h], SD = 0.38 m/s [1.37 km/h]). However, there were no differences (Z = −1.42, p = 0.16, r = 0.08) between the average speed of e-scooter riders (M = 3.00 m/s [10.80 km/h], SD = 1.47 m/s [5.29 km/h]) and cyclists (M = 3.56 m/s [12.82 km/h], SD = 1.24 m/s [4.46 km/h]). Average speeds are presented in Fig. 3.

Table 2
Usage of infrastructures by different road users at the locations STR (straight road), INT (intersection), and SHA (shared space). The most frequently used infrastructures at each location is highlighted in bold.

Locations	Object	Infrastructures	N	%
STR	E-scooter	Pedestrian Crossing	84	9.8
		Pedestrian Path	56	6.5
		Roadway	718	83.7
	Bicycle	Pedestrian Crossing	414	5.4
		Pedestrian Path	315	4.1
		Roadway	6971	90.5
INT	E-scooter	Pedestrian Crossing	396	38.2
		Pedestrian Path	129	12.5
		Roadway	511	49.3
	Bicycle	Pedestrian Crossing	557	7.0
		Pedestrian Path	1069	13.5
		Roadway	6301	79.5
SHA	E-scooter	Pedestrian Crossing	102	18.0
		Pedestrian Path	281	49.7
		Roadway	183	32.3
	Bicycle	Pedestrian Crossing	132	7.9
		Pedestrian Path	639	38.4
		Roadway	893	53.7

Table 3
Riding direction on the roadway of the location STR across road users.

Object	Direction	N	%
E-scooter	right	167	81.1
	wrong	39	18.9
Bicycle	right	1937	85.6
	wrong	325	14.4

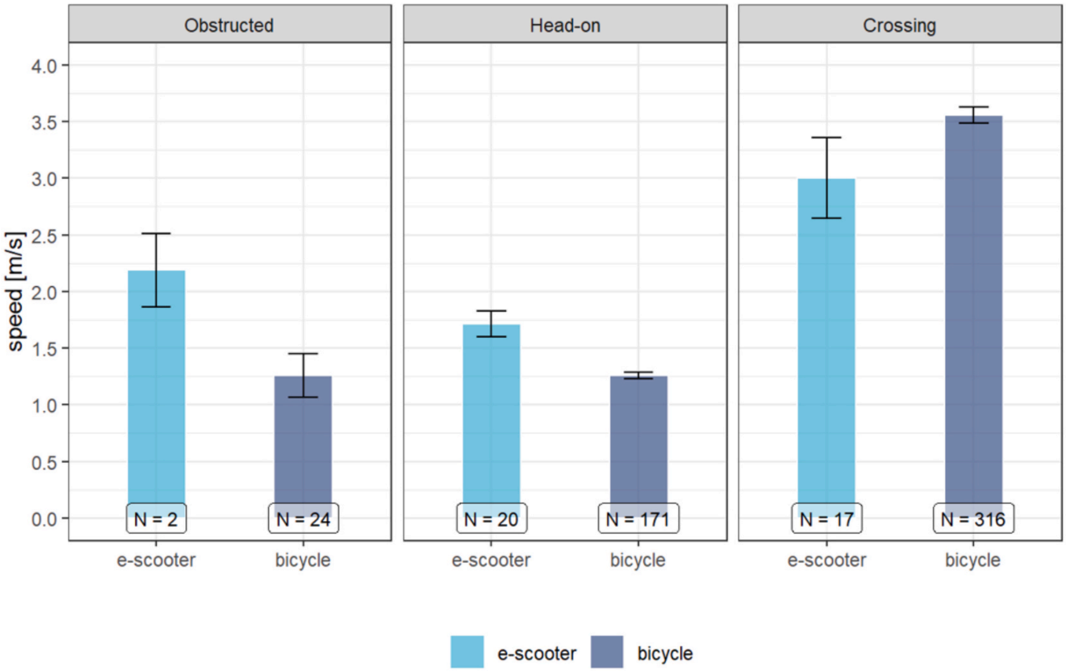

Fig. 3. Mean and standard deviation of average speeds of e-scooters and bicycles across different interaction types. E-scooters move faster than bicycles in obstructed and head-on interactions, but slower in crossing interactions. Note: Results should be interpreted with caution due to unbalanced sample sizes.

