Speed Behaviour of E-scooter Riders in Non-motorized Shared Spaces: Insights from Naturalistic Riding Data

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Short summary

E-scooter use has grown sharply in recent years, with riders frequently engaging in risky and illegal behaviours. Previous naturalistic studies with e-scooters have primarily focused on safety-critical events. However, few studies have analyzed the movement of e-scooter riders in natural riding conditions. This study analyses the speed behaviour of 16 e-scooter riders in non-motorised shared spaces. The data were collected in a naturalistic riding experiment in France using e-scooters instrumented with smartphones. Vulnerable road users were automatically detected from video data, and their characteristics were manually annotated. A linear mixed-effects regression model that accounts for unobserved heterogeneity among riders and among trips was estimated. The results show that e-scooter riders tend to ride significantly faster in the morning, when they are male, when they are not at intersections and when there are fewer cyclists in their field of view. These findings offer concrete inputs for stakeholders aiming to improve mobility management and safety in shared spaces.

Keywords: E-scooter, Naturalistic data, Shared spaces, Vulnerable road users, Linear mixed-effects models.

1 Introduction

1.1 Context

The increasing penetration rate of e-scooters in urban areas has been driven by technological advancements, the expansion of shared micro-mobility services, and the implementation of policies promoting sustainable transportation (International Transport Forum, 2024). However, it has also raised concerns about traffic safety and the coexistence of different vulnerable road users in shared spaces. Test-track studies have shown that e-scooters differ significantly from bikes in terms of braking and steering performance (Li et al., 2023; Dozza et al., 2023; Naude et al., 2025). In addition, e-scooter riders are often perceived as more risky than cyclists (Useche et al., 2022). Previous studies (Haworth et al., 2021; Curl & Fitt, 2019) have shown that e-scooters are frequently ridden on footpaths, leading to regular interactions with pedestrians. These interactions are often perceived negatively, as surveys indicate that most pedestrians find them annoying (Šucha et al., 2023). Among contributing factors, a higher riding speed has been associated with increased pedestrian discomfort (Suzuki et al., 2024; Che et al., 2021) and higher frequency and severity of e-scooter-related injuries (Mehranfar & Jones, 2024). A common suggestion to improve traffic safety is designing dedicated spaces for e-scooter riders and separate them from pedestrians, which can be challenging in terms of design throughout a city (Mehranfar & Jones, 2024). In this context, a better understanding of the behaviour of e-scooter riders in shared spaces appears essential.

1.2 Studies on e-scooter riders interacting with vulnerable road users on shared spaces

This section reviews studies examining the movement (i.e., speed and trajectory) of e-scooters on spaces shared with vulnerable road users (i.e., pedestrians and users of other micro-mobility vehicles). A recent literature review (C. Zhang et al., 2023) highlighted that these studies on

interactions can be classified as either controlled experiments, field observations, and riding data collection. Questionnaire surveys and studies that focused on crashes or near-crashes were here excluded.

Controlled studies, conducted either on dedicated test tracks or within virtual reality environments, have examined the behavior of e-scooter riders in the presence of vulnerable road users under predefined interaction scenarios. These scenarios have replicated, for example, following encounters (Lee et al., 2021), meeting encounters (Sim & Cho, 2025; Jafari & Liu, 2024; Gioldasis et al., 2023), crossing encounters (Gioldasis et al., 2023), and passing encounters (Sim & Cho, 2025; Jafari & Liu, 2024). The conclusions from these studies is, for instance, that early evasive actions or anticipation factors by micro-vehicle users play a crucial role in enhancing pedestrian safety. These studies usually present a high internal validity and a limited external validity due to the experimental design. On the other hand, studies on open roads have predominantly relied on field observations or fixed-camera recordings, including on pedestrian streets (Valero et al., 2020; M. Zhang et al., 2026; Pazzini et al., 2022). These data collection methods are constrained by the observation sites and may therefore limit the representativeness of the collected data.

