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Electric bike navigation comfort in pedestrian crowds

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ABSTRACT

The emergence of electric bikes (e-bikes) has brought a paradigm shift in shared mobility with a promise to move towards the mission of sustainable cities. Whereas an in-depth understanding of e-bike riding characteristics is crucial to effectively design the infrastructure for active mobility, it remains an open area of research. We take the first step towards modelling the e-bike navigation comfort in pedestrian crowds. Through a laboratory-controlled field experiment, we collect trajectories of e-bike riders under different pedestrian crowding levels in both opposite- (meeting) and same-direction (passing) encounters. For each trajectory, we obtain e-bike speed, e-bike lateral distance, and pedestrian crowding after processing the data obtained from four stationary cameras. Considering the riding comfort as a latent variable, we adopt a Bayesian network to represent the relationship between observed and the latent variables. Subsequently, we use fundamental principles of conditional probability to identify the causal effect of pedestrian crowding on e-bike riding comfort. Controlling for the demographic heterogeneity, we also estimate the relationship between the comfort of an e-bike rider, pedestrian crowding, and her riding characteristics (e.g., speed and lateral distance). The results of this study would guide policymakers in ex-ante evaluations of the infrastructure decisions for active mobility.

1. Introduction and motivation

The emerging public interest in cycling has encouraged researchers to investigate various aspects of cycling activities such as comfort, level of service (LOS), safety, and psychological stress (Fitch, Thigpen, & Handy, 2016; Kamel, Sayed, & Bigazzi, 2020). Different policies and programs have been introduced from governments across the world to support cycling mode (Nikiforiadis & Basbas, 2019). For instance, the bike sharing system is admired to increase the level of physical activity for users and can be used as a substitute for the motorised vehicle (Abolhassani, Afghari, & Borzadaran, 2019; Leister, Vairo, Sims, & Bopp, 2018; Lu, Hsu, Chen, & Lee, 2018; Reynaud, Faghih-Imani, & Eluru, 2018; Soriguera & Jiménez-Meroño, 2020). However, the physical effort for pedalling in cycling activity has been recognised as an obstacle in the adoption of this travel mode (Liu & Suzuki, 2019). Electric bike (e-bike) addresses this limitation via providing an additional propelling force powered by an electric motor, which assists users in achieving higher speed and reaching hills with lesser effort (Mohamed & Bigazzi, 2019). Such characteristics are the key reasons behind the emergence of e-bike as a sustainable mode for active transport (Langford, Cherry, Bassett, Fitzhugh, & Dhakal, 2017).

E-bikes and bikes have similar size; however, the electric motor introduces several substantial differences in their performance function and travel utility. First, the speed regime of bikes and e-bikes could differ by 2–9 kilometres per hour (Baptista et al., 2015; Schleinitz, Petzoldt, Franke-Bartholdt, Krems, & Gehlert, 2017). Furthermore, e-bikes are mainly classified as bikes, and consequently, the facilities designed for bikes/pedestrians can be shared with e-bikes (Bai, Liu, Chan, & Li, 2017). Thus, whereas the speed gain makes e-bikes attractive, the consequent speed differences relative to other sustainable travel modes present a compatibility challenge. This issue becomes more critical in mixed-traffic conditions when e-bikes interact with pedestrians because the frequency of passing and meeting is very high due to a substantial difference in speed regimes of pedestrians and e-bikes. Consequently, the navigation of an e-bike through pedestrian crowd imposes some difficulty for the e-bike riders as they have to adjust their speed and lateral positions to avoid potential conflicts and serious collisions. Second, acceleration and deceleration characteristics of e-bikes are much different from bikes. The heavier frame of e-bikes compared to bikes also cause differences in riding behaviour of these two modes. Third,

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considering the high speed of e-bikes and the need for less physical exertion than bikes, e-bikes can be used to commute in case of medium-to-long distance trips as has happened during COVID-19 pandemic (Kazemzadeh & Koglin, 2021). This feature may introduce different expectations of e-bike users (e.g., related to the design of facilities) as they count on e-bikes for regular and utilitarian purposes. The above-mentioned differences between e-bikes and bikes call for a different framework to model e-bike's microscopic characteristics because the results of previous studies for pedestrian-bikes interactions would not be directly applicable to plan infrastructure facilities when e-bikes share the same space.

