Who Owns the Space? A Near-Accident Perception of e-Scooters Riders in Interaction with Pedestrians

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Abstract. The rapid growth of e-scooter usage in urban environments has introduced new safety challenges, particularly in shared spaces with pedestrians. This study investigates near-collision interactions between e-scooter riders and pedestrians in a pedestrianized area in Thessaloniki, Greece, based only on 100 observed near-miss incidents. A multidimensional approach is adopted to analyze behavioral responses and interaction dynamics. Ordinal Logistic Regression is employed to examine the factors influencing changes in e-scooter speed (acceleration, no reaction, and varying levels of deceleration) when riders encounter pedestrians. Subsequently, behavioral personas for both e-scooter riders and pedestrians are identified, and a Firth Logistic Regression model is applied to assess the likelihood of high-risk conflicts arising from different persona combinations. The results reveal that while most riders adopt defensive behaviors, a significant proportion of risky responses persists, particularly in the presence of inattentive or unresponsive pedestrians. The findings indicate that near-collision risk is primarily driven by behavioural interactions, while environmental conditions such as congestion further amplify these effects. The results are particularly relevant for urban planners, transport engineers, and policymakers, as they provide evidence to support the design of safer shared spaces and the development of targeted interventions addressing both rider and pedestrian behaviour.

Keywords: E-scooters · Micromobility safety · Pedestrian interactions · Risk perception · Collision avoidance behaviour

1 Introduction

While e-scooters are appearing to be used mainly in shorter distances and for the First- and Last-Mile commutes [1], they also appear to win ground in the "competition" between alternative modes. However, it raises concerns regarding rider and non-rider safety [2]. Since the widespread adoption of e-scooters there has been a significant

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increase in injuries and admissions [3]. To study the safety perspective of e-scooters is important to identify the socio-economic and behavioral background of the users. For example, low-income e-scooter users are increasing the use of this mode compared to other transportation modes [4]. Additionally, older riders with good physical condition and riders of private e-scooters and leisure travelers are more likely to use e-scooter for their commute [5].

Shared spaces give access to micromobility in urban environments, however the presence of various transport modes, such as cyclists, pedestrians and e-scooters, create concerns about safety since every commuter has a different perception of space. For instance, in Sweden female e-scooter riders feel less safe in shared spaces compared to their male counterparts. Additionally, young adults feel safer when overtaking other road users rather than encountering them head-on [6]. As it appears from [7] maneuvers and interaction with another road user consist two of the main accident causation. Main focus should be given on the relation between e-scooter riders and pedestrians where these users have the most different speed regimes in off-road facilities and these differences increase the chance of interactions, conflicts and potential collisions [8] and is considered as a weakness to the use of e-scooters [9].

Based on the EU regulation many countries have enforced their legislations on the use of e-scooters, focusing on some minimum age and maximum speed limitations but also on the space of allowing e-scooter riders to ride. For example, in Greece the minimum age of using e-scooter is 15 years with a maximum speed 25 km/h and a compulsory on wearing helmet. E-scooter riders are allowed to ride only on the cycle path and on the road, but only if the speed limit is 50 km/h and they are not allowed to ride on pavement, unless the e-scooters cannot go faster than 6 km/h [10]. Based on [11] 44,4% of the respondents in a survey from 22 European countries reported riding e-scooters on pedestrian pavement or sidewalk at least once, fact that indicates that e-scooter riders do not follow the current legislations.

Despite the growing body of literature on e-scooter safety, most existing studies rely on crash data, survey-based approaches, or general behavioural observations, which often fail to capture the detailed dynamics of interactions in shared spaces. In particular, limited attention has been given to near-collision events as indicators of potential risk, as well as to the role of behavioural typologies of both e-scooter riders and pedestrians in shaping these interactions. This study addresses these gaps by introducing a person-based analytical framework that combines near-collision observational data with the classification of users into distinct behavioural profiles. Furthermore, it proposes a risk classification approach based on observed behavioural responses and examines the combined effects of interaction context and congestion-related conditions on rider behaviour.

