Pedestrian behaviour when interacting with micro-mobility vehicles: a virtual reality exeperiment

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Short summary

The presence of micro-mobility vehicles (MMVs), such as bicycles and e-scooters, is rapidly increasing in spaces shared with pedestrians. Previous studies have mainly focused on pedestrian interacting with MMVs on sidewalks. However, more complex interactions in areas such as pedestrian streets remain underexplored. This study examines pedestrians interacting with multiple MMVs in pedestrian streets. Data were collected from a virtual reality (VR) experiment under scenarios that varied in initial lateral distance, MMV type, number of MMVs, and density levels. Lateral clearance, longitudinal distance, perceived difficulty, risk, and expected accidents were analyzed using statistical tests and a linear mixed-effects model. The results show that the lateral clearance is larger with an initial lateral distance of 0.6 m than 0 m, with bicycles than e-scooters, and with a single MMV than multiple MMVs. The longitudinal distance is larger in single MMV scenarios. These findings can inform the design of safer and more comfortable pedestrian streets.
Keywords: pedestrian behaviour, micromobility vehicles, virtual reality experiment, pedestrian street, linear mixed-effects model.

1 Introduction

MMVs, such as (e-)bicycles, (e-)scooters, and Segways, have rapidly emerged as sustainable urban transport alternatives (McQueen et al., 2021). As MMVs become more prevalent, pedestrians increasingly interact with them, particularly in environments where both users share the same space. The distinct operational characteristics of MMVs, such as higher speeds, greater momentum, and longer stopping distances compared to pedestrians shape how pedestrians perceive risk and adapt their avoidance strategies (Zhang et al., 2023). In this study, *pedestrian street* refers to urban street environments where motorized vehicles are restricted and pedestrians share the infrastructure with micromobility users without strict physical separation (Beitel et al., 2018). Understanding how pedestrians navigate and respond to interactions with micromobility users in these environments is essential to ensure their safety and comfort (Jafari & Liu, 2024; Kuo et al., 2019).

On road and virtual reality experiments have been used to study pedestrian interacting with MMVs. VR experiments offer immersive, repeatable, and fully controllable conditions, allowing examination of complex interactions (Van Leeuwen et al., 2018; Sanchez-Sepulveda et al., 2019; Feng et al., 2021). Investigating pedestrian responses in VR settings that enable the study of dynamic interactions difficult to capture in real world conditions is essential for improving safety, developing realistic behavioural models, and guiding infrastructure design and policy.

Previous studies have examined pedestrian interacting with MMVs from operational, safety, and behavioural perspectives (Zhang et al., 2023). Previous findings indicate that pedestrian behaviour is influenced by factors such as MMV speed, road user density, lateral distance, interaction type, and type of MMV among the others (Suzuki et al., 2024; Hussain et al., 2024a; Guo et al., 2020; Hasegawa et al., 2018; Arshi et al., 2026). For example, pedestrians tend to perceive greater risk and initiate avoidance maneuvers earlier when encountering MMVs at higher speeds (Suzuki et al., 2024; Hussain et al., 2024a; Guo et al., 2020). Pedestrians maintain greater lateral clearance and perceive higher safety when lateral distances from approaching MMVs are larger (Suzuki et al., 2024; Hasegawa et al., 2018; Arshi et al., 2026). The interaction type also influences pedestrian

responses. Pedestrians perceived the highest risk in meeting interactions, followed by crossing interactions, and the lowest risk in overtaking interactions (Hasegawa et al., 2018). During overtaking interactions, pedestrians initiated avoidance manoeuvres at shorter distances than during meeting interactions (Sim & Cho, 2024). The type of MMV can influence movement behaviour and perceived comfort. Arshi et al. (2026) reported that pedestrians maintained greater lateral clearance when avoiding bicycles compared to e-scooters, while longitudinal distances remained similar. In another study, Kuo et al. (2019) found that pedestrians tend to be more cautious around unfamiliar MMV types.