Some recent studies have been conducted on a fixed route with e-scooters instrumented with sensors and cameras. Pashkevich et al. (2022) analyzed speed and gaze behaviour in a shared path with bikes, pedestrians and e-scooters and found an average speed of 16.8 km/h for e-scooters in shared roads. Similarly, Kegalle et al. (2025) investigated the speed and gaze behavior of recruited participants riding instrumented e-scooters across different types of road segments. Their results indicated, for example, a similar average speed of 16.7 km/h on pedestrian-shared paths. In addition, a lower fixation count in these environments suggests that riders perceive pedestrian-shared paths as more predictable and safer than roads or cycle lanes. However, they only investigated pedestrian-shared path in low-density conditions and did not directly model the influence of the pedestrians on the rider's behaviour.

1.3 Research gaps and research objectives

Previous studies have investigated e-scooter behaviour in controlled experiments, which can suffer from limited external validity, and using fixed-camera observations, which are constrained by their deployment sites. Few studies have utilized instrumented e-scooters, and most have neglected to examine how characteristics of vulnerable road users, such as their number, direction, and type, influence rider speed.

Naturalistic studies provide higher external validity than other data collection methods (Klauer et al., 2006), and allow the consideration of many factors simultaneously and greater representativeness than fixed observations. Previous studies have used naturalistic data to investigate speed behavior of car drivers (Richard et al., 2020), cyclists (Yan et al., 2025) and e-bikes riders (Schleinitz et al., 2017). However, similar investigations with naturalistic data remain relatively scarce for e-scooters and focus on safety-critical events (Pai & Dozza, 2025; White et al., 2023; Z. Zhang et al., 2022). As a result, there are still limited insights from naturalistic riding data on how e-scooter riders adapt their speed when interacting with vulnerable road users.

The objectives of this study are the following: (i) to identify interactions between e-scooters and vulnerable road users based on data collected in a naturalistic riding experiment, (ii) to analyse the speed behaviour of e-scooter riders in these situations based on variables related to traffic conditions, infrastructure, and rider characteristics.

2 Methodology

2.1 Data collection and extraction

The naturalistic riding data were collected by Naude et al. (2026) in France. The data included the daily journeys during a two month period of 56 e-scooter riders in the urban areas of Paris, Lyon and Aix-Marseille. In total, 3,019 e-scooter trips were collected for a total of 7,660 km. Only adults who had previous prior experience in e-scooter riding were recruited for the study. The experiment was conducted in accordance with approved ethical procedures. The e-scooters were equipped with removable Samsung Galaxy S8 as data collection systems, mounted on the handlebars using 3D-printed holders. The data were collected by a dedicated application, recording speed and GPS position at 1 Hz, video at 30 Hz, and acceleration and angular speeds at 100 Hz. In this study, only trips on non-motorized shared spaces (i.e., where only vulnerable road users share the road

without any visual segregation) were analysed. The GPS coordinates of these spaces were retrieved from OpenStreetMap (2026) using the tag *'highway=pedestrian'*, which represents a total of 392.7 km of roads for the study area. A 12 m buffer around each streets axis was applied to account for road width while minimizing the occurrence of false positives. Additionally, the main pedestrian squares in the study area were added, which represented a total of 6.4 km^2. Since not all squares are non-motorized, only the main non-motorized ones were retained. Each GPS point recorded by the instrumented e-scooters was matched with the geospatial layers of pedestrian streets and of squares to select clips where at least 20 seconds of continuous data were matched. Notably, GPS errors in dense urban environments can reach up to approximately 5 m. However, this level of accuracy was deemed sufficient to avoid incorrect road matching. This step resulted in a total of 6.31 hours of data for the shared spaces and 1h of data for the squares (cf. Figure 1, step 1). The clips were manually reviewed and a large proportion was discarded as false positives. Additionally, clips that presented degraded signal or video quality, were corrupted, had improper camera positioning or partially occluded views, or were recorded in low light or fog were excluded from the final dataset. In total, approximately 13% of the clips were retained after this visual check (cf. Figure 1, step 2). A random subset of the clips was then annotated and retained for the analysis (cf. Figure 1, step 3). Then, timestamps corresponding to observations involving large obstacles were excluded. In addition, data points with steering speed from the gyroscope exceeding 20°/s were removed to exclude potential turning maneuvers. Observations with speeds below 2 km/h were also removed to exclude situations where the rider deliberately stopped the vehicle (cf. Figure 1, step 4). Finally, the dataset results in 25 trips from 16 riders for a total of 1,264 s. The riders are 8 females and 8 males and have a mean age of 31.4 years (SD = 11.6 years). Two drove near Paris, five in Aix-Marseille and nine in Lyon.

