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Wriggling in the crowd: An inquiry into the interactions between electric bikes and pedestrians in a shared space

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ABSTRACT

Shared spaces for active mobility aim to offer safe and comfortable mobility for vulnerable road users by separating them from motorised vehicles. However, the distinct navigation characteristics of these users may increase the complexity of their interactions. The emergence of e-bikes which are faster and heavier than regular bikes has further increased this complexity. This study aims to shed light on the interdependency of e-bikes and pedestrians behaviours in shared spaces, and investigate how they influence each other's navigation. Through a controlled experiment in Lund, Sweden, data were collected on a total of 1520 trajectories of e-bike and pedestrians, their demographics and cycling experience. A simultaneous equation model was used to quantify the interactions between the participants. Results demonstrate significant correlations among variables, highlighting the model's capacity to effectively capturing the hypothesized interdependencies. The findings can inform the development of level-of-service indices and surrogate safety measures for shared spaces.

1. Introduction

Car dependency has contributed to a range of pressing societal issues, encompassing environmental impacts, traffic congestion, noise pollution, and a sedentary lifestyle (Abolhassani et al., 2019; Carroll et al., 2021; Haghaniet al., 2023). Active mobility plays a pivotal role in driving the transition towards sustainable cities by offering a viable and eco-friendly transport system that effectively addresses these challenges (Kazemzadeh et al., 2021; Nikiforiadis & Basbas, 2019). While cycling[1] and walking form the foundation of active transport, their applicability for specific trip purposes can be constrained by factors such as steep terrain, physical limitations, and the need for long-distance planning (Bigazzi et al., 2022; Fitch et al., 2022). However, with the emergence of electric bikes (e-bikes), cyclists have access to an additional propulsion force that allows them to achieve higher speeds and conquer hills with less effort (Mohamed & Bigazzi, 2019). E-bikes also empower older adults to engage in active mobility and undertake long-distance trips (Kazemzadeh & Koglin, 2021; Van Cauwenberg et al., 2019). They also alleviate the physical strain associated with navigating steep roads, thereby enhancing the overall cycling experience through electrically assisted riding and improved mobility functionality (Handy & Fitch, 2022).

The benefits of e-bikes have contributed to a rapid growth in the global e-bike market, projected to reach 48 billion dollars by 2028. In 2023, over 300 million e-bikes were operated worldwide (Jenkins et al., 2022). E-bikes, particularly pedelec types, are classified as bikes in several European countries such as Sweden and Norway, allowing them to be used in bike lanes and shared spaces[2] alongside cyclists and pedestrians (Fishman & Cherry, 2016; Fyhri & Fearnley, 2015). However, e-bikes exhibit different navigation characteristics compared to other vulnerable road users, including variations in speed regime, acceleration, and braking systems (Hung & Lim, 2020). Notably, e-bikes and pedestrians experience the highest speed differences in shared spaces, necessitating careful analysis of their interactions to ensure the safety and comfort of all users (Zhou et al., 2023). Understanding the dynamics of e-bike-pedestrian interactions and how they influence one another in shared spaces is essential to ensure that the benefits of e-bikes are not compromised at the cost of their safety (Kazemzadeh, Laureshyn, Ronchi, et al., 2020).

Despite the widespread use and significant presence of e-bikes in the

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[1] In this study, regular or conventional bikes refer to bikes solely powered by human effort, without any engine assistance.
[2] in this study, shared space denotes areas within the transport infrastructure exclusively designated for non-motorised transport modes, including pedestrians, bikes, e-bikes, and e-scooters.

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transport system, there is a noticeable lack of conceptual and empirical research with a focus on analysing the interactions between e-bikes and pedestrians (Fu et al., 2023). Existing studies have primarily concentrated on investigating the impact of pedestrians on e-bike navigation characteristics (Kazemzadeh & Bansal, 2021b; Lee et al., 2021). However, understanding the dynamics and interactions between e-bikes and pedestrians in shared spaces are less known.

To address this research gap, our study aims to investigate the mutual influence and interactions between e-bikes and pedestrians through a controlled laboratory experiment. By examining the interdependency between these two road user groups, we aim to gain valuable insights into the complex dynamics that govern their behaviours, decision-making processes, and interactions. Specifically, our research seeks to understand the discomfort experienced from the perspectives of both e-bike riders and pedestrians, thus contributing to the development of shared spaces that effectively accommodate both groups. Ultimately, this knowledge may promote harmonious interactions, enhance safety, and create a more enjoyable experience for all road users.

The paper is structured as follows: Section 2 provides an overview of the contextual literature, highlighting relevant studies in the field. Section 3 outlines the data and methodology employed in this study. The findings and discussions are presented in Section 4, offering a comprehensive analysis of the results. The practical relevance of this study is provided in Section 5. Finally, Section 6 concludes the paper, summarising the key findings, limitations, and future research directions. Fig. 1 represents the workflow of this study:

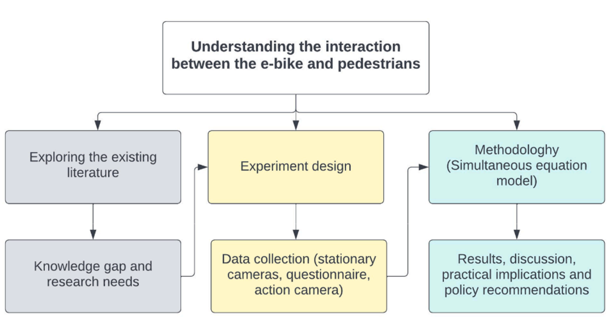

Fig. 1. The adopted workflow of the study.

2. Background

This section provides a brief overview of the contextual literature pertaining to i) types of interactions between cyclists and other vulnerable road users, ii) observational and experimental studies on those interactions, iii) simulation studies around e-bikes and pedestrian interactions, and iv) knowledge gaps and research needs.