Although research on pedestrian interacting with MMVs has advanced in recent years, several important gaps remain. Most studies have focused on sidewalks, and relatively few have investigated pedestrian behaviour in pedestrian streets (Kazemzadeh & Afghari, 2024). Understanding pedestrian behaviour in these environments is important because pedestrian streets involve more complex interactions with MMVs, which can affect safety and comfort. Scenarios involving multiple MMVs are rarely examined. To the best of our knowledge, only one study considered more than one MMV in their experiment, but it was limited to sidewalk contexts with the focus on the effectiveness of line separation (Sim & Cho, 2024). Comparative analyses of different MMV types in pedestrian streets remain limited (Sim & Cho, 2024; Arshi et al., 2026; Kuo et al., 2019). Moreover, the influence of surrounding pedestrians and the their level of density on movement behaviour remains underexplored. While some field experiments examined perceived risk and comfort, the effect of level of density on pedestrian movement behaviour remains insufficiently understood. (Zheng et al., 2020; Jafari & Liu, 2024; Pham et al., 2015). Although lateral distance has been shown to affect pedestrian safety perceptions on sidewalks, it remains unclear whether these patterns generalize to pedestrian streets (Suzuki et al., 2024; Hussain et al., 2024b; Hasegawa et al., 2018; Arshi et al., 2026).

To address these gaps, this study investigates how the number of MMVs, type of MMV, road user density, and lateral distance influence pedestrian movement behaviour and perceived risk in pedestrian streets. A controlled VR experiment was conducted using multiple scenarios designed to replicate realistic interactions. Statistical tests and a linear mixed-effects model were used to analyse lateral clearance, longitudinal distance, perceived difficulty, risk, and expected accidents.

The remainder of this article is organized as follows. The Method section presents the participant recruitment and characteristics, the VR environment and scenarios, the experimental procedure, and the statistical analysis methods. The Results section reports the findings of the study. Finally, the Discussion and Conclusion section provides the main conclusions and outlines directions for future research.

Method

Participant characteristics

Participants were required to be aged 18–65, have no physical impairments affecting VR use, and be comfortable with VR technology. Following approval from the University of Leeds Ethics Committee (Reference code: BESS+ FREC 3541), 32 participants were recruited using the University of Leeds Driving Simulator (UoLDS) database and social media advertisements. The final sample included 14 females and 18 males, aged 20–62 years, with a mean age of 36.75 ± 12.29 years. Two participants were excluded from the analysis due to atypical behaviour that could compromise the validity of the results. One participant exhibited a mobility limitation that affected walking, while the other did not follow task instructions and demonstrated unusually delayed avoidance behaviour. The final sample therefore consisted of 30 participants (14 females and 16 males).

Experimental environment

The experiment was conducted at the Institute for Transport Studies, University of Leeds, in a room of $13.6\,\text{m} \times 5.6\,\text{m}$ (Figure 1a). Participants experienced an immersive virtual reality simulation developed in Unity 3D (version 2020.3.35f1), representing a typical pedestrian street in the UK. The VR setup used an HTC Vive Pro Eye HMD with a Vive Wireless Adapter and a portable battery pack. Position tracking was performed using six HTC base stations (Figure 1b), three per side, recording spatial coordinates at 60 Hz. Before each session, the VR system was calibrated to ensure accurate tracking. A visual boundary grid was also used to maintain participants' safety during the experiment.



(a) Walking space area



(b) Base stations (x6)

Figure 1: Experimental environment

Scenarios and procedure

Sixteen scenarios were implemented using a full factorial design ($2 \times 2 \times 2 \times 2$). The factors analysed were the MMV type (bicycle, e-scooter), the number of MMVs (1, 2), the initial lateral distance (0 m, 0.6 m), and road user density defined based on pedestrian level of service (LOS A and LOS B) from the Highway Capacity Manual (HCM, 2022). Participants encountered MMV(s) approaching from the opposite direction (i.e., meeting interactions) and were surrounded by multiple virtual pedestrians walking. The number of pedestrians was based on the level of density. These pedestrians moved according to a Social Force Model at a speed of 1,m/s, whereas the MMVs moved at a constant speed of 2.5,m/s. Each scenario was repeated twice per participant in randomized order. A single-MMV scenario and a two-MMV scenario are shown in Figure 2a and Figure 2b, respectively.