For analyzing the perception of e-scooter users and non-users, several studies used data from surveys [12, 13]. This study utilizes near-collision data between e-scooter riders and pedestrians collected on a pedestrian street in Thessaloniki, Greece. The research adopts a multidimensional approach. Initially, it examines the conditions under which e-scooter riders choose to accelerate, decelerate, or exhibit no reaction, considering contextual factors such as pedestrian density. Subsequently, the study explores the behavioral characteristics of both e-scooter riders and pedestrians and estimates the likelihood of

high-risk collisions arising from different combinations of risk-prone behaviors between the two groups. The findings provide valuable insights for local authorities and policy-makers, supporting the development of safer shared environments that accommodate both user groups while minimizing collision risks.

The remainder of this paper is structured as follows. Section 2 presents the data collection process and methodology adopted in this study. Section 3 provides the results of the statistical analysis, including the ordinal logistic regression model and the Firth logistic regression model, along with the proposed risk classification framework. Finally, last section, the paper concludes.

2 Methodological Framework

The methodological framework developed in this study provides a step-by-step approach for analyzing the factors that shape the behavioral characteristics of e-scooter riders. It further identifies distinct behavioral personas for both e-scooter riders and pedestrians sharing the same space, and determines which of these personas are more prone to collision risk.

To achieve this, the first step of the methodological framework involved the collection of near-collision incident data from a pedestrian street in the Kalamaria district of Thessaloniki, Greece. These data were subsequently used to identify the factors influencing the behavioral responses of e-scooter riders, namely acceleration, deceleration, or no reaction, upon encountering pedestrians in their path, using an Ordinal Logistic Regression model.

Furthermore, the study identified and examined distinct behavioral personas of both e-scooter riders and pedestrians within shared spaces, and assessed how different combinations of these personas contribute to collision risk. Specifically, the likelihood of high-risk collisions associated with various persona interactions was estimated using a Firth Logistic Regression model, alongside the effect of each individual persona type.

2.1 Data

For the purposes of this study, field observations were conducted in pedestrianized areas of the Kalamaria district in Thessaloniki, Greece. The observations focused on incidents involving interactions between e-scooter riders and both moving and stationary pedestrians, as well as hazardous situations with an evident potential to result in collisions. In total, 100 near-miss were recorded. An “incident” is defined as any interaction between an electric scooter (e-scooter) and one or more pedestrians within the study area that poses a potential threat to the physical safety of at least one of the involved parties. The identification and classification of incidents were based on the observer’s qualitative judgment in real time, considering factors such as proximity, abrupt maneuvers, and perceived collision risk. Therefore, the dataset used in this study exclusively includes interactions between e-scooter riders and pedestrians. No data regarding other mobility users, such as bicycles, motorcycles, or motor vehicles, were collected or analyzed.

The collected data provided all the necessary information for the analysis conducted in this study, as summarized in Table 1. The dataset captures multiple dimensions of

interactions between e-scooter riders and pedestrians. In most cases, e-scooter riders undertook avoidance actions (91%), whereas pedestrians exhibited significantly lower response rates (15%), indicating an imbalance in reactive behavior. Similarly, awareness levels were higher among e-scooter riders (83%) compared to pedestrians (33%), suggesting that pedestrians are more likely to remain unaware of approaching conflicts. The majority of incidents occurred outside designated cycling infrastructure (88%), and helmet usage among riders was notably low (12%).

Regarding behavioral responses, deceleration was the most common reaction, with moderate (26%) and strong (22%) deceleration accounting for nearly half of all cases, while acceleration and no reaction were observed in 19% of incidents each. Most interactions occurred under relatively low-to-moderate pedestrian densities (LoS A–B: 85%), indicating that conflicts are not limited to highly congested environments. Additionally, both riders (77%) and pedestrians (64%) generally had sufficient spatial margins to perform avoidance maneuvers, although conflicts still occurred. Overall, the descriptive statistics of the data highlight critical a range of potential behavioral and environmental factors influencing near-collision dynamics in shared pedestrian spaces.