3.2.2. Minimum distance

E-scooter riders and cyclists generally maintained a distance of more than 1.5 m from pedestrians. According to the Wilcoxon rank sum test, no differences were found between the minimum distance of e-scooter riders and cyclists in obstructed ($Z = -1.43$, $p = 0.15$, $r = 0.28$; e-scooter: $M = 1.60$ m, $SD = 0.02$ m; bicycle: $M = 6.46$ m, $SD = 5.87$ m), head-on ($Z = -0.85$, $p = 0.39$, $r = 0.06$; e-scooter: $M = 3.53$ m, $SD = 1.50$ m; bicycle: $M = 3.37$ m, $SD = 1.90$ m), and crossing ($Z = 0$, $p = 1$, $r = 0$; e-scooter: $M = 5.16$ m, $SD = 2.13$ m; bicycle: $M = 5.40$ m, $SD = 2.62$ m) interactions with pedestrians. Minimum distances are presented in Fig. 4.

3.2.3. Minimum TTC

The Wilcoxon rank sum test showed that the minimal TTC of e-scooter riders ($M = 1.87$ s, $SD = 0.30$ s) was slightly lower ($Z = -1.79$, $p = 0.07$, $r = 0.35$) than that of cyclists ($M = 4.51$ s, $SD = 2.16$ s) in obstructed interactions. Similarly, in head-on interactions, the minimal TTC of e-scooter riders ($M = 2.46$ s, $SD = 0.77$ s) was slightly lower ($Z = -1.9$, $p = 0.06$, $r = 0.14$) than cyclists ($M = 2.98$ s, $SD = 1.17$ s). However, there were no differences ($Z = -1.47$, $p = 0.14$, $r = 0.08$) between the minimum TTC of e-scooter riders ($M = 3.09$ s, $SD = 1.0$ s) and cyclists ($M = 2.69$ s, $SD = 1.08$ s) in crossing interactions. Minimum TTC values are presented in Fig. 5.

4. Discussion

The aim of the study is to reveal the riding behavior of e-scooter riders and cyclists in terms of usage of infrastructures as well as to investigate risky behavior in interactions with pedestrians. For this purpose, traffic at three locations in Berlin, Germany, was observed by a research vehicle equipped with two cameras. The trajectories of e-scooters and bicycles, as well as the e-scooters or bicycles involved interactions with pedestrians were extracted and analyzed. According to the analysis, compared with cyclists, e-scooter riders used pedestrian infrastructures more often. Additionally, e-scooter riders exhibited wrong-way riding behavior more often than cyclists. In terms of interactions with pedestrians, there was little difference between e-scooter riders and cyclists. In head-on interactions with pedestrians, e-scooter riders showed riskier behavior than cyclists.

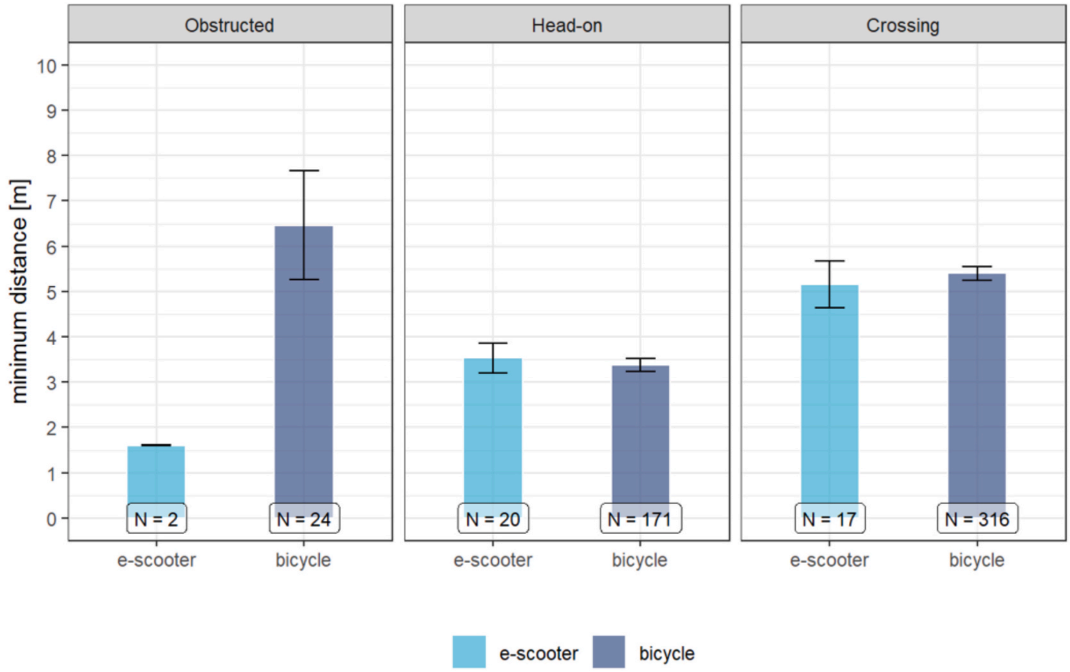

Fig. 4. Mean and standard deviation of minimum distances of e-scooters and bicycles across interaction types. Bicycles generally maintained greater minimum distances than e-scooters in obstructed interactions. Differences were smaller in head-on and crossing interactions. Note: Results should be interpreted with caution due to unbalanced sample sizes.