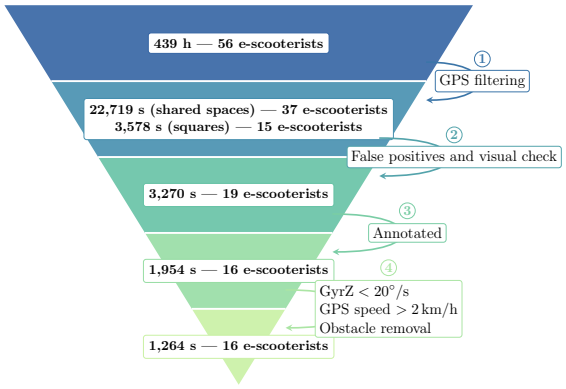


Figure 1: Data filtering pipeline

2.2 Variable extraction

2.2.1 Image processing and annotation

To extract relevant variables, a pipeline consisting of computer vision techniques and manual annotation was performed. First, a transformer-based detector based on the RF-DETR Large architecture (Robinson et al., 2025) was applied to automatically identify road users present in the field of view of the smartphone camera. Each detected object was associated with a bounding box and a confidence score. A tracking algorithm based on the BotSORT (Aharon et al., 2022) was used to assign a unique track identifier to each detected road user. Based on camera calibration parameters, the distance to each detected vulnerable road user was approximated using the vertical position of the bottom of their bounding box in the image plane, assuming a flat ground plane. Only road users estimated to be within 15 m of the rider were retained for analysis. With these outputs, two annotators underwent parallel training to annotate all detected vulnerable road users in accordance with a predefined codebook. The annotation procedure was conducted as follows. First, false positives (e.g., shadows and advertisements) were manually removed. Second, vulnerable road users who were either separated from the rider by a physical element (e.g., a curb, a barrier, a window) or seated on benches or terraces were not considered to be interacting with the rider and were therefore also excluded. For each interaction event that was not discarded, several variables were annotated, as the type of interacting road user, the type of interaction based on the angle, the gait and the approximate age group of the interacting road users. Finally, potential

false negatives were identified, manually tracked and annotated as described above. Notably, the annotated vulnerable road users reflect those visible to the camera despite to occlusions, rather than the total number present in the environment. Two inter-rater reliabilty metrics were assessed: percentage agreement and Cohen's Kappa (Cohen, 1960), computed using the `cohen_kappa_score` function from the Python package `scikit-learn`. The results are presented in Table 1.

Table 1: Inter-rater reliability for VRU annotations

Variable	**Level**	N_1	N_2	**Agr. (%)**	κ
Confirmed encounter	Reject	158	158	87.6	0.73
	Accept	229	229		
VRU type	Pedestrian	191	191	100.0	1.00
	Cyclist	8	8		
	E-scooter	1	1		
Interaction type	Same-direction	69	67	89.8	0.86
	Opposite-direction	66	63		
	Crossing	41	40		
	Stationary	24	28		
	Unknown	0	2		
Pedestrian gait	Standing	24	28	83.0	0.56
	Walking	143	156		
	Running	23	6		
	Unknown	10	10		
VRU age group	Child	14	17	92.2	0.65
	Adult	181	169		
	Elderly	3	14		
	Unknown	2	0		
Weather	No adverse	9	9	100.0	—
Lighting conditions	Daylight	9	9	100.0	—
Surface condition	Dry	6	5	88.9	0.77
	Wet	3	4		
Rider's companion	Solo	9	9	100.0	—

Note: Agr. = percentage agreement; N_1 and N_2 = number of annotations by rater 1 and rater 2; κ = Cohen's kappa coefficient. Interpretation of κ: 0.21–0.40 = Fair, 0.41–0.60 = Moderate, 0.61–0.80 = Substantial, 0.81–1.00 = Almost Perfect (Landis & Koch, 1977).

The results indicate a substantial level of agreement between the two raters for the variables 'confirmed encounter', 'VRU type', 'VRU age group', 'interaction type', and 'surface condition', with Cohen's Kappa values above 0.61 (Landis & Koch, 1977). For the variable 'pedestrian gait', the Cohen's Kappa value is lower, which may be attributed to skewed category distributions known to affect Kappa statistics (Feinstein & Cicchetti, 1990). The variable was therefore not considered for the analysis.