2.1. Type of interactions

In the field of cycling research, the interactions between cyclists and other vulnerable road users are commonly categorised based on the direction of encounters. Passing events involve same-direction encounters, while meeting events entail opposite-direction approaches (Nikiforiadis et al., 2020). This classification aims to capture the underlying mechanisms related to safety and comfort issues and experienced discomfort associated with each type of encounter. In passing events, cyclists evaluate the situation and plan their manoeuvres accordingly, whereas in meeting events, both parties are involved in planning the interaction (HCM, 2016).

Furthermore, research has delved into uncovering the distinct characteristics of passing and meeting events. Various types of interactions, such as active passing, paired passing, delayed passing, and meeting, have been considered for estimating user comfort (Hummer et al., 2006). For example, delayed passing refers to a situation where a faster cyclist desires to overtake but must wait for a suitable opportunity (Nikiforiadis et al., 2020). The aim is to replicate the real-world characteristics of road users as they interact in different situations, allowing for the evaluation of their perceived discomfort and safety levels (Kazemzadeh & Bansal, 2021a).

2.2. Observational and experimental studies

Observational and experimental studies have played a significant role in analysing the interaction between e-bikes/bikes, pedestrians, and other road users in various settings. The foundational study by Botma and Papendrecht (1991) examined the passing and paired riding interactions of bikes and mopeds on bike paths in the Netherlands. Their work collected data on speed, volume, and lateral positions using tape switches and video cameras. This study highlighted the limitations of using mean speed as a level of service (LOS) indicator and emphasised the influence of interactions on facility LOS. Building upon this research, Botma (1995) extended the concept of hindrance and developed a letter-based LOS classification based on the frequency of passing and meeting events over time.

Subsequent studies have addressed and expanded upon the limitations of Botma's framework. Hummer et al. (2006) developed a hindrance-based concept to estimate bike LOS in various facilities, considering factors such as delayed passing, path width, and the presence of a centreline. Li et al. (2013) classified passing data into free, adjacent, and delayed passing positions based on lateral displacement, while HCM (2016) classified interactions as active passing, delayed passing, and meeting for BLOS estimation. Nikiforiadis et al. (2020) considered different types of events, including delayed passing, and proposed a weighted frequency of events as a new LOS indicator based on user surveys and analytic hierarchy process analysis. These studies demonstrate the evolution of methodologies and variables used to analyse interactions and estimate LOS in bike-pedestrian facilities.

2.3. Simulation studies

Simulation studies have been employed to understand user interactions in the context of active mobility. While microsimulation models are commonly used for analysing interactions on highways, their direct application to active transport modes is challenging due to the unique riding, flow, and physical characteristics of these modes. Therefore, alternative modelling approaches have been developed.

Cellular automata (CA) models have been used in recent studies to simulate the mixed traffic flow of bikes. Jia et al. (2007) and Jiang et al. (2004) utilised a Burger CA (BCA) model for a mixture of slow and fast bikes, generating fundamental diagrams to assess the quality of service (QOS) for cycling facilities. However, these models were not calibrated with real-world data. Xue et al. (2017) extended the BCA model to improve the representation of mixed bike flow by ensuring a smooth transition from free flow to congested states and more realistic estimates of critical density. They calibrated and validated the model through experimental studies. It is important to note that existing BCA models do not account for lane-changing behaviour.

In a study by Gould and Karner (2009), a CA model for heterogeneous multi-lane bike flow was proposed, considering the lane-changing behaviour of cyclists. The model enabled simulation of different facility scenarios, taking into account user profiles and traffic volume, which is valuable for LOS analysis. Although the model was calibrated with observational data from the UC Davis campus, it had limitations as the observed bike flows did not exceed capacity.

2.4. Knowledge gap and research needs

While research on the interaction of vulnerable road users in shared spaces has advanced in the past decade, there are still significant gaps that need to be addressed. Firstly, there is a lack of understanding regarding the interaction between e-bikes and pedestrians in shared spaces, hindering the seamless and safe integration of e-bikes into active mobility infrastructure. Secondly, the mutual influence and dynamics of e-bikes and pedestrians during their interactions remain unknown, limiting our comprehension of traffic flow characteristics among vulnerable road users in shared spaces. Lastly, there is a need for research focused on developing metrics for assessing the LOS for e-bikes and pedestrians in shared spaces. Such metrics would serve as valuable tools for planners and policymakers in evaluating the quality of these facilities from the user's perspective.

To address these knowledge gaps, this study aims to investigate the inter-dependency between the movement behaviours of e-bikes and pedestrians in shared spaces. A controlled experiment was conducted to gather data on their interactions. It is hypothesised that the interaction between e-bikes and pedestrians is bi-directional, where pedestrians' movement behaviour is influenced by their perceived risk caused by e-bikes, while e-bikes' mobility behaviour is influenced by the available space for manoeuvring that is not occupied by pedestrians (Kazemzadeh et al., 2020). The study contributes to the advancement of knowledge in the field of shared space interactions between e-bikes and pedestrians, providing insights into their mutual influence and behaviours.

3. Methodology

3.1. Data

Video data were collected in a controlled experiment in Lund, Sweden on March 21, 2018. The experiment took place during daytime under sunny weather conditions. Participants were recruited from the university network at Lund University and received compensation of 120 SEK (Swedish Krona) per hour for their participation. The experiment was specifically designed to capture detailed data on the interactions between e-bike riders and pedestrians.[3] Same-direction encounters (passing) and opposite-direction encounters (meeting) were defined based on the navigation of e-bikes through pedestrian areas during each run of the experiment. To ensure a diverse range of interactions, the roles of the e-bike rider and pedestrians were alternated in each run. The experiment was conducted approximately 60 times, but only 40 runs were selected for further analysis due to process failures in certain runs.