The alluvial plot in Fig. 1 illustrates the relationships between e-scooter rider behavior, environmental conditions, and incident characteristics, highlighting clear patterns in reaction types. Overall, deceleration (particularly moderate and strong deceleration) dominates across most conditions, indicating that riders generally adopt defensive responses when encountering pedestrians. However, a notable presence of acceleration and no-reaction behaviors persists, especially in cases where no avoidance action is taken, suggesting higher-risk interactions. Importantly, even when sufficient margin of avoidance exists and pedestrian density is low (LoS A–B), conflicts still occur across all reaction types, implying that the availability of space alone does not ensure safe behavior. Additionally, most incidents take place outside designated cycle paths, which is a fact that should be considered by local authorities since this is against the EU and national legislation about e-scooters. These findings indicate that near-collision dynamics are primarily driven by behavioral factors rather than purely environmental conditions, emphasizing the importance of both rider and pedestrian behavior in shaping safety outcomes in shared spaces.

As for the second alluvial plot in Fig. 2 it further explores the role of pedestrian-related factors in shaping interaction dynamics and confirms the patterns observed in the previous Figure. Specifically, although a margin of avoidance is available for pedestrians in most cases, avoidance actions are rarely undertaken, as reflected by the dominance of "NO" responses. This lack of reaction is consistently associated with a broader spread of e-scooter responses, including riskier behaviors such as acceleration and no reaction. Additionally, even under low to moderate pedestrian densities (LoS A–B), a wide range of incident categories and reaction types is observed, reinforcing the notion that unsafe interactions are not confined to high-density conditions. Compared to the previous figure, which emphasized rider behavior, this visualization highlights the critical role of pedestrian passivity in the emergence of near-collision events. Overall, the findings suggest that both insufficient pedestrian response and rider behavior jointly contribute to conflict formation, further supporting the argument that safety in shared spaces is driven by the interaction of behaviors rather than infrastructure conditions alone.

Table 1. Variables Description from Near-Collision Measurements

Variable	Description	Levels
Avoidance_Action_escooter	Action from the e-scooter rider to avoid possible collision with pedestrian	Yes: 91% No: 9%
Avoidance_Action_pedestrian	Action from the pedestrian to avoid possible collision with e-scooter rider	Yes: 15% No: 85%
Awareness_from_escooter	Awareness from e-scooter riders for noticing pedestrians in time in order to avoid possible collision	Yes: 83% No: 17%
Awareness_from_pedestrian	Awareness from pedestrians for noticing pedestrians in time in order to avoid possible collision	Yes: 33% No: 67%
Category	Categories of incidents as identified from the verbal descriptions recorded in the field during the measurement period	Rear Side: 23% Very Close: 16% Stop and Walk: 11% Corner Meeting: 9% School-Student Incident: 6% Other: 35%
DV_category	Difference between the e-scooter speed before noticing the pedestrian and immediately after noticing the pedestrian	Acceleration ($DV < 0$): 19% No Reaction ($DV = 0$): 19% Mild Deceleration ($1 \leq DV \leq 4$): 14% Moderate Deceleration ($5 \leq DV \leq 9$): 26% Strong Deceleration ($DV > 9$): 22%
Cycle_Path	If the incident was captured inside or outside the cycle path.	Outside: 88% Inside:12%
Helmet	If the e-scooter rider wears a helmet	Yes: 12% No: 88%
Margin_of_Avoidance_escooter	Margin of avoidance (in terms of available space) for the e-scooter rider to perform an evasive action in order to avoid a potential incident with the pedestrians	Yes: 77% No: 23%

(*continued*)

Table 1. (*continued*)

Variable	Description	Levels
Margin_of_Avoidance_pedestrian	Margin of avoidance (in terms of available space) for the pedestrian to perform an evasive action in order to avoid a potential incident with the e-scooter rider	Yes: 64% No: 36%
Pedestrian_Density	The classification of the pedestrian Level of Service (LoS) based on the pedestrian density in the area where the incidents were recorded.	LoS A: 31% LoS B: 54% LoS C: 14% LoS D: 1%