In this study, we aim to model an e-bike navigation comfort in pedestrian crowds using the data collected through a laboratory-controlled field experiment in the city of Lund, Sweden. Our analysis uses information on same- and opposite-direction encounters movements of e-bikes and pedestrians on a dedicated path for cyclists. The novelty of this study is twofold. First, this is the first study that models microscopic characteristics of e-bike in pedestrian crowds. Second, we model the effect of the latent riding comfort on driving characteristics of e-bike riders (e.g., speed and lateral distance) and capture the heterogeneity in these dependencies across sociodemographic characteristics of rider (e.g., age and gender). To this end, we adopt a Bayesian network, which represents relationships between observed and latent variables via a directed acyclic graph (DAG). We thus provide a framework for planners and policymakers to evaluate e-bike riding comfort, with applications in LOS studies. Our results are also valuable inputs in microsimulation of the interactions between e-bikes and other vulnerable road users in shared and dedicated lanes. Both LOS and microsimulation models are crucial in the design of an infrastructure shared by various active modes of transport. The proposed framework is presented in Fig. 1.

The remaining of this paper is organized as follows: Section 2 reviews the contextual literature to identify the research gaps. The originality and scope of the paper is provided at the end of this section. Section 3 describes the controlled experiment, data collection, and data extraction. Section 4 details the formulation of the proposed probabilistic graphical model. Section 5 discusses results and their practical implications. Key takeaways and avenues for future research are summarized in Section 6.

2. Literature review

In this section, we discuss previous studies related to – i) interactions between cyclists and other vulnerable road users in shared spaces; ii) quantifying riding comfort of cyclists; and iii) relationship between riding comfort and LOS. The section concludes with highlighting originality and scope of this research.

2.1. Interactions between cyclists and other vulnerable road users in shared spaces

Interaction in shared mobility is important to study because different travel modes adopt different speed regimes. Early bike flow studies considered the analysis of the interaction between bike riders and other users as a mean to estimate the riding comfort of cyclists. For instance, Botma (1995) introduced the concept of the *hindrance* as a proxy to quantify interactions or manoeuvres of road users and eventually estimate the riding comfort of Dutch cyclists. The author classified interactions based on the direction of an encounter – same-direction (passing) and opposite-direction (meeting), and found that the meeting resulted in lesser hindrance as compared to passing. Khan and Raksuntorn (2001) conducted a similar study in the US and analysed the characteristics of passing and meeting encounters on a dedicated bike track. Different variables such as comfortable speed difference threshold, average speed, and lateral spacing were used in their model. Several previous studies have also evaluated other traffic characteristics associated with passing encounters (overtaking). Hoogendoorn and Daamen (2016) documented the distribution of headways of the following bike and classified them into constrained and unconstrained headways. Chen, Yue, and Han (2018) investigated a situation when a moped overtakes a bike and analysed the consequence of such an overtaking phenomenon for the bike riders. They suggested that widening the bike lane and reducing the speed limit could diminish the overtaking disturbances. Yuan, Daamen, Goñi-Ros, and Hoogendoorn (2018) conducted a laboratory experiment to study the interaction behaviour of cyclists. They found that cyclists employ a visible evading manoeuvre in meeting encounters. All the above-discussed studies focus on the riding comfort of cyclists. Modelling such interactions is a critical step towards understanding the riding comfort and riding characteristics of e-bike riders.