Following this assessment, the remaining video recordings were randomly allocated to one of the two annotators. After this annotation procedure, the video frames were synchronized with the IMU and GPS signals. Since everything was collected by a smartphone, the beginning and end timestamps were already matched. To limit potential offsets between the videos and the IMU, the gyroscope was compared with the camera motion observed in the videos and resynchronized. After the synchronization, the dataset was reduced to 1 Hz. Each numerical variable was assigned the median value across the 1s-timestep.

2.2.2 Infrastructure characteristics extraction

To analyze the effect of infrastructure characteristics, road width and intersection locations were extracted from geographic satellite imagery (Google Earth) and matched to the recorded GPS points. The polygons of each shared space were manually extracted. Road width was then measured at each GPS point by computing its cross-sectional length perpendicular to the estimated travel direction. On the other hand, every timestamps where the GPS fall into an intersection were labeled as intersection. Each point where two paths crossed was considered an intersection.

2.3 Data analysis

The final dataset with all variables considered is presented in Section 4. A linear mixed-effects model was developed to analyze the factors that influence speed behaviour. The dependent variable represents the observed speed, derived from GPS positions. Similar to previous models predicting pedestrian behaviour (Antonini et al., 2006), the observed choice made by the current decision-maker has been measured 1-s forward in time. As a consequence, the last position of each trajectory are not used. To account for correlations between repeated measurements and produce unbiased estimates of fixed-effect parameters, random intercepts were included for each participant and for each trip. These random intercepts capture variability in rider behaviour and in trip conditions, similar to previous studies of bicycle speed (Yan et al., 2025). The model assumes that the speed y_{ijt} of rider i at timestamps t of trip j can be expressed as:

$$y_{ijt} = \beta_0 + \sum_{k=1}^{K} \beta_k x_{tk} + u_i + u_j + \varepsilon_t,$$

with β_0 denoting the intercept, β_k the regression coefficients associated with explanatory variables x_{tk}, u_i and u_j random terms capturing respectively unobserved individual-specific or trip-specific heterogeneity (assumed to follow a normal distribution $\mathcal{N}(0, \sigma^2)$) and ε_t, the observation-specific error term assumed to follow a normal distribution $\mathcal{N}(0, \sigma_\varepsilon^2)$. Continuous variables were centered in the mean and divided by the standard deviation. Categorical variables were on the other hand encoded as dummy variables, and the most frequent category was used as the reference level. The model was tested using maximum likelihood (ML) estimation, then fitted using restricted maximum likelihood (REML) estimation, to enable model comparison and provide reliable estimates of random-effect variances. This estimation was done using the R package `lme4` (Bates et al., 2015). A forward procedure was applied, iteratively adding variables presented in Section 4 and keeping them if there were significant at the 5% level based on the likelihood-ratio test. To avoid collinearity issue, the Pearson's correlation between covariates was checked to remain under the threshold of 0.5. Model specifications were evaluated by conducting likelihood-ratio tests for nested model comparisons or by comparing values of the Akaike Information Criterion (AIC) when the models were not a restricted version of the other one. In addition, marginal and conditional R^2 were computed. The marginal R_m^2 represents the proportion of variance explained by the fixed effects alone, while the conditional R_c^2 reflects the variance explained by both fixed and random effects (Nakagawa & Schielzeth, 2013). They were computed using the R package `MuMIn`. For each significant variable, marginal means were computed while holding all other variables constant. Confidence intervals were derived to capture the uncertainty of the fixed effect estimates, and prediction intervals were calculated to account for uncertainty arising from both fixed and random effects. The plots are presented in Figure 2.