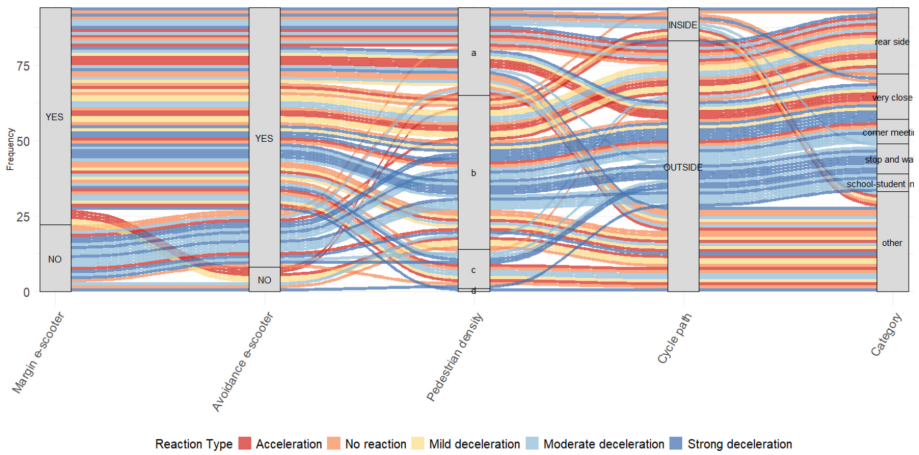

Fig. 1. Alluvial Representation of E-Scooter Rider Behavior, Environmental Conditions, and Near-Collision Characteristics

2.2 Ordinal Logistic Regression Model

Ordinal Logistic Regression is applied when the dependent variable consists of three or more ordered categories, where the intervals between categories are not necessarily equal. This modeling approach estimates the relationship between a set of explanatory variables and an ordinal outcome by assessing the likelihood of an observation falling into higher versus lower categories of the dependent variable. Specifically, the model assumes a cumulative logit structure, where the estimated coefficients represent the effect of the explanatory variables on the log-odds of being at or above a certain category threshold. A key assumption of the model is the proportional odds (parallel lines) assumption, which implies that the effect of each explanatory variable is constant

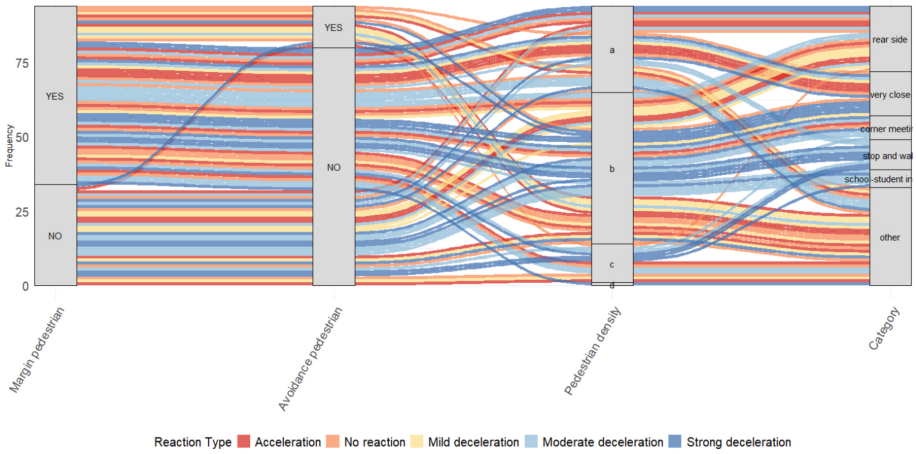

Fig. 2. Alluvial Representation of Pedestrian Behavior, Environmental Conditions, and Near-Collision Characteristics

across all category thresholds [14]. In this study, the ordinal model is used to examine how various behavioral and environmental factors influence the response of e-scooter riders in terms of speed change (i.e., acceleration, no reaction, and different levels of deceleration) when encountering pedestrians.