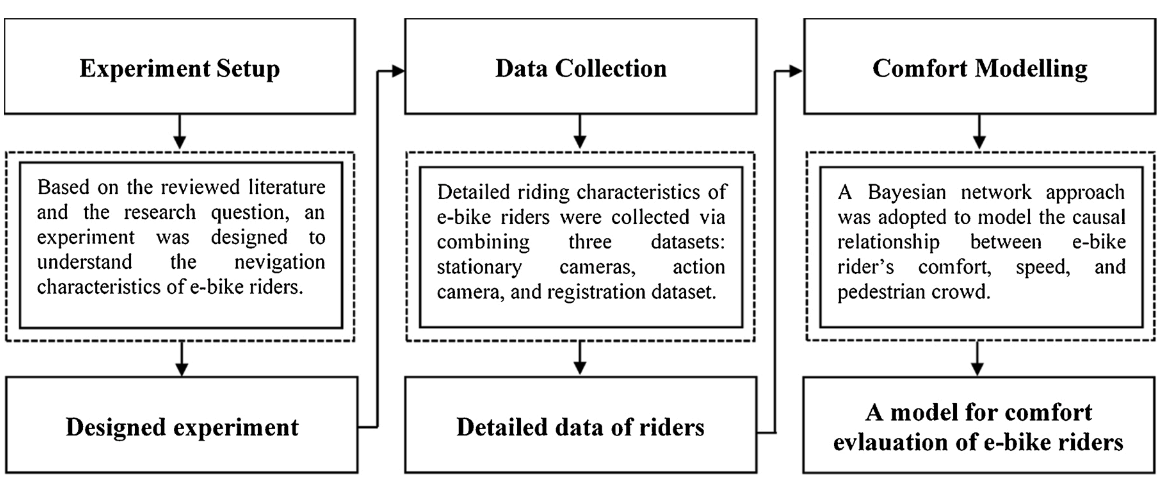

Fig. 1. The proposed framework to model the microscopic characteristics of e-bike riders.

2.2. Quantifying riding comfort of cyclists

Comfort is harmony between human and environment, which encompasses different dimensions such as physical, psychological and sociological characteristics (Slater, 1985). The term *comfort* provides a concise metric for clustering the quality of urban facilities for cycling (Ghodrat Abadi & Hurwitz, 2018). Various terminologies such as bikeability, bike friendliness, and stress level are interchangeably used to quantify riding comfort (Lowry, Callister, Gresham, & Moore, 2012). Among all, *stress* is a commonly used term in this literature. Mekuria, Furth, and Nixon (2012) developed the Level of Traffic Stress (LTS) method based on three variables, namely the number of vehicle lanes, speed limit, and bike lane width. Lowry, Furth, and Hadden-Loh (2016) classified cycling stress using the marginal rates of substitution. They considered the association of input parameters representing cycling stress with the number of lanes and speed limits of a street. Based on this analysis, they identified areas that can be expected to have a better situation for cycling. Caviedes and Figliozzi (2018) conducted a study in the US to measure physiological stress as cyclists travel across different types of bike facilities. They matched video and GSR data to identify the correspondence between the stress of the subjects and situations that they pass through. Leveraging the subjectiveness associated with the definition and measurement of riding comfort, we illustrate how the latent variable modelling approach is suitable for quantifying e-bike riders' comfort in a controlled experimental setting.

2.3. Level of Service (LOS) and riding comfort

LOS is a tool to quantify the comfort offered by a transport facility from the user's perspective. This concept was first introduced by highway capacity manual in 1965. LOS index often represents through a letter system (A–F) which reflects the user's perspective of the comfort and quality of the facility. The representation of the complex numerical computation into simple letter scale makes this index very practical (HCM, 2016). Various studies have evaluated cycling LOS via aggregation of related variables such as motor vehicle speed, motor vehicle volume, the volume of pedestrians and cyclists, the presence of median (Beura & Bhuyan, 2017; Foster, Monsere, Dill, & Clifton, 2015; Jensen, 2007). In similar vein, the freedom of manoeuvring in mixed traffic has also been used as a proxy for riding comfort of cyclists. After the introduction of the notion of *hindrance* during *interactions* by Botma (1995), this idea was adopted in HCM to estimate cyclists LOS in dedicated cycling facilities (HCM, 2016). Nikiforiadis, Basbas, and Garyfalou (2020) used the same concept to estimate LOS in shared pedestrian and bike facilities. They indicated that passing and meeting have similar impact on riding comfort.