Participants were familiarized with the VR environment in a practice trial and instructed to walk naturally while interacting with the MMVs. In each scenario, participants walked forward for 10 m, until they saw a virtual capsule that informed them to return to the starting position. After each scenario, participants answered three questions that assessed perceived difficulty in the pedestrian street, perceived risk, and the expected accidents when walking in that scenario daily for a month. Finally, participants completed a post-experiment questionnaire collecting sociodemographic information, walking habits, familiarity with VR technology, pedestrian behaviour, and attitudes towards MMVs.

Each participant completed 32 experimental scenarios, resulting in 960 potential observations. However, some observations could not be analysed due to occasional disconnections, data loss, and other technical issues during the experiment. After data cleaning, a total of 875 valid observations remained for the study.

Dependent variables

The study focused on two pedestrian behaviour characteristics: the *lateral clearance* and the *longitudinal distance at avoidance*. Lateral clearance ($LatClear$) measures the side-to-side distance between the pedestrian and the MMV at closest approach (Suzuki et al., 2024; Hussain et al., 2024b; Arshi et al., 2026). The lateral clearance is defined in Equation 1:

$$LatClear = |y_p(t^*) - y_m(t^*)|, \tag{1}$$



(a) Scenario: One MMV, Bike



(b) Scenario: Two MMVs, E-scooter and Bike

Figure 2: Examples of VR meeting interaction scenarios: (a) a single bicycle approaching with an initial lateral distance of 0,m under LOS A; (b) two MMVs (an e-scooter followed by a bicycle) approaching with an initial lateral distance of 0 m under LOS A.

where $y_p(t^*)$ and $y_m(t^*)$ denote the lateral positions of the pedestrian and MMV at the closest approach time t^*, defined as the moment when their longitudinal positions are equal.
Longitudinal distance at avoidance ($LongDist$) quantifies the distance along the walking direction between the pedestrian and the approaching MMV at the moment the pedestrian initiates an avoidance manoeuvre. The onset of avoidance was operationally defined as the time when the pedestrian's lateral displacement exceeded 0.1 m from their initial trajectory (Suzuki et al., 2024; Arshi et al., 2026)). It can be expressed as in Equation 2:

$$LongDist = x_m(t_a) - x_p(t_a), \tag{2}$$

where $x_p(t_a)$ and $x_m(t_a)$ denote the longitudinal positions of the pedestrian and MMV at the avoidance onset time t_a.

Explanatory variables

In this section, variables related to traffic conditions, individual behavioural traits, subjective perception variables, and socio-demographic characteristics used for analysis are introduced.
Traffic condition variables include MMV type (bicycle, e-scooter), number of MMVs (1, 2), initial lateral distance (0 m, 0.6 m), and road user density (LOS A and LOS B).
Individual behavioural traits were assessed using the Pedestrian Behaviour Questionnaire (PBQ) (Deb et al., 2017). The PBQ is adapted from the Driver Behaviour Questionnaire framework and includes several dimensions: violations, referring to deliberate rule-breaking behaviours (Reason et al., 1990); errors, reflecting misjudgements or lack of knowledge (Reason et al., 1990; Rasmussen, 1980); lapses, associated with inattention or memory failures (Reason et al., 1990); aggressive behaviours, expressing anger toward other road users (Lawton et al., 1997; Baxter et al., 1990); and positive behaviours, representing cautious and rule-compliant actions (Ozkan & Lajunen, 2005).
Subjective perception variables were collected after each scenario. Three measures were used: PercDiff, representing perceived difficulty, PercRisk, representing perceived risk in the given scenario, and ExpAcc captures the number of accidents participants expected if they were exposed to the same scenario daily for one month (i.e., 30 times). PercDiff and PercRisk variables were measured on a 10-point Likert scale (1 = extremely easy/no risk, 10 = extremely difficult/maximum risk), where higher scores indicate greater perceived difficulty and risk (Fuller et al., 2005).
Socio-demographic characteristics include age and gender reported by the participants in the questionnaire.