In this experiment, a comprehensive data collection approach was employed. The collection of road users' trajectories involved the use of four stationary cameras strategically positioned along a 3.5 m wide track, with a straight section of 120 m. These cameras covered both sides of the track and were carefully overlapped to ensure smooth tracking of the agents. The T-Analyst software, a semi-automated tool, was utilized to generate trajectories based on the images captured by the stationary cameras. The positions of the agents were manually marked at a frequency of two times per second for pedestrians and four times per second for cyclists, allowing for accurate interpolation and speed estimations. This process resulted in a resolution of 15 Hz, which has been validated in a previous study for similar experiments (Laureshyn & Nilsson, 2018). Fig 2[4] showcases a screenshot of the T-Analyst software during the process of generating trajectories for road users.

To complement the trajectory data, a questionnaire-based survey was conducted to collect demographic characteristics of the participants. Additionally, an action camera was mounted on the handlebar of the e-bike to capture more detailed interactions between the e-bike and pedestrians. The high-definition quality of the action camera provided a dataset with rich information on pedestrian behaviours during interactions. Fig. 3 illustrates the view captured by the action camera, showcasing its detailed perspective.

The analysis phase involved matching the trajectory data with sociodemographic characteristics of the participants. This was achieved by simultaneously analysing the action camera footage and questionnaire datasets. By manually comparing the images of individuals captured by the stationary cameras and the action camera, corresponding trajectory data and respective traffic variables were identified and linked with the participants' sociodemographic information.

The merging of datasets significantly enhanced the richness of the traffic data, incorporating valuable behavioural information. Given that the derived dataset encompasses multi-dimensional measurements over time, it presents an opportunity for panel data analysis. To facilitate data analysis and modelling, the collected data, which was originally based on the frame of the camera, was aggregated using fixed distance-intervals along the path. To ensure accurate discretisation of the path, factors such as the length of the e-bike and the configuration of pedestrians were considered. Consequently, a zone length of 5 m and a path width of 3.5 m (reflecting its actual dimensions) were chosen. While the total path length was 120 m, the middle 60 m were selected for analysis, as the beginning and end portions of the path could introduce biases due to warm-up and cool-down riding phases. Each experimental run involved the definition of 12 zones based on the zone dimension. For the identification of passing and meeting events within the aggregated datasets, a binary variable was introduced, with passing represented as 1 and meeting as 0.

In this study, the variables were classified into two categories: endogenous and exogenous variables. Previous models of bike and pedestrian interactions have considered factors such as lateral distance, longitudinal distance, and interaction angle as endogenous variables (Alsaleh & Sayed, 2020; Liang et al., 2012; Mohammed et al., 2019). Based on the extracted trajectories, specific traffic variables were calculated within the discretised path. These included pedestrian crowds, e-bike speed, and e-bike lateral distance. Pedestrian crowds were quantified by determining the number of pedestrians within each zone. The lateral distance referred to the absolute distance between the start and endpoint of each zone, perpendicular to the direction of e-bike movement. E-bike speed was computed as the average of the instantaneous speeds within each zone. These endogenous variables provide crucial information about the dynamics of interactions between road users.

On the other hand, exogenous variables such as age, sex, and riding experience were extracted from the questionnaire datasets for all participants. This demographic data was then matched with the endogenous variables dataset. In the model, a combination of these variables was employed to assess their statistical significance. The final model identified e-bike rider experience, pedestrian age, and sex as significant factors, contributing to a comprehensive understanding of the factors influencing bike and pedestrian interactions in the study.

3.2. Simultaneous equation model

Defining a cause-effect relationship between variables underlying the interaction of e-bikes and pedestrians can be challenging because these variables are often inter-related. For example and in a situation where an e-bike and a pedestrian approach one another in an opposite direction, it is difficult to indicate whether the pedestrian's kinematics cause the e-bike to accelerate/decelerate or the e-bike's kinematics cause the pedestrian to adjust his/her speed.

Classical regression models are often employed to explore such relationships between a dependent variable and independent variables. However, a fundamental assumption of these models is that the independent variable must be exogenous i.e. must not be influenced by the dependent variable. When this assumption is violated (e.g. in the above example), the variables are said to be endogenous and classical regression models produce biased estimates of their effect on one another. To

[3] For additional information, such as details about the experiment design, survey design, trajectory extraction, and sample size, readers refer to a recent publication by Kazemzadeh and Bansal (2021).

[4] Figure 1 and Fig. 2 image credit: Kazemzadeh and Bansal (2021).