3 Results

The estimation results of the model are presented in Table 2 and the statistics are presented in Table 3. In total, five explanatory variables were significant at the 5 % level. The addition of two random errors capturing respective unobserved heterogeneity among riders and trips show an improvement of the model based on likelihood-ratio tests. The marginal R^2 indicates that fixed effects explain 27 % of the variance in e-scooter speed, while the conditional R^2 shows that rider-level and trip-level random effects increase the explained variance to 79%. The final model

specification is:

$$
\begin{aligned}
\hat{y}_{ijt} = \mu
&+ \beta_{\text{Male (ref : Female)}} \cdot \mathbb{1}_{\{\text{Male (ref : Female)}\}} \\
&+ \beta_{\text{N visible cyclists} < 15\text{m}} \cdot \tilde{x}_{\text{N visible cyclists} < 15\text{m}} \\
&+ \beta_{\text{Proportion of same-direction encounters}} \cdot \tilde{x}_{\text{Proportion of same-direction encounters}} \\
&+ \beta_{\text{Intersection (ref : No)}} \cdot \mathbb{1}_{\{\text{Intersection (ref : No)}\}} \\
&+ \beta_{\text{Afternoon (ref : Morning)}} \cdot \mathbb{1}_{\{\text{Afternoon (ref : Morning)}\}} \\
&+ u_i \quad u_i \sim \mathcal{N}(0, \sigma^2_{\text{rider}}) \\
&+ u_j \quad u_j \sim \mathcal{N}(0, \sigma^2_{\text{trip}}) \\
&+ \varepsilon_t \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2_{\varepsilon})
\end{aligned}
$$

Parameter	Value	Std. err.	t-stat.	p-value
μ	12.6152	1.9208	6.568	0.0000
$\beta_{\text{Male (ref : Female)}}$	5.5602	2.5703	2.163	0.0495
$\beta_{\text{N visible cyclists} < 15\text{m}}$	-0.2456	0.1090	-2.254	0.0244
$\beta_{\text{Proportion of same-direction encounters}}$	-0.4173	0.1023	-4.081	0.0000
$\beta_{\text{Intersection (ref : No)}}$	-4.3989	0.6052	-7.268	0.0000
$\beta_{\text{Afternoon (ref : Morning)}}$	-4.9036	1.4953	-3.279	0.0044
σ_{rider}	4.8794	—	—	—
σ_{trip}	1.6885	—	—	—
σ_{ε}	3.2699	—	—	—

Table 2: Estimated parameters of the linear mixed-effects model predicting the speed

Statistics	Value
N_{obs}	1239
N_{riders}	16
N_{trips}	25
K	6
$\mathcal{LL}(\text{cst})$	-4267
$\mathcal{LL}(\hat{\beta})$	-3272
$R^2_m = \frac{\sigma^2_f}{\sigma^2_f + \sigma^2_{\text{rider}} + \sigma^2_{\text{trip}} + \sigma^2_{\varepsilon}}$	0.2752
$R^2_c = \frac{\sigma^2_f + \sigma^2_{\text{rider}} + \sigma^2_{\text{trip}}}{\sigma^2_f + \sigma^2_{\text{rider}} + \sigma^2_{\text{trip}} + \sigma^2_{\varepsilon}}$	0.7925
LRT $\chi^2(1)$ vs $\sigma_{\text{rider}} = 0$	13.55
p-value LRT $\sigma_{\text{rider}} = 0$	0.0002
LRT $\chi^2(1)$ vs $\sigma_{\text{trip}} = 0$	151.87
p-value LRT $\sigma_{\text{trip}} = 0$	0.0000

Table 3: Statistics of the linear mixed-effect model predicting the speed

Results show that male riders traveled at higher speeds than female riders, with this effect being the highest in terms of magnitude among the binary variables. Riders also had a lower speed when the number of visible cyclists was higher. When the proportion of same-direction encounters is higher, e-scooter were more likely to ride slower. E-scooter riders also tended to ride more slowly at intersections. Finally, they were significantly slower in the afternoon compared to the morning. Variables related to rider's age and experience, the surface condition, the environment type, the lighting conditions, the weather condition, the number and proportion of stationary, crossing and opposite encounters, and the number of visible pedestrians, children and elderly were not significant and therefore not included in the final model.