Statistical analysis

The influence of the explanatory variables on lateral clearance was analysed using a linear mixed-effects model. The model predicting the lateral clearance $LatClear_{ij}$ for participant j in trial i was defined in Equation 3:

$$LatClear_{ij} = \beta_0 + \boldsymbol{\beta}^\top \mathbf{X}_{ij} + u_j + \epsilon_{ij}, \tag{3}$$

where $\mathbf{X}_{ij}$ is the vector of independent variables, $\boldsymbol{\beta}$ is the vector of fixed-effect coefficients, $u_j \sim N(0, \sigma_u^2)$ is the participant-specific random error term, and $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$ is the observation-specific error term.

The models were estimated using the `lmer` function in the R package `lme4` (Bates et al., 2015), which allows the specification of random effects to capture correlations between repeated measurements from the same individual. Marginal means and confidence intervals were computed using the R package `emmeans` (Lenth, 2023). The final model was estimated using a backward stepwise procedure based on statistical significance ($p < 0.05$). The process began with a full model including all considered explanatory variables related to traffic conditions, individual behavioural traits, subjective perception variables, and socio-demographic characteristics. At each step, the least significant variable was removed, and the model was re-estimated until only statistically significant variables remained. This process continued until all remaining variables were statistically significant. All continuous variables were centred in the mean value.

For longitudinal distance at avoidance, participants' repeated measurements within each scenario were first averaged to obtain a single value per participant per factor level. Differences between factor levels were then assessed at the individual level using the Wilcoxon Signed-Rank Test (Wilcoxon, 1945), a non-parametric method suitable for paired comparisons, where each participant serves as their own control. The test was implemented using the `stats` package in R. In addition, spearman's rank correlation analyses were conducted to examine the relationships between pedestrian traits and longitudinal distance.

Moreover, participants' subjective ratings of PercDiff, PercRisk, and ExpAcc were analysed to examine the effects of experimental factors. Differences in ratings across factor levels were assessed using the non-parametric Mann–Whitney U test.