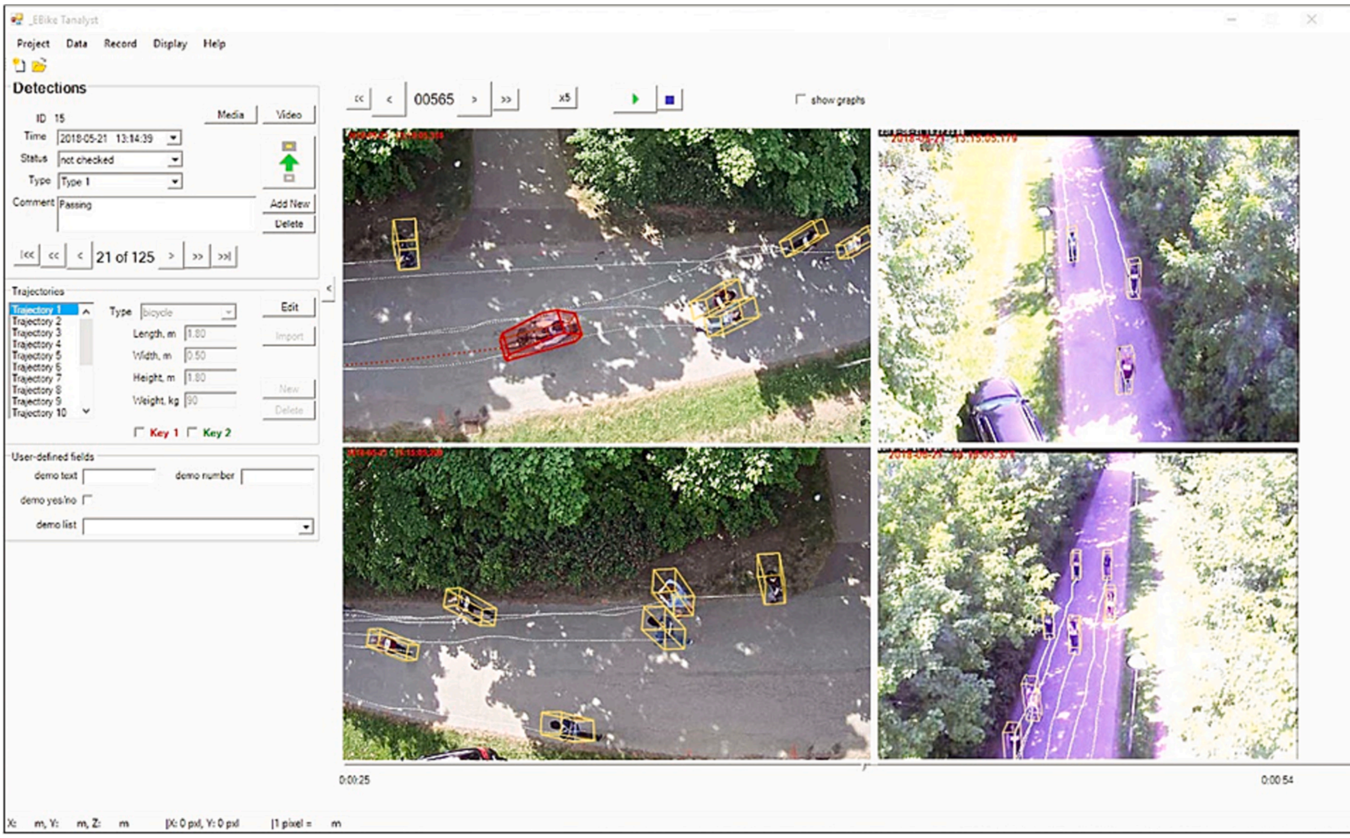

Fig. 2. A screenshot of T-Analyst software. (E-bike and pedestrians inside red and yellow boxes respectively).

Fig. 3. Meeting (left picture) and Passing (right picture) conditions seen from the action camera placed on the e-bike representing the rider's perspective.

address this issue, simultaneous equation modelling approach can be utilised, considering the joint dependency among variables (Washington et al., 2020).

Let y_1, y_2 and y_3 be the three dependent variables in this study (representing e-bike's speed, e-bikes lateral distance, and pedestrian crowdedness, respectively). In simultaneous equation modelling, a system of structural equations is defined as follows (Eq1):

$$\begin{aligned} y_1 &= \beta_1 X_1 + \gamma_2 y_2 + \gamma_3 y_3 + \varepsilon_1 \\ y_2 &= \beta_2 X_2 + \gamma_1 y_1 + \gamma_3 y_3 + \varepsilon_2 \\ y_3 &= \beta_3 X_3 + \gamma_1 y_1 + \gamma_2 y_2 + \varepsilon_3 \end{aligned} \tag{1}$$

where X_i are exogenous (independent) variables, β_i and γ_i are model parameters, and ε_i are error terms. To address the above endogeneity, it is assumed that the error terms of the above equations are correlated with an expected value of 0 ($E(\varepsilon) = 0$) and a variance–covariance matrix $\boldsymbol{\Sigma}$:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} \tag{2}$$

where the error terms are further assumed to follow a multivariate distribution (e.g., multivariate normal distribution). This system of equations can be solved using Three-Stage Least Squares (3SLS) estimation approach in which, the endogenous variables are first instrumented on one or more exogenous variables (denoted by Z_i):

$$\widehat{y_1} = \alpha_1 Z_1$$
$$\widehat{y_2} = \alpha_2 Z_2$$
$$\widehat{y_3} = \alpha_3 Z_3$$

where $\widehat{y_1}$ are predicted values of the instrumented variables and α_i are estimable parameters. These parameters are estimated using Ordinary Least Squares (stage 1):

$$\min\left[\sum (y_i - \widehat{y_i})^2\right]$$

The predicted values of the instrumented variables ($\widehat{y_i}$) from stage 1 are then used in the original system of equations and the estimated equations are used to compute the residuals from which cross-equation error term correlations are calculated (stage 2):.

$$y_1 = \beta_1 X_1 + \varphi_2 \widehat{y_2} + \varphi_3 \widehat{y_3} + \varepsilon_1$$
$$y_2 = \beta_2 X_2 + \varphi_1 \widehat{y_1} + \varphi_3 \widehat{y_3} + \varepsilon_2$$
$$y_3 = \beta_3 X_3 + \varphi_1 \widehat{y_1} + \varphi_2 \widehat{y_2} + \varepsilon_3$$

Finally, generalized least squares (GLS) approach is used to estimate the original model parameters (stage 3) (Washington et al., 2020). The newly employed (instrumented) variables are not subject to endogeneity anymore since they are predicted using exogenous covariates. However, finding strong exogeneous covariates to predict the endogenous variables can be challenging.

4. Results and discussions

A total of 18 individuals participated in the study, with an average age of 28 years (ranging from 18 to 38 years). Among the participants, 56 % were female, 88 % were regular cyclists, and 33 % had prior experience with e-bike riding. Table 1 provides a summary statistics of the variables included in this study.

Several 3SLS models were estimated using various specifications and their statistical fit was compared to determine the optimal model. We introduced variables into the models through a stepwise variable selection criterion. Additionally, we conducted tests for multicollinearity among explanatory variables by calculating Pearson correlation coefficients. Variables displaying unacceptably high correlation coefficients (>0.7) were excluded from the models. For brevity, we omit the detailed results of different modelling specifications, but we provide the specifications of the superior models in Table 2. In addition, we conducted simultaneous modelling of passing and meeting experiment data to enhance statistical robustness and uncover differences in relationships between both experiments. This was achieved by incorporating interactions of the passing indicator with covariates.