2.4. Originality and scope

Our review of the literature demonstrates the importance of measuring comfort in defining LOS of infrastructure facilities and how the concept of hindrance (meeting and passing) is relevant to the comfort measurement. It also illustrates that within the realm of comfort modelling in active mobility, little is known about e-bike riders' comfort. Considering that e-bikes share off-road facilities with other vulnerable road users (e.g., pedestrian and cyclists), high heterogeneity in the speed regimes of different travel modes is the main challenge in comfort (and subsequently LOS) modelling. Therefore, earlier models of active mobility would not be directly applicable in the new era of e-bikes.

Specifically, there is no study with a focus on the evaluation of riding comfort of e-bike riders when they interact with different pedestrian crowds. We take the first step towards understanding the e-bike rider's navigation comfort in pedestrian crowds. The difference in speed of e-bikes and pedestrian increases the frequency of their interactions with pedestrians. Therefore, the estimation of the comfort perceived by an e-bike rider is crucial in defining LOS index of a dedicated bike lane, especially when the proportion of e-bikes is considerably high. This research is the need of this hour due to increasing adoption of e-bikes and emerging interest of governments in promoting e-bike as a sustainable and active mode of transport.

From a methodological perspective, we contribute by illustrating the application of the Bayesian network in comfort modelling. The Bayesian network provides a flexible and interpretable framework to model the joint distribution of random variables and include dependencies. In particular, we represent e-bike riding comfort as a latent variable in a Bayesian network and analyse the data obtained from an experiment where the pedestrian crowding is controlled exogenously. By including lagged effects in the model and supporting distributional assumptions on random variables through empirical data, we identify the causal effect of pedestrian crowding on the comfort of an e-bike rider. We also estimate the relationship between comfort and other riding characteristics such as lateral distance and speed of an e-bike rider. The modelling procedure adopted in this study is general and can be used in modelling comfort in different interactions such as e-bike-bike and bike-pedestrians.

3. Experiment design and data preparation

3.1. Data collection procedure

We conducted an experiment in May 2018 at Lund, Sweden. On the day of the experiment, the weather was sunny and there was no strong wind. We controlled the pedestrian crowding levels on the bike track while participants rode an e-bike. The length of the track was 120 m, with a width of 3.5 m (see Fig. 2). The width of the selected track is similar to a typical bike path in Sweden which is often shared by different vulnerable road users such as bikes, e-bikes, and pedestrian. The dimension of the selected case study (120 * 3.5 m) is also spatially adequate to collect trajectories of road users using multiple cameras and is in line with the previous studies related to the modelling of e-bike interactions (Xu, Liu, Song, & Jin, 2018). We used four stationary cameras, one action camera, and an online questionnaire to collect comprehensive data of the experiment. We selected the experiment site based on three criteria. First, the area was not used frequently in the time of the experiment. When we observed non-participants on the site, we removed runs from the video data. Second, the site of the experiment was close to the health centre to be prepared for unexpected incidents. Third, the location was a straight path without any complexity in geometry such as gradient and curve. The experiment site also had good pavement conditions and was entirely cleaned from possible trashes. The start and end of the experiment site were temporarily painted to guide participants. The procedure of data collection is detailed in the following subsections.

3.1.1. Data from the registration process

We recruited 18 participants via university campus announcements and paid 120 SEK (Swedish Kroner) per hour to each participant. Participants were requested to fill out an online questionnaire prior to the experiment. Table A1 (Appendix A) represents socio-demographic characteristics of participants. The online questionnaire required users' information such as sociodemographic characteristics, e-bike riding habits, and basic information for payment. We provided e-bike to participants at Lund University every day for one month prior to the experiment day to ensure that the participants have experience of riding an e-bike. On the day before the experiment, we sent an email to all participants with instructions about the experiment. We took written consent from all participants as a part of the registration process in the field. We informed participants that they could dispense the experiment whenever they want. In each phase of the experiment, we made sure that e-bike riders use helmet for safety. We did 38 runs of e-bike on the bike path, each for passing and meeting interactions. We had to discard data from 3 meeting runs in the analysis due to technical issues. In each run of the experiment, the e-bike rider was chosen randomly from the participants.