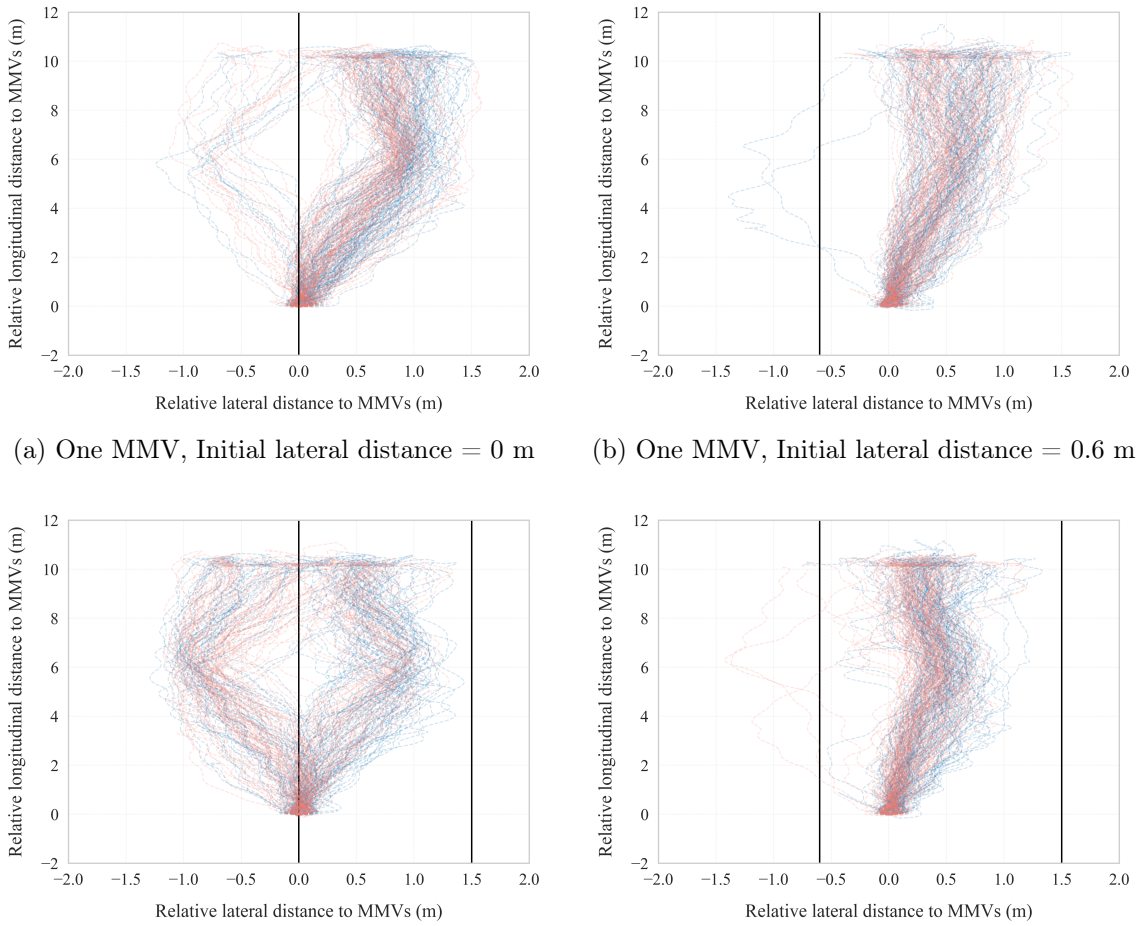
2 Results

Figure 3 shows the trajectories of pedestrians during interactions with MMVs under different initial lateral distances and number of MMVs. The trajectories show that pedestrians mostly chose the right side of their path, except in Figure 3c, where nearly half of the trajectories are on the left side.

The average ratings for PercDiff, PercRisk, and ExpAcc across experimental factors are presented in Table 1. A Mann–Whitney U test was used to compare differences in ratings between factor levels. Pedestrians reported significantly higher PercDiff, PercRisk, and ExpAcc when the MMV approached with an initial lateral distance of 0 m (i.e., directly aligned with the pedestrian's path), compared to an initial lateral distance of 0.6 m (PercDiff: $U = 108208.0$, $p = 0.001$; PercRisk: $U = 109382.5$, $p = 0.000$; ExpAcc: $U = 105359.5$, $p = 0.007$). There was no significant difference between MMV types for any of the questions (PercDiff: $U = 99859.0$, $p = 0.262$; PercRisk: $U = 101663.5$, $p = 0.108$; ExpAcc: $U = 99225.5$, $p = 0.313$). Scenarios with two MMVs were rated as significantly more difficult, risky, and accident prone than those with a single MMV (PercDiff: $U = 50695.0$, $p = 0.000$; PercRisk: $U = 48927.0$, $p = 0.000$; ExpAcc: $U = 63034.5$, $p = 0.000$). In level of density B, pedestrians reported significantly higher perceived difficulty, risk and expected number of accidents compared to level of density A (PercDiff: $U = 81294.0$, $p = 0.000$; PercRisk: $U = 84818.0$, $p = 0.003$; ExpAcc: $U = 87312.5$, $p = 0.028$).

Table 1: Subjective ratings for each experimental factor level.

Factor	Level	PercDiff	PercRisk	ExpAcc
Lateral distance	0.0 m	3.13	3.25	3.96
	0.6 m	2.70	2.79	3.28
MMV type	Bike	2.97	3.10	3.72
	E-scooter	2.88	2.95	3.55
MMV number	1	2.23	2.30	2.61
	2	3.59	3.71	4.59
Density	A	2.70	2.85	3.32
	B	3.15	3.20	3.95



(a) One MMV, Initial lateral distance = 0 m

(b) One MMV, Initial lateral distance = 0.6 m

(c) Two MMVs, Initial lateral distance = 0 m

(d) Two MMVs, Initial lateral distance = 0.6 m

Figure 3: Trajectories of pedestrians during avoidance of MMV(s): Solid black lines represent the trajectories of the approaching MMV(s). Light red dashed lines indicate pedestrians encountering an e-scooter, and light blue dashed lines represent pedestrians encountering a bicycle. The colour indicate the first MMV encountered in the scenarios with two MMVs.