In this study, an Ordinal Logistic Regression model was employed to analyze the factors influencing changes in e-scooter speed in response to pedestrian presence. The dependent variable captures the rider's behavioral response and is categorized into three ordered outcomes: acceleration, indicating an increase in speed upon noticing a pedestrian; no reaction, indicating no change in speed; and deceleration, indicating a reduction in speed. This classification allows for the assessment of how various explanatory factors affect the likelihood of transitioning between different levels of speed adjustment.

2.3 Firth's Logistic Regression Model

To address issues related to small-sample bias and potential data separation, Firth's bias-reduced logistic regression method was employed. This approach is particularly suitable for binary outcome models where conventional maximum likelihood estimation may produce biased or unstable estimates, especially in the presence of rare events or complete/quasi-complete separation. Maximum likelihood estimates in standard logistic regression are known to be prone to bias in small samples. To mitigate this issue, Firth [15] proposed a penalized likelihood approach, which introduces a correction term to the likelihood function, resulting in more reliable and finite parameter estimates.

In this study, a binary logistic regression model based on Firth's method was developed, where the dependent variable represents the occurrence of high-risk conflicts. Specifically, the response variable takes the value of 1 for high-risk incidents and 0 for low- or moderate-risk incidents. High-risk incidents are defined as interactions in which the e-scooter rider accelerates upon detecting a pedestrian, while the pedestrian does not undertake any avoidance action, indicating a lack of behavioral adaptation from both

parties and an increased likelihood of conflict. This formulation enables the identification of behavioral personas, both for e-scooter riders and pedestrians, that are more prone to high-risk collision scenarios.

3 Application and Results

This chapter presents the results of the empirical analysis, focusing on the behavioral responses of e-scooter riders and their interactions with pedestrians in shared spaces. The analysis is structured in two main parts. First, the factors influencing changes in e-scooter speed are examined using an Ordinal Logistic Regression model. Second, behavioral personas for both e-scooter riders and pedestrians are identified, and their combined effects on the likelihood of high-risk conflicts are assessed using a Firth Logistic Regression model. The findings provide insights into the key behavioral and environmental determinants of near-collision events.

3.1 Factors Influencing E-Scooter Speed Adjustment in Pedestrian Interactions

An ordinal logistic regression model was estimated to examine how different factors influence the reaction behaviour of e-scooter riders and specifically the riders' reaction intensity with three ordered levels: acceleration, no reaction, and deceleration. The results are presented in Table 2, which indicate that the levels of only two variables (Category and Pedestrian Density) have, statistically, significant effect, which are the categories of incidents as identified from the qualitative descriptions recorded in the field during the observation period and the classification of the pedestrian Level of Service (LoS) based on the pedestrian density in the area where the incidents were recorded.

Due to the fact variable "Category" had many levels with small counts, which was the reason that the ordinal model was providing non-statistically significant variables, some of the levels were grouped. For the case of the category variable the levels "rear side" and "very close" were grouped as "passing", the levels "corner meeting" and "stop and walk" were grouped as "interaction" and the levels "school-student incident" and "other" were grouped as "other". As for the dependent variable the different levels of acceleration were grouped into one grouped, namely, "acceleration".

The analysis shows that the type of interaction between pedestrians and e-scooter riders (as denoted in the variable "Category") significantly influences rider behaviour. From the results both "passing" conflicts and "other" incidents present statistically significant coefficients compared with the reference category ("interaction" conflicts). The negative coefficients of both levels indicate that, compared with interaction conflicts, these incidents are less likely to lead to stronger deceleration actions. The odd ratios of the levels' estimates indicate that passing conflicts reduce the probability of stronger braking reactions by approximately 85%, while other types of incidents reduce the probability of stronger braking reactions by approximately 83%. These findings suggest that interaction conflicts, where pedestrians and e-scooter riders directly negotiate shared space, are more likely to trigger stronger deceleration behaviour from the rider.