3.1.2. Data from stationary cameras

We collected video data based on a laboratory-controlled field experiment. In order to cover the experiment area, we mounted four fix RGB cameras on a 12-metre height mobile pole. These cameras were partly overlapped to provide the smooth transfer of the tracked agents among different cameras with a continuous track of the agents.

We extracted the trajectories of the e-bike and pedestrians using a semi-automated software T-Analyst. T-Analyst is a powerful tool to handle multiple cameras with a promising accuracy of transferring a tracked user in different cameras. In T-Analyst, the positions of users are retrieved based on the matching of a pre-defined wire-frame model to its images. We calibrated all cameras separately by TSAI-model (Tsai, 1987) to convert the image position to the Cartesian coordinate system. For this conversion, we matched a group of points with known points that we measured in real-time during the experiment by a digital theodolite. In T-Analyst, the users should be marked manually to construct a trajectory of each user. We marked two pedestrians to four e-bikes per second and interpolated their within positions at the resolution of 15 Hz. Previous evaluations by Laureshyn and Nilsson (2018) show that the process used for trajectory extraction is promising to provide a good enough accuracy for this experiment. A screenshot of the T-Analyst during data processing is shown in Fig. 3.

3.1.3. Action camera and data merging

Considering that the height of the stationary cameras was 12 m, there was a risk of error in matching the sociodemographic characteristics of participants with their trajectories. To identify users, a high definition action camera was mounted on the handlebar of the e-bike in all run of the experiment. Fig. 4 shows the screenshot from the video of the action camera.

Participants were numbered randomly, and the laminated numbers were attached to them with soft strings. These numbers helped in matching data from the stationary cameras and the action camera. The participant was manually identified from the action camera to match with the questionnaire dataset. The final dataset includes the traffic and sociodemographic characteristics of participants for each run of the experiment.

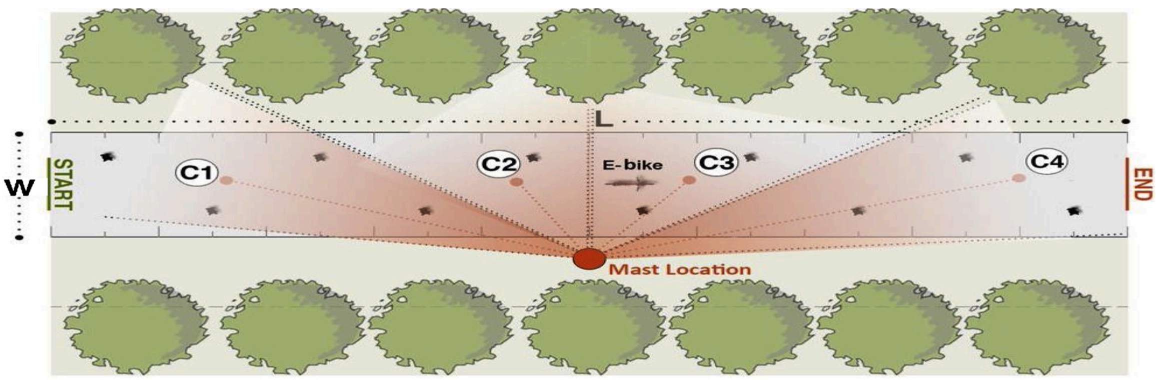

Fig. 2. A schematic representation of the experimental site (not shown to scale) and location of the cameras. (W: width of path ~3.5 m; L: length of path: 120 m, C1 to C4 camera station; adapted from Kazemzadeh, Laureshyn, Ronchi, D'Agostino, & Hiselius, 2020).