Lateral clearance

Descriptive statistics showed that pedestrians maintained an average lateral clearance of 1.05 m (SD = 0.18 m), from 0.40 to 1.50 m. Residuals were normally distributed at both the observation and participant levels.

The final linear mixed-effects model explaining pedestrian lateral clearance is presented. The goodness of fit statistics are reported in Table 2, and the estimated coefficients are presented in Table 3. All fixed effect parameters are statistically significant at the 5% level. The marginal R^2_m indicates that fixed effects explain 38.0% of the variance in pedestrian lateral clearance, while the conditional R^2_c shows that the individual specific error term increases the explained variance to 63.5%.

The estimation results show that pedestrians increased their lateral clearance when the initial lateral distance was 0.6 m compared to 0 m. They reduced the clearance when the MMV was an e-scooter compared to a bicycle and when two MMVs approached. Male pedestrians maintained a smaller clearance than females. Higher violation scores were associated with slightly larger clearance, whereas higher expected accidents corresponded to smaller clearance. Density and age did not have significant effects.

To analyse the effect of each explanatory variable on lateral clearance, predicted lateral clearance was calculated by varying one explanatory variable at a time while holding the remaining variables constant. Figure 4 presents the results for the categorical variables, and Figure 5 shows the results for the continuous variables. The patterns observed are consistent with the previous analyses reported in this section. When we compare the different variables, we notice that the initial lateral

Table 2: Statistics of the linear mixed-effects model for pedestrian lateral clearance

Statistic	Value
Number of participants	30
Number of parameters associated with the explanatory variables	6
Number of observations	875
Constant log likelihood	372.88
Final log likelihood	641.04
$R_m^2 = \frac{\sigma_f^2}{\sigma_f^2 + \sigma_u^2 + \sigma_\epsilon^2}$	0.380
$R_c^2 = \frac{\sigma_f^2 + \sigma_u^2}{\sigma_f^2 + \sigma_u^2 + \sigma_\epsilon^2}$	0.635

Table 3: Estimation results of the linear mixed-effects model for pedestrian lateral clearance

Parameter	Estimate	t statistic	p value
Intercept	1.07202	38.507	< 0.001
Lateral distance (0.6 m)	0.17892	23.427	< 0.001
MMV type (E-scooter)	-0.07016	-9.361	< 0.001
MMV number (2)	-0.04672	-5.333	< 0.001
Violations	0.03908	2.265	0.031
Gender (Male)	-0.09666	-2.555	0.016
ExpAcc	-0.00628	-2.701	0.007
σ_u (participant)	0.0977	-	-
σ_ϵ (residual)	0.1105	-	-

Note: Fixed-effect estimates are reported using REML.

distance has the strongest impact on lateral clearance, followed by gender and MMV type.

Longitudinal distance

Pedestrians initiated avoidance manoeuvres at an average longitudinal distance of 20.19 m (SD = 4.19 m), with a minimum of 7.09 m and a maximum of 26.02 m. The normality of the residuals assumption was violated for the linear mixed effects model for the longitudinal distance. Therefore, a Wilcoxon Signed-Rank Test was conducted to examine whether pedestrians reacted differently between the levels of each factor. The test results are presented in Table 4.
The analysis shows that only the MMV number had a statistically significant effect on the longitudinal distance at the 5% level. Pedestrians maintained a shorter longitudinal distance when two MMVs approached compared to a single MMV, with a mean difference of approximately 0.56 m. No significant differences were observed for the initial lateral distances, MMV type, and level of density.
Spearman's rank correlation analyses were conducted to examine the relationships between pedestrian traits and longitudinal distance. Age ($\rho = -0.15$) and aggressive behaviours ($\rho = -0.13$) were negatively associated with longitudinal distance, indicating that older pedestrians and those exhibiting more aggressive behaviours maintained shorter longitudinal distances. In contrast, violations ($\rho = 0.11$) were positively associated, suggesting that pedestrians with a greater tendency to commit violations maintained longer longitudinal distances. Errors ($\rho = -0.03$), lapses ($\rho = 0.03$), and positive behaviours ($\rho = 0.01$) showed correlations close to zero.