The estimated coefficients for pedestrian density levels appear larger than the ones in "Category" and statistically significant. As can be seen from the results of this variable,

when there is enough space for movements e-scooter riders are less likely to decelerate but they instead are more likely to accelerate. Compared to Level of Service D (less space due to the increase of pedestrian density) LoS A is a factor that urges e-scooter riders to accelerate. LoS B acts the same but by less extent and LoS C lees than LoS A but higher than LoS B. From a safety perspective, pedestrian density can be interpreted as a proxy for congestion conditions in shared spaces. Higher levels of congestion increase the frequency of interactions between e-scooter riders and pedestrians, while simultaneously reducing available maneuvering space and reaction time. Under such conditions, even small behavioural differences may significantly influence the likelihood of near-collision events. The findings suggest that in less congested environments (LoS A and B), riders are more likely to accelerate, potentially increasing risk if sudden interactions occur. Conversely, higher density levels constrain movement but also create more complex and unpredictable interaction patterns, which may elevate safety risks when combined with inappropriate behavioural responses.

Additionally, the results from the Ordinal Logistic Regression indicate that situations involving direct interaction conflicts between pedestrians and e-scooter riders are more likely to trigger stronger deceleration actions compared with passing or other types of encounters. This suggests that when spatial interactions require active negotiation, such as in face-to-face or crossing movements, riders are more inclined to adjust their speed and adopt safer manoeuvres. In contrast, passing or less direct interactions tend to elicit weaker responses, with riders more likely to maintain their speed.

The substantial differences in coefficient magnitude between pedestrian density and interaction category indicate that congestion-related conditions exert a significantly stronger influence on rider behaviour than the type of interaction itself. While the interaction category captures the specific geometry and nature of encounters, pedestrian density reflects the broader environmental context in which these interactions occur. The much larger coefficients associated with density levels suggest that riders primarily adjust their behaviour in response to space availability and crowding conditions, which continuously constrain movement and decision-making. In contrast, interaction type appears to influence behaviour more locally, at the moment of the encounter, rather than shaping overall response intensity.

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

3.2 Identification of Personas

While the perception of space remains unclear between e-scooter riders and pedestrians, it is important to identify which “personas” of users interact within a shared environment. These persona types emerge from the behavioral characteristics and actions of both groups. Based on the available data, personas were derived using a rule-based classification approach grounded on observed behavioral indicators (e.g., speed adjustment, awareness, avoidance actions, and helmet use), rather than purely qualitative judgment. Accordingly, five types of e-scooter riders and three types of pedestrians were identified.

Furthermore, e-scooter riders were classified into four behavior-based persona types:

- Aggressive: e-scooter riders that accelerate when noticing the pedestrian and do not conduct an evasive maneuver for avoiding the pedestrian.

Table 2. Estimation results of the ordinal logistic model for e-scooter speed adjustment

Variables	Estimates (Std. Error)	Thresholds	Estimates (Std. Error)
Category: Other	−1.79 * (0.82)	Acceleration | No reaction	−17.20 *** (0.59)
Category: Passing	−1.84 * (0.84)	No reaction | Deceleration	−16.17 *** (0.57)
Pedestrian Density: LoS A	−14.36 *** (0.40)		
Pedestrian Density: LoS B	−14,01 *** (0.34)		
Pedestrian Density: LoS C	−14.25 *** (0.48)		
Akaike Information Criterion (AIC): 179.27			

- Inattentive: e-scooter riders that decelerate when noticing the pedestrian and are unaware but are unaware are not aware of pedestrians and do not wear helmet.
- Cautious: e-scooter riders that are aware of pedestrians while riding and are proceeding with avoiding actions and deceleration once they notice a pedestrian and also wear a helmet while riding.
- Responsive: e-scooter riders that are aware for pedestrians and decelerate when noticing one but do not wear helmet.
- Risky: e-scooter riders that either accelerate or do not change there speed when noticing a pedestrian but are proceeding with an avoidance action.