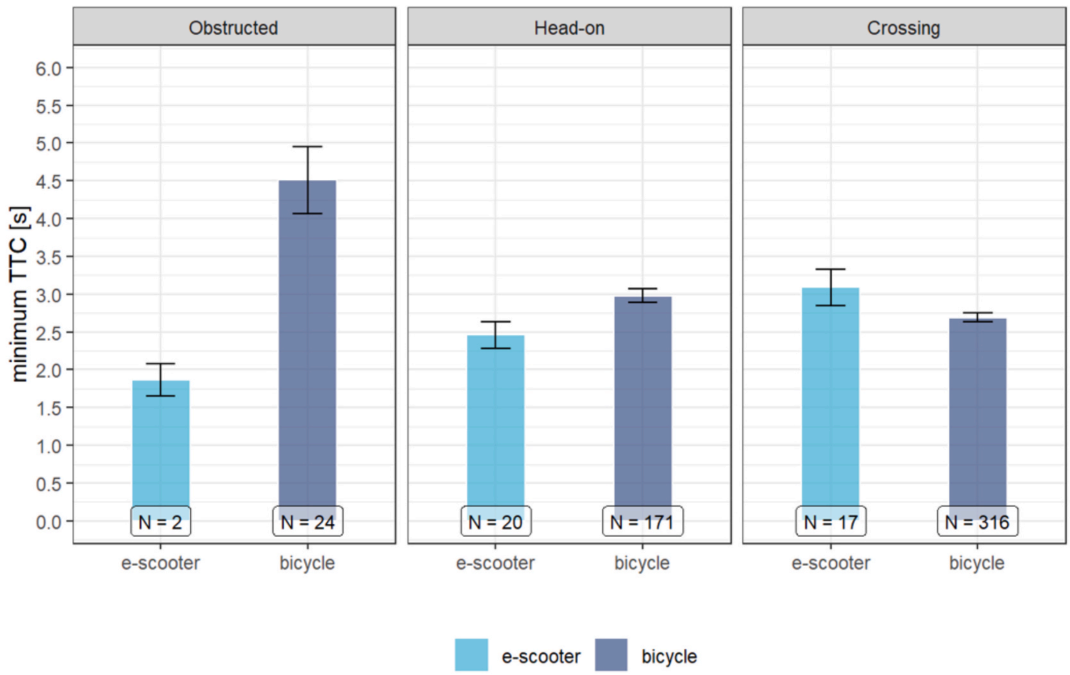

Fig. 5. Mean and standard deviation of minimum TTC for e-scooters and bicycles across interaction types. Bicycles generally maintained greater minimum temporal distances than e-scooters in obstructed interactions. Slight differences were found in head-on and crossing interactions. Note: Results should be interpreted with caution due to unbalanced sample sizes.

4.1. Usage of infrastructures

E-scooters are regarded as counterparts to bicycles, as they have comparable regulations and are required to use the same infrastructure (at least in Germany). However, our results revealed differences in infrastructure usage between e-scooter riders and cyclists. E-scooter riders were found to use pedestrian infrastructure illegally more frequently than cyclists across all three locations: straight road (STR), intersection (INT), and shared space (SHA). Our results are consistent with the findings of a previous observation study (Pazzini et al., 2022), which reported that e-scooters appear more frequently on pedestrian paths, particularly when bicycle lanes are not separated from the roadway. A recent study (Uluk et al., 2022) reviewed the locations of e-scooter accidents, showing that approximately one-quarter of the accidents occurred on pedestrian paths. This suggests that e-scooter riders are more likely to be involved in risky interactions with pedestrians on pedestrian paths.

It should be noted that the aforementioned study also reported that tourists are the main participants in e-scooter accidents (Uluk et al., 2022). Different regulations across countries may lead to the significant amount of improper usage of infrastructures in this study's results. Guiding e-scooter riders to use the correct infrastructure is still a challenge that road planners and e-scooter providers may need to face. A combination of clearer regulations, improved infrastructure design, and targeted education may be necessary.