4.1. First stages of the 3SLS regression model

Within the first stage of 3SLS model, demographic attributes (age and sex) and prior cycling experience were used as exogenous variables to predict the endogenous variables. These external variables are

Table 1
Summary statistics of the variables used in the study.

Variable	Mean	SD	Min	Max
Traffic variables				
E-bike speed (metre/sec)	3.93	1.26	0	6.21
E-bike lateral distance (metre)	0.51	0.65	0	3.33
Pedestrian crowds (count)	1.8	0.89	0	4
Passing event (percentage)	52	–	–	–
Socio-demographic variables				
Age	28	4.82	18	38
Sex (1: female, 0: male) (percentage)	56	–	–	–
Cycling regularly (1: being a regular cyclist, 0: otherwise) (percentage)	88	–	–	–
E-bike riding experience (1: with prior experience, 0: no experience) (percentage)	33	–	–	–

Table 2
Estimation results of the first stage within the 3SLS regression model (N = 876).

Variable	Estimates	Standard error	t-stat	[95 % Conf.	Interval]
Eq (1): E-bike's speed as the dependent variable					
Constant	1.992***	0.716	2.78	0.586	3.398
Passing	−0.134*	0.086	−1.55	−0.304	0.036
Sex (Female)	−0.494**	0.194	−2.54	−0.876	−0.112
Cycling experience (1 = Yes)	−1.110[a]	0.087	−1.25	−0.282	0.062
Age	0.081**	0.026	3.06	0.028	−0.132
Eq (2): E-bike's lateral distance as the dependent variable					
Constant	−0.262[a]	0.373	−0.70	−0.995	0.469
Passing	0.176***	0.045	3.88	0.086	0.264
Sex (Female)	−0.165*	0.101	−1.63	−0.364	0.034
Cycling experience (1 = Yes)	−0.007[a]	0.046	−0.15	−0.096	0.083
Age	0.012[a]	0.014	0.85	−0.015	0.469
Eq 3: Pedestrian crowdedness as the dependent variable					
Constant	1.695***	0.507	3.34	0.699	2.692
Passing	−0.025[a]	0.062	−0.41	−0.146	0.095
Sex (Female)	−0.341**	0.138	−2.47	−0.612	−0.071
Cycling experience (1 = Yes)	−0.053[a]	0.062	−0.84	−0.174	0.069
Age	−0.021[a]	0.019	−1.12	−0.058	0.016

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; [a]: not statistically significant.

essential in controlling for potential endogeneity. Tables summarizes the results of this model.

The constant term in Equation (1) (for the e-bike speed) suggests that e-bikes travel at an average speed of approximately 1.992 m per second (m/s) when all other variables are held constant. Notably, the "Passing" variable has a significant negative parameter (-0.134), indicating that passing events have a slight dampening effect on e-bike speeds. Sex (female) exhibits a statistically significant negative parameter (-0.494), suggesting that, on average, female e-bike riders tend to have slightly lower speeds compared to their male counterparts. On the other hand, the parameter of having cycling experience on e-bike speed is not statistically significant, implying that prior cycling experience does not significantly affect e-bike speeds. Age has a significant positive parameter (0.081), implying that, older e-bike participants are more likely to maintain higher speeds. These results offer further insight into how external factors interplay with the e-bike speed. The negative impact of passing events suggests that manoeuvring around other objects or vehicles may lead to reduced speeds. Additionally, the sex differences in e-bike speeds may be influenced by various factors, such as riding style or comfort level. The positive relationship with age suggests that older individuals tend to ride e-bikes at higher speeds, which could be attributed to their experience or riding habits.

The parameter estimates within Equation (2) (lateral distance) reveals intriguing findings too. The constant term does not show a statistically significant impact (-0.262), indicating that, on average, lateral distance does not significantly vary under typical conditions. The "Passing" variable demonstrates a significant positive parameter (0.176), suggesting that e-bikes tend to maintain a larger lateral distance when passing pedestrians. Sex (female) exhibits a statistically significant negative parameter (-0.165), indicating that, on average, female e-bike riders tend to maintain a slightly smaller lateral distance compared to their male counterparts. However, both having cycling experience and age show non-significant effects on lateral distance. These findings shed light on the factors influencing lateral distance during e-bike rides. The positive effect of passing events on lateral distance suggests a cautious approach to ensure pedestrian safety. Sex differences in lateral distance may reflect varying comfort levels or riding styles, with females tending to maintain shorter distances. The non-significant impact of cycling experience and age implies that these factors do not significantly influence lateral distance.

Finally and within Equation 3 (for pedestrian crowdedness), the constant term does not yield a statistically significant parameter suggesting that crowdedness remains relatively consistent under typical conditions. The "Passing" variable and variables related to having cycling experience, age, and passing events do not yield statistically significant parameters either. However, sex (female) shows a statistically significant and negative parameter (-0.341), indicating that, on average, female e-bike riders are more likely to encounter slightly less crowded pedestrian areas. These results imply that pedestrian crowdedness remains relatively stable, with minor variations under typical conditions. The impact of passing events, cycling experience, age, and passing events on crowdedness appears to be non-significant. In contrast, the significant negative effect of sex suggests that female e-bike riders tend to navigate slightly less crowded pedestrian areas, which may be attributed to riding preferences or route choices.

4.2. Second and third stages of the 3SLS regression model

Within the second and the third stages of the 3SLS model, e-bike speed, e-bike lateral distance, and pedestrian crowdedness were used as endogenous variables and their impact on one another was determined. Table 3 summarizes the results of this model.