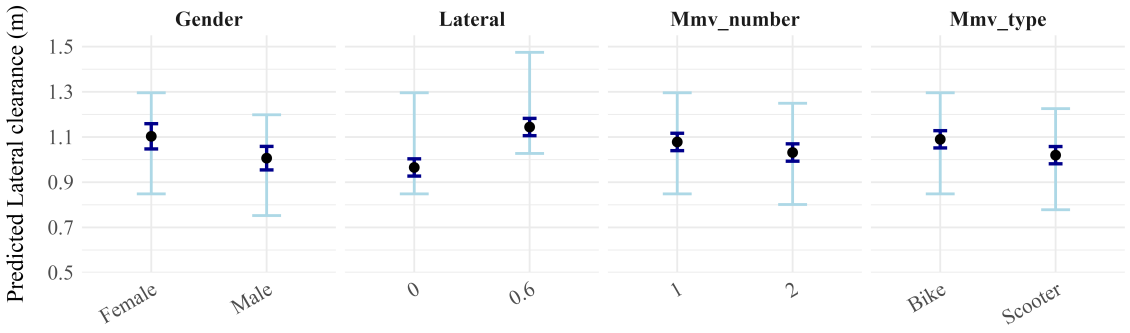


Figure 4: Effect of the categorical explanatory variables on the lateral clearance. Black dots indicate the predicted lateral clearance, dark blue error bars show 95% confidence intervals, and light blue error bars show 95% prediction intervals.

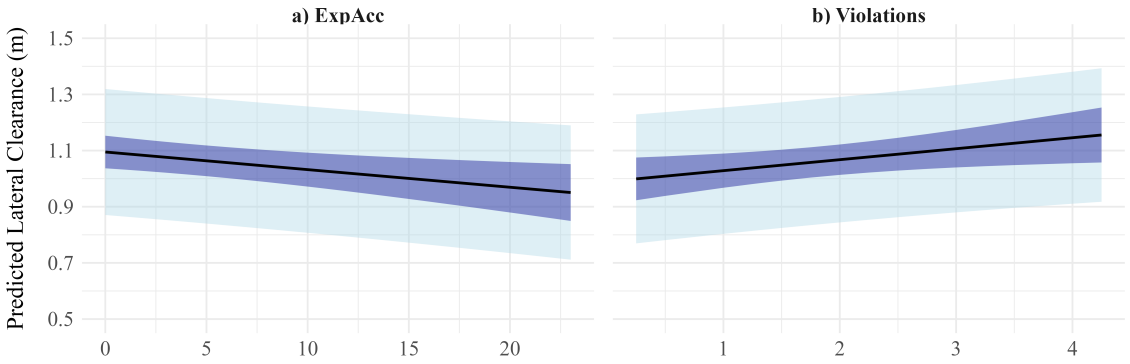


Figure 5: Effect of the continuous explanatory variables on the lateral clearance. Black solid lines indicate the predicted lateral clearance, dark blue ribbons show 95% confidence intervals, and light blue ribbons show 95% prediction intervals.

Table 4: Wilcoxon signed-rank test results for pedestrian longitudinal distance.

Factor	Level	N	Mean ± SD (m)	Wilcoxon statistic	p-value
Lateral distance	0 m	30	20.50 ± 2.82	178.0	0.271
	0.6 m	30	20.00 ± 2.83		
MMV type	Bike	30	20.45 ± 2.69	147.0	0.080
	E-scooter	30	20.09 ± 2.87		
MMV number	1 MMV	30	20.56 ± 2.81	129.0	0.033
	2 MMVs	30	20.00 ± 2.72		
Density	A	30	20.18 ± 2.72	188.0	0.371
	B	30	20.37 ± 2.74		

3 Discussion and conclusion

This study aimed to assess pedestrian behaviour during interactions with MMVs in pedestrian streets using a VR experiment. Sixteen scenarios were designed, including different MMV type (bicycle, e-scooter), number of MMVs (1 or 2), initial lateral distance (0 m or 0.6 m), and road user density (A or B). The effect of these factors on the lateral clearance and the longitudinal distance at avoidance was analysed using a linear mixed effect model and statistical tests, respectively.