4.2. Wrong-way behavior

On the roadway of the STR, more frequent wrong-way behavior of e-scooters was detected. The result is consistent with the previous study (Bai et al., 2014). Typically, in our study, wrong-way behavior occurred when there were vehicle platoons on the roadway (see Fig. 6). One possible explanation is that e-scooter riders and cyclists may avoid waiting by traversing crowded traffic flow to reach the relatively empty opposite lane. As a result, they may have to face increased risks of conflict with oncoming road users. Our results showed that e-scooter riders were more likely than cyclists to ride in the opposite direction. One argument is that the high steering maneuverability of e-scooters allows riders to quickly overtake vehicle platoons, even by traveling in the wrong direction. However, e-scooter riders and cyclists both rarely traveled in the opposite direction at the INT and the SHA. On the one hand, there are more lanes at the INT (two or three vehicle lanes and one tram lane in each direction), so wrong-way riding may lead to a higher risk than at the STR. On the other hand, there are fewer roadways at the SHA, and the correct direction was not clear.

4.3. Interaction with pedestrians

Interactions of e-scooter riders and cyclists with pedestrians were investigated in order to reveal potentially risky behaviors. Three typical interactions were considered: obstructed, head-on, and crossing. Instances involving e-scooters or bicycles at the STR, the INT and the SHA were separately extracted. Due to the small sample size ($N = 2$), the comparison results in obstructed interactions are not discussed.

Overall, e-scooter riders and cyclists showed similar and acceptable behavior patterns in head-on and crossing interactions with pedestrians: the average speed of both road users was less than 4 m/s (~15 km/h). The minimum distance to pedestrians for both road users was more than 1.5 m, while the minimum TTC to pedestrians was more than 1.5 s. Generally, the minimum TTC of e-scooter riders and cyclists with pedestrians was greater than 1.5 s, which was above the critical TTC threshold in a previous study (Van Der Horst, 1990). However, it should be noted that this threshold was defined for interactions between motorists, and a widely accepted critical TTC threshold for interactions between pedestrians and cyclists or e-scooter riders could not be identified. None of these metrics fell into the interval of risky riding. In terms of minimum distance and minimum TTC, there were no differences between e-scooters and bicycles. In head-on interactions with pedestrians, the average speed of e-scooter riders was higher than that of cyclists,

Fig. 6. Screenshots of e-scooter wrong-way riding.

which may lead to a failure of reaction for both interaction partners.

This study discussed the differences between e-scooters and bicycles in terms of risky riding, and the indicators used may more likely reflect proximity to pedestrians and, by extension, the probability of collision. However, the validity of the probability of collision using the TTC threshold is challenged, especially in crossing scenarios, where the TTC may still be below the critical threshold under controlled conditions (Yastremska-Kravchenko et al., 2022). Therefore, future research could consider more indicators (e.g., T2, the time of the second road user arriving at the conflict area (Laureshyn et al., 2010)) or define risky behavior through video annotation.

4.4. Policy Implications and Recommendations

Effective penalties may serve to improve rule compliance. In Germany, every e-scooter is required to display a license plate. However, the penalty for not displaying the plate is relatively minor, which may limit the effectiveness of this measure in promoting compliance. For bicycles, only those with electric assistance that support speeds above 25 km/h (so-called S-Pedelecs) are required to have a license plate. Regular e-bikes and pedelecs with assistance up to 25 km/h do not need a license plate. We assume that expanding on this approach, implementing a visible identification number system for both e-scooters and bicycles could further enhance safety and accountability. Additionally, this system would facilitate incident reporting by other road users and support data-driven improvements in urban mobility planning.

Additional policy options include mandatory safety training for new e-scooter users, potentially integrated into rental app onboarding processes. Depending on the provider, videos or brief explanations are offered on a voluntary basis in Germany. Creating dedicated infrastructure, such as separate lanes for e-scooters and bicycles, could help minimize conflicts with pedestrians. Finally, real-time monitoring and geo-fencing technologies may be used to prevent e-scooters from operating in restricted areas. This is already implemented in some locations in Germany, for example, to prevent e-scooters from being used in parks or other designated zones. However, riding in the wrong direction is not yet actively prevented by these systems. In some countries, though, speed limits are enforced via geofencing, so that e-scooters and e-bikes automatically slow down when traveling on sidewalks or in pedestrian areas (STANDARD (2024) and DRISI (2020)). In Munich, Germany, it was shown that establishing no-parking zones in combination with designated legal parking areas increased the rate of legal e-scooter parking from 71 % to 90 % (JPI Urban Europe, 2023). In Santa Monica, USA, speed reductions down to a complete stop were implemented to largely eliminate conflicts along the beach. As a result, rides in that area were reduced by 70 % (Cutter, 2020). Nevertheless, there is still a lack of evidence and detailed before-and-after comparisons that clearly demonstrate the benefits of geofencing for e-scooters. In addition to the previously mentioned direct actions, data-driven dashboards could also be useful for identifying locations with accidents or frequent violations to improve road planning. User feedback options should also be considered to gain better insights into the use and user-friendliness of the infrastructure (Nikiforiadis et al., 2023). Additional road safety campaigns can be used to further raise awareness among both e-scooter riders and cyclists.