Then, the segmentation of the pedestrian personas was followed concluding with the following persona types:

- Attentive: pedestrians that are aware of e-scooters and proceed to avoid action when noticing one.
- Unresponsive: pedestrians that are aware of e-scooters but do not proceed to avoid action when noticing one.
- Inattentive: pedestrians that are fully unaware and do not proceed to avoid action when noticing an e-scooter.

Like with the e-scooter riders this segmentation reduces multiple pedestrian variables into meaningful behavioral categories. Therefore, these behavioral segmentations create different e-scooter rider and pedestrian groups whose interactions will be analyzed in terms of risk of a near collision.

3.3 E-Scooter Riders and Pedestrians near Risk Collision

This application provides feedback on the near collision risk that exists when different behavioral types of e-scooter riders and pedestrians exist and commute in the same space. From a road safety perspective, risk can be conceptualized through three interrelated

components: occurrence, exposure, and vulnerability. Occurrence refers to the likelihood of a conflict taking place, exposure reflects the presence and interaction of users within a shared space, and vulnerability captures the severity of outcomes given a conflict. In this study, the proposed risk classification primarily reflects the vulnerability component, as it is based on the behavioral responses of e-scooter riders and pedestrians during near-collision events. While exposure and occurrence are implicitly present through the observed interactions, they are not explicitly modeled.

For instance, in Australia more of 50% of the participants in a survey had engaged in risky behaviors (i.e., speeding, doubling, not wearing a helmet and use of a smartphone) while riding [16]. Based on the recorded incidents in this study three levels of risk were identified:

- Low Risk: Occurs when the e-scooter rider decelerates upon detecting a pedestrian in their trajectory, and the pedestrian actively performs an avoidance maneuver. This reflects mutual awareness and cooperative conflict resolution.
- Moderate Risk: Occurs when the e-scooter rider maintains their speed despite detecting a pedestrian, while the pedestrian initiates an avoidance action. In this case, risk is partially mitigated by the pedestrian's response, but the rider does not contribute to conflict avoidance.
- High Risk: Occurs when the e-scooter rider accelerates upon detecting a pedestrian, and the pedestrian does not take any avoidance action. This represents a lack of adaptation from both parties, leading to a significantly increased likelihood of conflict.

Based on the recorded incidents every near-collision occasion was evaluated, and two risk values were given, one referring to the action taken from e-scooter riders and one for pedestrians. The mean value of both risk values was calculated and thus a risk index was provided for the combination of different e-scooter riders and pedestrian personas (Fig. 3).

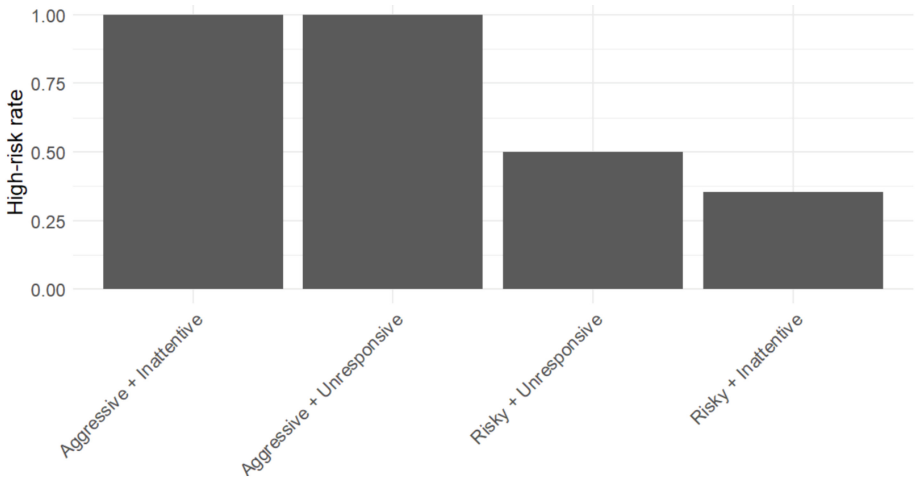

Fig. 3. High Risk by Meaningful Rider-Pedestrian Combinations

The rest of the possible combination produced zero risk and thus were not presented in the figure. Moreover, the findings indicate that aggressive and risk-prone e-scooter riders, in combination with inattentive and unresponsive pedestrians, represent the most hazardous interaction profiles. These results should be carefully considered by local authorities and policymakers when designing and implementing targeted enforcement measures in shared spaces, with the aim of reducing the likelihood of conflicts and preventing potential collisions between the two user groups.