Fig. 3. A screenshot of the T-Analyst software (E-bike and pedestrians inside red and yellow boxes respectively).

Fig. 4. A screenshot of the action camera.

3.2. Variable extraction

Previous studies have used different variables to understand interactions between bikes and pedestrians – lateral distance, longitudinal distance, speed, yaw rate, and steering angle (Alsaleh & Sayed, 2020; Mohammed, Bigazzi, & Sayed, 2019). In this study, we calculated pedestrian crowding, e-bike lateral distance, and e-bike speed to investigate the behaviour of e-bike rider. As detailed earlier, we designed the experiment in a way that pedestrian crowding remains the only exogenous variable and the effect of confounding variables such as weather conditions, path geometry, and pavement conditions on the behavior of an e-bike rider can be ignored. Thus, we argue that the tactical behavior of the e-bike rider is *caused* by pedestrian crowding within a given influence area (IA). For this experiment, we used the rectangle as IA to count pedestrians. The rectangle has been used in a similar bike and pedestrian studies to measure the density of pedestrians (Guo et al., 2020). We considered the width of the IA to be same as the width of the bike path (3.5 m) and the length of the IA to be 5 m. If (x_{min} , x_{max}) and (y_{min} , y_{max}) are the maximum and minimum of x and y positions of an IA, and x_p and y_p represent the position of a pedestrian, then we counted pedestrians inside the IA based on Eq. (1):

$$\text{Pedestrians count in IA} = \{(x_p, y_p) | x_{min} \le x_p \le x_{max}, y_{min} \le y_p \le y_{max}\} \quad (1)$$

The lateral distance is defined as the deviation of the e-bike strategical path from the joint points of the straight line that connects the entrance and exit of the IA. Based on the experiment design, it can be assumed that the rider would have kept the straight-line path within the defined IA in unhindered conditions. However, the strategical preference of the rider would change in a hindered condition, in this case, in the presence of pedestrians. We numerically estimated the lateral distance based on the perpendicular absolute distance between an e-bike rider's entrance and exit points of the IA.

We extracted the e-bike speed from the T-Analyst software. Histogram of all observed variables are presented in Fig. 5. Apart from the traffic characteristics, we also obtained sociodemographic variables such as age, gender, and e-bike riding experience of participants. This information was required for the experiment registration and the process to pay participants. The datasets from matching questionnaire, action camera, and stationary cameras enabled us to match the traffic variables of each e-bike rider to her sociodemographic characteristics.

4. Probabilistic graphical model

In this study, we represent the data generating process with DAGs and use the fundamental principles from probability and statistics to obtain the impact of the exogenous pedestrian crowding on the e-bike rider comfort. We also specify how the comfort affects speed and lateral distance of e-bike rider and estimate these relationships simultaneously. We treat the e-bike rider comfort as a latent variable. Fig. 6 represents the DAG for this study.

We consider that the first and last 30 m of the bike path are warm up and cool down periods for an e-bike rider, and therefore, e-bike trajectories on middle 60 m of the bike path are used for analysis. We partition the 60-metre-long bike path into 12 equal segments (i.e., IA). Overtaking (passing) and meeting experiments were repeated 38 and 35 times (i.e., $N = 73$; $T = 12$). We model overtaking and meeting experiment data simultaneously to enrich the statistical power and unveil statistical differences in relationships under both experiments by incorporating interaction of meeting indicator with covariates.