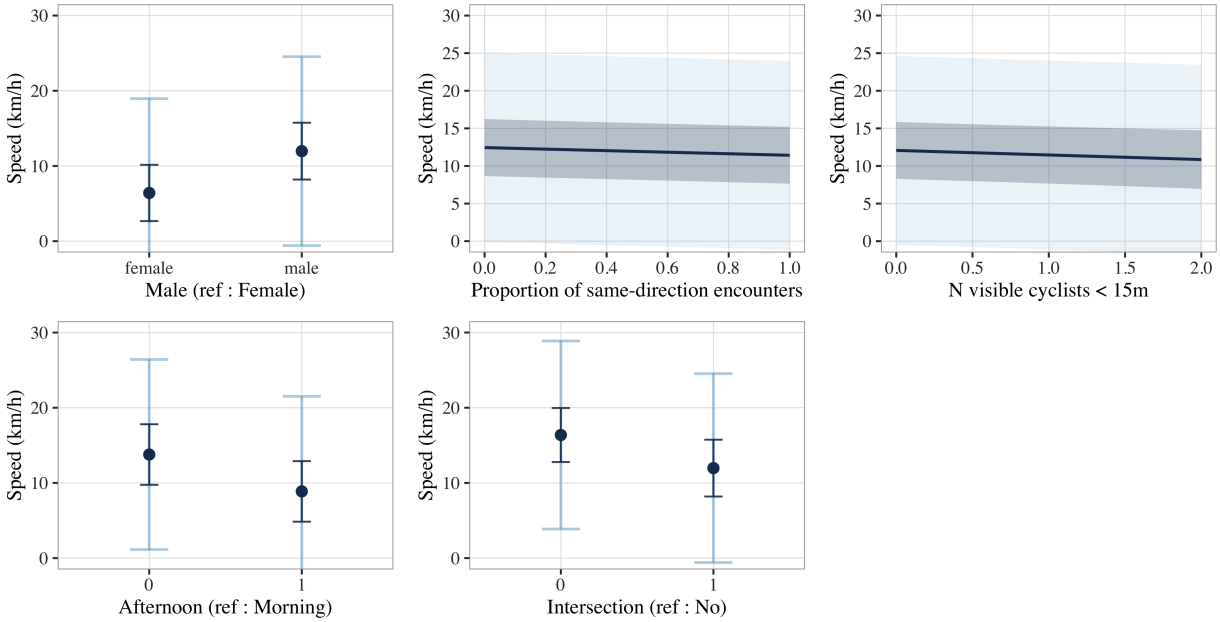


Figure 2: Effect of the significant variables on the speed. Black dots indicate the predicted speed, dark blue error bars show 95% confidence intervals, and light blue error bars show 95% prediction intervals.

4 Discussion and conclusion

The study is a first attempt to describe the speed behaviors of e-scooter riders in different non-motorized shared spaces based on data collected in a naturalistic riding experiment. It proposed a methodology to extract relevant video footage, annotate and extract variables, and model the speed behavior of e-scooter riders using linear mixed-effects models.

The results highlight some significant factors to explain the chosen speed for e-scooter riders in shared spaces. Male riders tended to ride faster than female riders, though this result should be interpreted cautiously given the small sample of 8 male and 8 female riders. A previous study has shown that males, especially young males, behave in ways that increase their crash risk with e-scooters, such as riding at higher speeds (Janikian et al., 2024). Another study also found that, on average, males rode e-scooters faster than females on sidewalks and mixed-use routes (Arellano & Fang, 2019). At intersections, e-scooter riders tended to ride slower, which is consistent with a previous study for bikes (Yan et al., 2025). An increase in the number of cyclists within the camera's field of view was associated with lower e-scooter speeds. Previous studies have already showed that high density of pedestrians decreased cyclists' speed at intersections (Beitel et al., 2018) and crosswalks (Fu et al., 2025). In this study, the presence of VRUs under 15 m was used as a proxy for the density. The higher proportion of same-direction encounters was shown to significantly reduce e-scooter speed. This could possibly reflect that riders get stuck behind slower pedestrians, or this could reflect a higher discomfort experienced during such interactions, which would be consistent with findings from the e-bike literature suggesting that following scenarios generate more tension than meeting ones (Kazemzadeh & Bansal, 2021), notably due to non-verbal communications. Finally, trips conducted in the afternoon were significantly slower than those in the morning, possibly explained by the commuters who used their vehicle to go to work. This aligns with the findings of (Almannaa et al., 2021) who found for dockless e-scooters an average speed cluster higher from 3 AM to 12PM than the rest of the day.