Lateral clearance was influenced by initial lateral distance, MMV type, number of MMVs, violations, gender, and expected accidents. When the initial lateral distance increased to 0.6 m, pedestrians maintained a larger lateral clearance (1.14 ± 0.16 m) compared to 0 m (0.96 ± 0.15 m), consistent with previous studies (Suzuki et al., 2024; Hussain et al., 2024b). For example, Suzuki et al. (2024) reported values of 1.19 m, 1.30 m, and 1.63 m for initial distances of 0 m, 0.75 m, and 1.5 m, while Hussain et al. (2024b) found 0.79 m and 1.03 m for 0 m and 0.6 m, respectively. Regarding MMV type, pedestrians maintained greater clearance from bicycles (1.081 ± 0.17 m) than e-scooters (1.012 ± 0.18 m), consistent with previous findings that, at low speeds, pedestrians tend to maintain greater lateral clearance from bicycles than from e-scooters (Kuo et al., 2019; Arshi et al., 2026). This may be because pedestrians perceive bicycles as laterally unstable, leading them to anticipate less predictable movements and maintain larger safety margins (Kuo et al., 2019; Wang et al., 2024). In contrast, the presence of multiple MMVs reduced clearance (1.022 ± 0.16 m vs. 1.074 ± 0.19 m), likely due to spatial constraints and increased interaction complexity. Self-reported violation tendencies showed a positive association with lateral clearance, suggesting possible compensatory behaviour. This relationship needs further exploration based on a larger sample of participants. Males tended to maintain smaller lateral clearance compared to females, which may reflect greater risk-taking behaviour, consistent with previous studies (Arshi et al., 2026). The expected accident variable showed a small negative coefficient, suggesting that reduced lateral clearance is associated with a higher perceived likelihood of accidents, indicating that environmental constraints may influence subjective risk assessment.

For longitudinal distance, only the number of MMVs had a significant effect. Pedestrians initiated avoidance at shorter distances when interacting with two MMVs (20.00 ± 2.72 m) compared to one MMV (20.56 ± 2.81 m), likely due to increased decision-making complexity. Previous studies reported longitudinal distances ranging from 13.6 m to 23.0 m depending on speed (Suzuki et al., 2024). For instance, Arshi et al. (2026) found a distance of approximately 22 m at 10 km/h. In addition, the correlation analysis showed that longitudinal distance tended to decrease with age and aggressive behaviour, while it increased with violation trait behaviour.

Based on the findings of this study, several directions for future research are recommended. First, field studies in real pedestrian streets should be conducted to validate the results. Second, additional factors that occur frequently in real world conditions, such as pedestrian group movements and more complex traffic interactions, should be considered to improve the validity of the findings. Third, the role of MMV characteristics, including speed variability, acceleration behaviour, and rider behaviour, should be further examined to better understand their influence on pedestrian responses.

The findings of this study have important implications for both researchers and practitioners. The observed reduction in lateral clearance in scenarios with two MMVs indicates that higher MMV density can significantly constrain pedestrian movement and reduce safety margins. Therefore, regulatory measures should be considered to limit the number of MMVs operating simultaneously in pedestrian streets, particularly during peak hours with high pedestrian density. For example, time based access control strategies could be implemented, restricting MMV entry during periods of high pedestrian flow. In addition, the strong effect of initial lateral distance suggests that insufficient spacing at the beginning of interactions leads to unsafe conditions. Based on this, it is recommended that MMVs maintain a minimum lateral distance of at least 1.2,m from pedestrians when approaching, starting from a distance of approximately 15–20,m to allow sufficient time for safe trajectory adjustment.

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acquisition, project administration, resources, supervision, writing – review & editing. **Ludovic Leclercq**: conceptualization, methodology, supervision, writing – review & editing. **Natasha Merat**: methodology, resources, supervision. **Yee Mun Lee**: methodology, supervision. **Hsuan Chao**: software.
All authors reviewed the results and approved the final version of the manuscript.

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