Furthermore, for estimating which persona type of e-scooter riders and pedestrians are considered as risk-prone by there one a Firth Logistic Regression (FLR) model was developed using binary dependent variable, where the value 0 ("not high-risk conflict") concerned the low-risk incidents and the value 1 ("high-risk conflict") concerned the high-risk incidents and thus, this binary variable acts as a proxy for conflict severity. Table 3 presents the results from the analysis were the reference level for e-scooter personas was "Cautious" riders and for pedestrians was "Attentive". As can be seen from the table, the statistically significant Aggressive and Risky riders are both increasing the risk, compared to Cautious riders, of having a collision with pedestrians. Furthermore, compared to Attentive pedestrians, Inattentive and Unresponsive pedestrians also increase the risk of having a collision with e-scooter riders fact that validates the high-risk collision between the combinations as presented in Fig. 3.

Table 3. Estimation results of the Firth's Logistic Regression Model

Variables	Coefficients	Std. Error
Intercept	−7.36 ***	2.42
Aggressive Rider	5.44 ***	1.98
Risky Rider	2.30 *	1.47
Inattentive Pedestrian	4.50 **	1.97
Unresponsive Pedestrian	5.06 **	2.15
Akaike Information Criterion (AIC): 28.51		

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

These findings indicate the importance of understanding the different behavioral types of e-scooter riders and pedestrians that exist in a shared space and to be able to suggest possible solutions for avoiding collisions. Some suggestions might be the separation of e-scooter riders and pedestrians in urban mobility [17]. Another suggestion might be a stricter legislative framework that prevents e-scooter riders from disregarding regulations, combined with increased enforcement in shared public spaces.

4 Conclusions

This study investigated near-collision interactions between e-scooter riders and pedestrians in a shared pedestrian environment, emphasizing the role of behavioral dynamics in shaping safety outcomes. The findings indicate that although e-scooter riders predominantly adopt defensive strategies, such as deceleration, a non-negligible proportion of risky behaviors, namely acceleration and lack of reaction, persists across various conditions. The results further demonstrate that behavioral factors outweigh environmental conditions, as unsafe interactions occur even under low pedestrian density and sufficient spatial margins. In particular, pedestrian behavior plays a critical role, with inattentive and unresponsive pedestrians significantly increasing the likelihood of high-risk conflicts. Moreover, the combination of specific rider and pedestrian personas amplifies collision risk, highlighting that safety in shared spaces is inherently interaction-driven.

From a policy perspective, the findings suggest that infrastructure measures alone may be insufficient to ensure safety. Instead, targeted interventions focusing on behavioral awareness, enforcement, and regulation of both e-scooter riders and pedestrians are necessary. Strengthening legislative frameworks, improving compliance, and promoting mutual awareness among users can contribute to reducing conflicts in shared urban environments.

Despite the valuable insights provided, this study is subject to certain limitations. First, the analysis is based exclusively on near-miss incidents between e-scooter riders and pedestrians, and therefore does not account for actual collision events or interactions involving other mobility modes such as bicycles or motor vehicles. Second, although pedestrian density was considered as a proxy for congestion, the study does not explicitly model occurrence or exposure components of risk. Third, the dataset is based on observations from specific locations and may not fully capture the variability of behaviours across different urban contexts. These limitations should be considered when interpreting the results, and future research could expand the analysis by incorporating additional transport modes, broader datasets, and more comprehensive risk modelling approaches.

Future research should explore larger datasets and incorporate interaction effects more explicitly, as well as examine the impact of different urban designs and regulatory measures on user behavior and safety outcomes.

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