The main limitation of this study is the small sample size and the small number of riders (16). It should be noted that it was extracted from a larger dataset. Larger studies with more participants are needed to confirm the results. In addition, the assumed reaction time of 1 s was selected arbitrarily based on the data, as was the threshold of 15 m to classify encounters. Other values need to be tested to assess the robustness of the model. Finally, further analysis is warranted to assess the extent to which errors in GPS measurements may generate outliers in the model predictions and, in turn, affect the normality of the residuals. Future work will aim to refine the model specification, to enhance the automated detection and tracking pipeline, to estimate

the distance to vulnerable road users, and to conduct further quantitative analyses of interaction characteristics, including trajectory modifications.

CRediT authorship contribution statement

Martin De Jaeghere: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing.
Louis-Jacques Etaix: Conceptualization, Data curation, Methodology, Software.
Claire Naude: Data curation, Resources.
Ebrahim Riahi: Data curation, Resources.
Thierry Serre: Data curation, Resources.
Nour-Eddin El Faouzi: Writing – review & editing, Supervision.
Silvia Varotto: Conceptualization, Methodology, Writing – review & editing, Funding acquisition, Project administration, Supervision.

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Appendix

Table 4: Candidate variables for the linear mixed-effects model

Variable	Levels	Min	Mean	Max	Source
Kinematics					
Speed (km/h)	*cont.*	2.0	14.60	33.8	GPS
VRU — Presence					
Nb. pedestrians in frame	*cont.*	0.0	3.39	14.0	Video annotation
Nb. cyclists in frame	*cont.*	0.0	0.18	3.0	Video annotation
Nb. elderly persons	*cont.*	0.0	0.25	5.0	Video annotation
Nb. children	*cont.*	0.0	0.11	3.0	Video annotation
Nb. pedestrians running	*cont.*	0.0	0.08	3.0	Video annotation
VRU — Behaviour					
Nb. pedestrians crossing	*cont.*	0.0	0.43	8.0	Video annotation
Nb. pedestrians in opposite direction	*cont.*	0.0	1.40	8.0	Video annotation
Nb. pedestrians in same direction	*cont.*	0.0	1.29	10.0	Video annotation
Nb. pedestrians stationary	*cont.*	0.0	0.39	7.0	Video annotation
Nb. cyclists crossing	*cont.*	0.0	0.01	1.0	Video annotation
VRU — Trip proportion					
Proportion of same-direction encounters	*cont.*	0.0	0.46	1.0	Video annotation
Proportion of opposite-direction encounters	*cont.*	0.0	0.44	1.0	Video annotation
Proportion of crossing encounters	*cont.*	0.0	0.15	1.0	Video annotation
Proportion of stationary encounters	*cont.*	0.0	0.11	1.0	Video annotation
Environment					
Weather conditions	No adverse	0.0	0.99	1.0	Video annotation
	Adverse	0.0	0.01	1.0	
Lighting conditions	Daylight	0.0	0.94	1.0	Video annotation
	Dawn/Dusk	0.0	0.06	1.0	
	Unknown	0.0	0.01	1.0	
Surface condition	Dry	0.0	0.90	1.0	Video annotation
	Wet	0.0	0.10	1.0	
Geospatial					
Road width — perpendicular (m)	*cont.*	0.0	16.58	102.8	Google Earth
At an intersection	*cont.*	0.0	0.03	1.0	Google Earth
Temporal					
Hour of day	*cont.*	5.0	10.66	20.0	GPS timestamp
Weekend	*cont.*	0.0	0.13	1.0	GPS timestamp
Time-of-day period	Morning	0.0	0.60	1.0	GPS timestamp
	Afternoon	0.0	0.38	1.0	
	Evening	0.0	0.01	1.0	
	Night	0.0	0.02	1.0	
Season	Spring	0.0	0.41	1.0	GPS timestamp
	Summer	0.0	0.25	1.0	
	Autumn	0.0	0.34	1.0	
Socio-demographic					
Gender	male	0.0	0.49	1.0	Questionnaire
	female	0.0	0.51	1.0	
Age (years)	*cont.*	21.0	37.79	55.0	Questionnaire

continued ...

Table 4 (continued)

Variable	**Modality**	**Min**	**Mean**	**Max**	**Source**
	<0.5	0.0	0.25	1.0	Questionnaire
E-scooter experience	0.5-1	0.0	0.02	1.0	
(years)	1-2	0.0	0.09	1.0	
	>2	0.0	0.63	1.0	
Trip distance (km)	*cont.*	10.0	143.82	323.2	GPS