4.2.1. E-bike's speed as a dependent variable

In this equation, we posit that e-bike speed is influenced by two key factors: e-bike lateral distance and pedestrian crowds. This equation describes how the strategic speed of an e-bike rider varies in response to changes in these variables. Equation (4) illustrates the relationship between e-bike speeds and other endogenous variables (Eq (4)):

$$\text{E-bike speed } = 5.195 + 4.809 \text{ lateral distance} - \text{ pedestrian crowds} - 1.009 \text{ passing} \quad (4)$$

The coefficient for lateral distance (4.809) is both positive and statistically significant. This positive parameter signifies that increased lateral distance is associated with higher e-bike speeds. Conversely, the parameter for pedestrian crowds (-1.221) exhibits a negative correlation with e-bike speed, all other factors being equal. This suggests that as pedestrian crowds intensify, e-bike speeds decrease. Additionally, the negative parameter for the passing indicator (-1.009) highlights a negative correlation between passing encounters and e-bike speeds. In contrast with meeting scenarios, passing leads to speed reductions for e-bike riders. Finally, the statistically significant constant (5.195) plays a pivotal role in our simultaneous equation model, representing the baseline e-bike speed when all other variables are held constant.

Table 3
Estimation results of the second and third stages within the 3SLS regression model (N = 876).

Variable	Estimates	Standard error	Z-score	[95 % Conf. Interval]	
Eq (1): E-bike's speed as the dependent variable					
Constant	5.195	0.313	16.58	4.581	5.810
E-bike lateral distance	4.809	0.567	8.48	3.697	5.921
Pedestrian crowds	−1.221	0.273	−4.47	−1.758	−0.686
Passing	−1.009	0.253	−3.98	−1.506	−0.512
Eq (2): E-bike's lateral distance as the dependent variable					
Constant	−1.080	0.097	−11.09	−1.271	−0.889
E-bike speed	0.207	0.022	9.10	0.163	0.252
Pedestrian crowds	0.254	0.042	5.95	0.170	0.338
Passing	0.209	0.048	4.32	0.114	0.304
Eq 3: Pedestrian crowdedness as the dependent variable					
Constant	4.235	0.804	5.27	2.659	5.812
E-bike lateral distance	3.925	0.767	5.12	2.422	5.429
E-bike speed	−0.814	0.197	−4.12	−1.201	−0.427
Passing	−0.823	0.242	−3.39	−1.299	−0.347

Note: $p < 0.01$

These estimation results are aligned intuitively with the following interpretations: As e-bike riders aim to maintain higher speeds, they must increase lateral distance to avoid collisions with pedestrians, leading to a positive correlation between lateral distance and speed. Conversely, as pedestrian crowds grow, e-bike riders reduce speed to enhance safety, allowing for better maneuverability amidst higher congestion. However, this adjustment may result in a reduction in LOS as riders must slow down to navigate obstacles, in this case, pedestrians.

The negative passing parameter indicates a speed reduction trend during same-direction encounters. This trend arises because in passing situations, e-bike riders have sole control over adjusting their strategic route. In contrast, during meeting encounters, both parties (e-bike riders and pedestrians) participate in decision-making, utilising non-verbal communication to adjust their positions and consequently reduce lateral distances. The disparity in parameters between passing and meeting emphasises the significance of considering discomfort weights for different encounter directions in LOS studies for e-bike riders in various conditions. This equation/model may not fully explain the variations in perceived LOS across different encounters. Furthermore, the positive intercept underscores the increasing trend in e-bike riding speed strategies. This trend may be linked to the nature of the power-assisted system in e-bikes, which provides assistance to riders, facilitating their travel.

4.2.2. E-bike lateral distance as a dependent variable

Equation (5) characterises variations in e-bike lateral distance based on e-bike speed and pedestrian crowds. It demonstrates how pedestrian crowds and e-bike speed, particularly during passing events, influence the strategic lateral distance of e-bike riding. Equation (5) elucidates the relationship between e-bike lateral distance and e-bike speed, pedestrian crowds, and passing events (Eq (5):

$$\text{Lateral distance} = -1.080 + 0.207\,\text{e-bike speed} + 0.254\,\text{pedestrian crowds} + 0.209\,\text{passing} \quad (5)$$

Analysis of Equation (5) reveals several key insights. The positive coefficient for e-bike speed (0.207) signifies that as e-bike speed increases, so does the lateral distance. A similar trend is observed with pedestrian crowds, where a positive coefficient (0.254) indicates that as crowd levels rise, e-bike lateral distance also increases. Moreover, the passing indicator, represented by a positive coefficient (0.209), implies a correlation between passing events and greater lateral distance. Conversely, the intercept in this equation is notable for its negative value (-1.080). This negative intercept signifies a baseline decrease in lateral distance in the absence of other influencing variables. Essentially, when none of the other factors are in play, there is a tendency for a reduction in lateral distance.

An examination of these results reveals that e-bike lateral distance exhibits a positive correlation with riding speed. This suggests that riders prefer to maintain greater lateral distance rather than reducing speed and using the brakes. This behaviour could stem from the riding tendencies of participants, who may find it easier to adjust their e-bike's position through lateral distance rather than slowing down and entering a slower speed regime. The positive relationship between crowd levels and lateral distance can be interpreted similarly to the speed-lateral distance relationship. In shared spaces, riders must either decrease speed (or stop) or adjust lateral distance to avoid conflicts and collisions. The positive trends in both speed and pedestrian crowds with lateral distance imply that riders generally opt for adjustments rather than reducing speed and potentially coming to a halt due to the presence of obstacles like pedestrians.

The positive coefficient for passing in this equation indicates that e-bike riders maintain greater lateral distance during passing situations compared to meeting scenarios. While this passing trend differs from that in Equation (4), both equations lead to the same trend in e-bike riding decisions. This underscores the significance of e-bike rider decisions in passing scenarios. As the sole decision-maker in this context, the evolution of e-bike riding strategies becomes crucial in safety analysis. In contrast to passing, during meetings, both users can communicate nonverbally, resulting in fewer impacts on e-bike lateral displacement. The negative intercept value represents the general pattern of decreasing e-bike lateral distance. This occurs because, in the absence of other variables influencing intentions, riders tend to follow their strategic path with minimal deviations from their intended route.