4.5. Limitations and future research

The main limitation of this study concerns technical aspects related to video-based image processing. Light conditions or clarity (e.g., rain, reflection, etc.) may affect the accuracy of the recognition. It rained in the last three hours of the second observation day, during which recognition performance was impaired due to reflections on the wet surfaces. In addition, the difference between the training and test datasets may also affect the accuracy of object recognition. In this regard, our algorithm demonstrated its reliability. Even some rare features of e-scooters (such as two on one e-scooter) could be recognized correctly. Given that the accuracy of the measurement impacts the results, future studies should consider accounting for weather and light conditions, as well as a more diverse training dataset. Furthermore, although a test dataset was consistently used during image processing to monitor sensitivity and specificity, the quantitative results were not retained. Therefore, in the absence of measurement metrics such as recognition rates, the results cannot be directly compared to other video recognition approaches.

Another limitation of this study is the specificity of the three measurement locations. As mentioned earlier, none of the three measurement locations have separate bicycle lanes. This may be one of the motivations for cyclists and e-scooter riders to use the pedestrian infrastructures. While the results focus on comparing the infrastructure usage of bicycles and e-scooters under the same conditions, the proportion of the usage is not suitable for lateral comparison with other measurement locations. It should be noted that data collection at each location was limited to only eight hours. Therefore, potential influences of the time of day and day of the week could not be considered, because of limited information value. Longer-term analyses are necessary to fully account for these factors.

A notable limitation of this study is the low number of e-scooter cases involved in obstructed interactions ($N = 2$), which may affect the representativeness and stability of the results for this interaction type. Furthermore, the overall sample sizes between e-scooter and bicycle observations were unbalanced, which could introduce bias and limit the generalizability of the findings. These results should therefore be interpreted with caution, particularly when comparing across vehicle types or interaction scenarios.

Future research should address several additional aspects. Recent accident studies (Kleinertz et al., 2023) and surveys (Oostendorp et al., 2022) have presented the nuisances caused by e-scooters to pedestrians suggesting that haphazardly parked e-scooters may impact other road users (e.g., pedestrians, bus drivers) experiences and even threaten their safety. The relationship between improper parking locations and the inappropriate use of infrastructures is worth investigating. Additionally, more types of behaviors, such as red-light violations as well as more types of interactions, such as with bicycles, cars, and public transportation, could also be studied for the analysis of e-scooters' risky behavior.

Moreover, research on riding behavior considering characteristics of riders seems promising. Previous studies have shown that gender and helmet use impact riding behaviors (Haworth et al., 2021; Ma et al., 2019; Stipancic et al., 2016). Optimized image recognition technology can help label the gender and helmet usage of the riders (Satiennam et al., 2020).

5. Conclusion

This study investigated and compared the riding behaviors of e-scooter riders and cyclists based on video-recorded observations and quantitative analysis of interactions with pedestrians.

E-scooter riders were more frequently involved in illegal use of pedestrian infrastructure, wrong-way riding, and head-on interactions with pedestrians, indicating a slightly higher potential safety risk compared to cyclists. In contrast, little difference was found in crossing interactions or other observed behaviors. These differences may stem from lower familiarity with traffic rules and a greater tendency to navigate around congestion using the e-scooter's high maneuverability.

While the overall differences in behavior between e-scooter riders and cyclists were limited, the specific deviations observed, particularly in the use of pedestrian areas and wrong-way riding, highlight the need for targeted interventions.

This study contributes, although sample size is partially limited, to the growing body of knowledge on micro-mobility safety and highlights the need for context-specific policies. The insights provided may support future research and influence the development of infrastructure and regulatory strategies aimed at improving safety for all road users.

CRediT authorship contribution statement

Meng Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Claudia Leschik:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Nils Kornfeld:** Writing – review & editing, Software, Methodology. **Michael Hardinghaus:** Writing – review & editing, Supervision, Project administration. **Kay Gimm:** Writing – review & editing, Supervision.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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