For an e-bike rider i, pedestrian crowds in segment t $(PD_{i,t})$ affects the latent comfort accumulated over the segment t, i.e. the comfort at the beginning of segment $t+1$ $(CT_{i,t+1})$. Moreover, $CT_{i,t+1}$, pedestrian crowds in segment $t+1$ $(PD_{i,t+1})$, and the lagged speed $(SP_{i,t})$ determine the speed of e-bike rider i in segment $t+1$ $(SP_{i,t+1})$. We include lagged

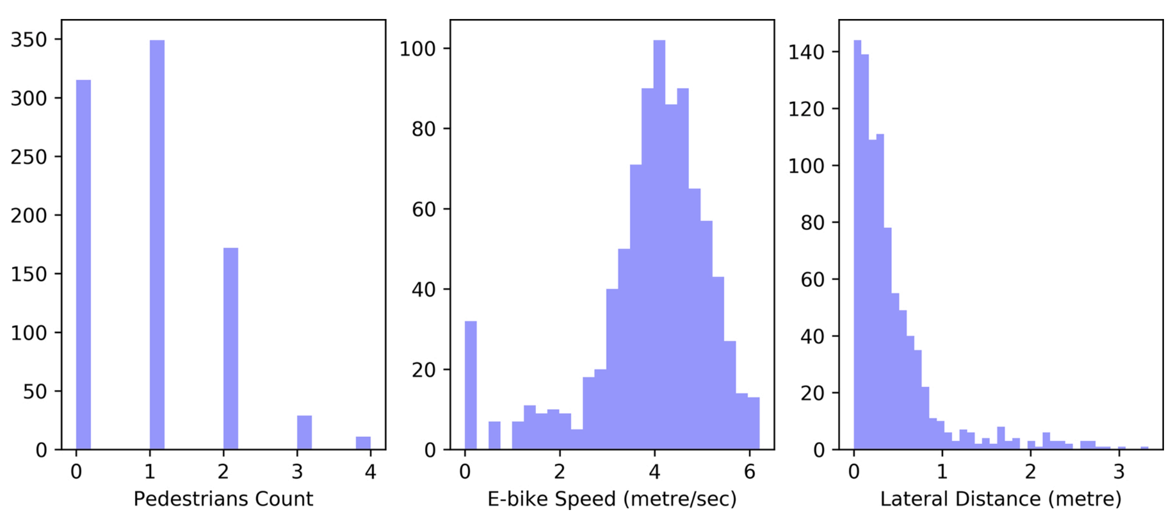

Fig. 5. Histogram of the observed variables.

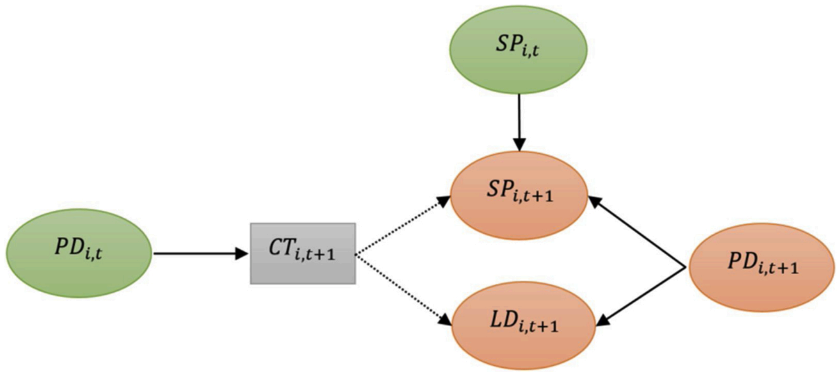

Fig. 6. Directed acyclic graph (DAG) of the data generating process.

speed as a covariate because the autocorrelation coefficient for speed time series is very high (0.504). We also consider that the lateral distance of e-bike rider i in segment $t+1$ $(LD_{i,t+1})$ depends upon $CT_{i,t+1}$ and $PD_{i,t+1}$. However, very low autocorrelation coefficient (0.007) for lateral distance time series suggests exclusion of the lagged relationship. We also do not connect speed and lateral distance nodes due to a low correlation of 0.024 between two time series.