4.2.3. Pedestrian crowds as a dependent variable

In this phase of our analysis, we delve into the influence of e-bike movements on pedestrian crowd levels within different zones. We postulate that e-bike lateral distance and speed can elucidate variations in crowd levels, contributing to a more comprehensive understanding of their interactions. Equation (6) advances our understanding of these relationships:

$$\text{Pedestrian crowds} = 4.235 + 3.925\,\text{lateral distance} - 0.814\,\text{e-bike speed} - 0.823\,\text{passing} \tag{6}$$

The positive coefficient for lateral distance (3.925) reveals an intriguing connection: increased lateral distance corresponds to higher levels of pedestrian crowds. This relationship can be attributed to lateral distance serving as a tangible indicator of obstacles within the strategic path of the e-bike rider. In settings with limited crowds, the need for substantial lateral distance diminishes, allowing pedestrians to move freely. Conversely, as crowd levels intensify, the demand for greater lateral distance becomes apparent, aligning with the observed trend.

Conversely, the negative correlation between e-bike speed (-0.814) and pedestrian crowds uncovers an intriguing dynamic. As e-bike speed decreases, pedestrians seem to feel safer and more at ease, resulting in a reduction in crowd levels. This suggests that e-bike riders tend to adapt their speed to maintain a consistent crowd environment. The negative coefficient for the passing parameter (-0.823) indicates a unique pattern during passing situations. This trend could be attributed to pedestrians' ability to visually perceive the approaching e-bike during encounters, prompting them to adjust their positions. This behaviour potentially leads to higher pedestrian counts compared to passing scenarios where pedestrians cannot visually detect the e-bike. However, interpreting this parameter presents challenges, given potential influences from factors such as visibility and experimental design. Finally, the positive intercept value (4.235) underscores the baseline level of pedestrian crowds in the absence of e-bike activity. This baseline highlights the inherent tendency for pedestrians to occupy the analysed zones when there are no e-bike traffic characteristics at play.

4.3. Statistical fit of the 3SLS regression model

Table 4 presents the goodness of statistical fit for the final 3SLS model. The RMSE values for all three equations indicate that the models are providing reasonably accurate predictions, as the average errors are not excessively high. The "E-bike lateral distance" equation has the lowest RMSE, indicating the most accurate predictions among the three equations.

Table 4
Model evaluation statistics for the final model specification (N = 876).

Equation	RMSE	Chi2
Eq1: E-bike's speed as the dependent variable	3.608	72.71
Eq (2): E-bike's lateral distance as the dependent variable	0.750	164.91
Eq 3: Pedestrian crowdedness as the dependent variable	2.945	26.32

Note: $p < 0.01$.

5. Practical implications and policy recommendations

Our findings have practical implications for both the research community and planners and policymakers. The choice of bidirectional or unidirectional sharing policies in shared spaces can significantly impact the perceived comfort of both user groups. The passing parameter primarily leads to more speed and lateral position changes, which could either be associated with user discomfort or reflect the user's riding strategy to navigate crowded areas without reducing speed or coming to a halt. This finding suggests that unidirectional mixed flows of users with substantial speed differences can introduce significant discomfort for users with higher speeds, while bidirectional flows may alleviate this issue. Given the limited available infrastructure, especially for active mobility, considering user discomfort in different scenarios can guide planners to make informed decisions.

Although shared spaces are designed to accommodate vulnerable road users, it is essential to recognise that some users are more vulnerable than others, and shared spaces should not compromise user safety. Our study shows that e-bike riders in overtaking scenarios tend to adjust their speed and position rather than stopping, and overtaking often occurs. This behaviour can increase the risk of conflicts and collisions. Considering the high speed and agility of e-bikes, navigation in some cases can be challenging. While e-bikes generally have a speed limit of 25 km/h in several countries, there may be a need for more specific speed limits in congested areas with narrow roads.

In addition, our study provides empirical evidence showing that the interaction between e-bike riders and pedestrian crowds is mutual. When pedestrian crowds intensify, the need for greater lateral distance becomes apparent, aligning with observed trends. These findings suggest that implementing strategies such as dedicated infrastructure markings for pedestrians, even in shared spaces, could enhance e-bike navigation and contribute to the safety of all road users.

The global efforts led by planners and policymakers to enhance the viability of e-bikes as sustainable transport alternatives to motorised vehicles are commendable. Noteworthy initiatives such as trial e-bike programs and financial incentives for e-bike acquisitions have been documented in the literature (Kazemzadeh and Ronchi, 2022). However, there is an urgent imperative to enhance the experience of e-bike users within existing infrastructure and consequently enhance user comfort and safety within the transport domain. Our findings underscore the pivotal role of dedicated infrastructure and sharing policies in shaping the comfort and experience of e-bike riders, ultimately influencing the sustainability of e-bikes as viable alternatives to car trips across urban and rural landscapes. Hence, collaborative efforts among stakeholders are indispensable in augmenting available infrastructure for e-bike riders, fortifying the role of e-bikes in the sustainable transport agenda.

Furthermore, our research highlights discernible disparities in road user behaviour based on gender, with female riders exhibiting a more cautious approach. This insight holds significant implications for policy formulation, emphasising the persistence of gender gaps in comfort perceptions, even within dedicated cycling facilities. In alignment with broader literature indicating women as underrepresented constituents of active mobility, this underscores the imperative of concerted efforts toward fostering inclusivity and comfort in cycling environments beyond mere infrastructure provision. While dedicated infrastructure is crucial for improving overall comfort and safety, addressing gender disparities requires additional measures such as targeted education, outreach, and community engagement initiatives to ensure that cycling environments are inclusive for all users (AitBihiOuali & Klingen,2022).

Overall, our findings suggest that improving the safety and comfort of both e-bike riders and pedestrians in shared spaces, while separating them from motorized vehicles, is imperative. The LOS metric plays a crucial role in achieving this goal, as it gauges user comfort from the perspective of each road user. Our study sheds light on how various factors, such as user speed and lateral position, are associated with user comfort, offering insights for the development of LOS standards tailored to shared spaces.

6. Overall discussion

Several studies have explored various facets of e-bikes as a mode of transport over recent decades, including modal substitution factors, comfort variables, user demographics, and safety concerns (Cherry & Cervero, 2007; Fukushige et al., 2021; Soren,2013). However, the evaluation of e-bike interactions with other road users remains an area necessitating further investigation. It is particularly critical to comprehend how e-bikes interact with pedestrians during overtaking or meeting events, given pedestrians' lower speeds and vulnerability to potential conflicts (Kazemzadeh & Bansal, 2021b).

This research contributes to the existing literature by meticulously analysing the interaction dynamics between e-bikes and pedestrians, elucidating the distinct riding and interaction behaviours exhibited by different demographic groups. Our findings reveal notable disparities, with female riders often exhibiting slightly lower speeds and maintaining smaller lateral distances compared to their male counterparts. These insights underscore the significance of demographic considerations in facility design and improvement initiatives. While prior research has acknowledged gender-based differences in riding behaviour, our study further underscores and expands upon these disparities (Fyhri & Fearnley, 2015).

Moreover, this study lays the groundwork for the development of LOS metrics tailored to e-bikes, offering insights into the interplay between e-bikes and pedestrians. A notable strength of our study in this regard lies in its comprehensive consideration of detailed traffic characteristics, demographic factors, and riders' experiences. The classification of road user interactions based on encounter direction aligns with established methodologies for developing LOS metrics, thus offering a robust foundation for the formulation of e-bike-specific LOS standards (HCM, 2016; Kazemzadeh (2021)).

Furthermore, our findings can significantly contribute to advancing microsimulation research on e-bikes. Specifically, they can facilitate the estimation of LOS for new cycling facilities and the evaluation of potential impacts resulting from facility improvements. Microsimulation models, renowned for their ability to simulate traffic dynamics under a myriad of scenarios, offer a powerful tool for predicting how different infrastructure configurations and interventions may affect the flow of traffic, including e-bikes. By integrating our empirical data into these models, researchers can enhance their accuracy and reliability, ultimately enabling more informed decision-making in urban planning and transport management.

Moreover, the field validation provided by our study lends further credibility to microsimulation models. By comparing the outputs of these models with real-world data collected in our experiments, we can verify the models' ability to accurately replicate e-bike interactions in shared spaces. This validation process not only enhances the confidence in the predictive capabilities of microsimulation models but also underscores the practical relevance and applicability of our research findings.

In summary, our research advances the understanding of e-bike interactions with pedestrians and lays the groundwork for developing tailored LOS metrics and informing microsimulation studies. By addressing critical gaps in the existing literature and providing empirical insights, our study contributes to the ongoing discourse on enhancing the safety, comfort, and efficiency of e-bike transportation within urban environments..

7. Conclusion and outlook

The evaluation of simulated interactions, coupled with the consideration of joint dependencies among variables, has provided a deeper understanding of the complexities of interactions in shared spaces. Structural Equation Modelling has offered a holistic view of variables when clear cause-effect relationships are not apparent within the model. This study takes the initial steps to comprehensively understand how e-bikes and pedestrians interact within shared spaces. By conducting a controlled experiment, we extracted trajectories of e-bikes and pedestrians, quantifying their mutual influence during shared space interactions. In this model, e-bike speed, e-bike lateral distance, and pedestrian crowdedness served as endogenous variables, while pedestrian age, sex, and e-bike rider experience acted as exogenous variables. We considered both same-direction and opposite-direction scenarios to compare e-bike-pedestrian interactions comprehensively. It is evident that all combinations of considered variables yielded statistically significant findings, both in the equation-by-equation analysis and in the holistic view.

This study holds practical applications in the realms of safety, interaction modelling, and LOS analysis. The findings contribute to a better understanding of e-bike and pedestrian interactions, potentially aiding in the calibration of microsimulation models. Furthermore, the results can inform the calculation of discomfort weights for passing and meeting events, facilitating the development of LOS indices tailored to shared spaces.

This study is not without limitations. Firstly, the experiment was designed to minimize the influence of confounding variables, such as complex road geometry, pavement conditions, and weather, which should be considered when generalizing the results. Secondly, this study assumes static segments to estimate e-bike and pedestrian characteristics, limiting insight into the dynamics of their movements over shorter distances. Thirdly, the study only considers the presence of e-bikes and pedestrians, overlooking the complexity of shared spaces that also accommodate other road users, such as cyclists and e-scooter riders. Lastly, while this study primarily focused on analysing interactions from a comfort perspective, it is essential to note that these interactions also carry safety implications. For instance, analysing interactions could contribute to developing surrogate safety measures and facilitate conflict analysis. However, this study did not comprehensively address these safety-related aspects.

Future research should encompass the presence of emerging transport modes like e-scooters in shared spaces and analyse how they impact interactions among road users in these facilities (Kazemzadeh et al., 2023). Additionally, there is a pressing need for the development of LOS indices for shared spaces, aiding planners and policymakers in prioritising improvements and maintenance while informing the design of new facilities. Furthermore, detailed experiments are required to understand how factors such as horn usage, the sound of e-bike engines, and the perception of high e-bike speeds influence pedestrians' decisions to alter their speed and direction, ultimately affecting their comfort and safety. Furthermore, future investigations should broaden their scope to include other emerging transport modes, such as e-scooters, within the transport network — an aspect that was not addressed in our analysis (Kazemzadeh and Sprei, 2024). Exploring the complex interactions among multiple transport modes presents a promising research avenue, offering insights into the evolving urban mobility landscape and guiding future policy intervention.

This study marks a significant step towards enhancing our comprehension of shared space dynamics, laying the groundwork for future research and practical applications in the field of active mobility and transportation planning.

CRediT authorship contribution statement

Khashayar Kazemzadeh: Conceptualization, Methodology, Investigation, Writing – review & editing. **Amir Pooyan Afghari:** Conceptualization, Methodology, Investigation, Writing – review & editing.

Declaration of Competing Interest

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

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