The joint likelihood of the DAG presented in Fig. 6 is shown in Eq. (2) (Bishop, 2006):

$$P\left(CT_{i,t+1}, SP_{i,t+1}, LD_{i,t+1} | PD_{i,t}, PD_{i,t+1}, SP_{i,t}\right) = P\left(ST_{i,t+1} | PD_{i,t}\right) \mathrm{P}\left(SP_{i,t+1} | SP_{i,t}, PD_{i,t+1}, CT_{i,t+1}\right) \mathrm{P}\left(LD_{i,t+1} | PD_{i,t+1}, CT_{i,t+1}\right). \tag{2}$$

As name suggests, the latent variable $CT_{i,t+1}$ is not observed. To evaluate the joint distribution presented in Eq. (2), we need to integrate out $CT_{i,t+1}$ as shown in Eq. (3):

$$\left(SP_{i,t+1}, LD_{i,t+1} | PD_{i,t}, PD_{i,t+1}, SP_{i,t}\right) = \int P\left(CT_{i,t+1}, SP_{i,t+1}, LD_{i,t+1} | PD_{i,t}, PD_{i,t+1}, SP_{i,t}\right) \mathrm{d}CT_{i,t+1} \tag{3}$$

Analytic evaluation of the above integral is challenging, and therefore, we approximate it using Monte Carlo simulation (see Eq. (4)). We take R draws from the probability density function of $CT_{i,t+1}$ and evaluate conditional probabilities $P(SP_{i,t+1}\ldots)$ and $P(LD_{i,t+1}\ldots)$ on each draw $CT_{i,t+1}{}^{(r)}$. To compute the joint likelihood, we final take an average of the product of both probabilities across draws (Bansal, Krueger, Bierlaire, Daziano, & Rashidi, 2020).

$$P\left(SP_{i,t+1}, LD_{i,t+1} | PD_{i,t}, PD_{i,t+1}, SP_{i,t}\right) = \frac{1}{R}\sum_{r=1}^{R} \mathrm{P}\left(SP_{i,t+1} | SP_{i,t}, PD_{i,t+1}, CT_{i,t+1}^{(r)}\right) \mathrm{P}\left(LD_{i,t+1} | PD_{i,t+1}, CT_{i,t+1}^{(r)}\right) \tag{4}$$

Thus, the loglikelihood (LL) the sample is:

$$LL = \sum_{i=1}^{N}\sum_{t=1}^{T-1} \log\left[P\left(SP_{i,t+1}, LD_{i,t+1} | PD_{i,t}, PD_{i,t+1}, SP_{i,t}\right)\right] = \sum_{i=1}^{N}\sum_{t=1}^{T-1} \log\left[\frac{1}{R}\sum_{r=1}^{R} P\left(SP_{i,t+1} | SP_{i,t}, PD_{i,t+1}, CT_{i,t+1}^{(r)}\right) P\left(LD_{i,t+1} | PD_{i,t+1}, CT_{i,t+1}^{(r)}\right)\right] \tag{5}$$

To compute the loglikelihood in Eq. (5), we need to define the distributions of random variables. For observed speed and lateral distance, we plot their empirical kernel density plot and accordingly assume them to follow truncated normal and exponential distributions, respectively. We assume comfort to be normally distributed. The mean values of these distributions are specified as a function of conditioned variables as shown in Eq. (6).

$$\left(CT_{i,t+1} | PD_{i,t}\right) \sim \mathcal{N}(\mu_{ST}, \delta_{CT}) \tag{6}$$

where $\mu_{ST} = f(PD_{i,t}; \boldsymbol{\alpha})$

$$\left(SP_{i,t+1} | SP_{i,t}, PD_{i,t+1}, CT_{i,t+1}\right) \sim TN_{[0,10]}(\mu_{SP}, \delta_{SP})$$

where $\mu_{SP} = f(\, PD_{i,t+1},\ SP_{i,t}\ ,\ CT_{i,t+1};\ \boldsymbol{\beta})$

$$\left(LD_{i,t+1} | PD_{i,t+1}, CT_{i,t+1}\right) \sim Exp(\lambda_{LD})$$

where $\lambda_{LD} = f(\, PD_{i,t+1},\ CT_{i,t+1};\ \boldsymbol{\gamma})$

The maximum likelihood estimation thus becomes an unconstrained optimization problem with $\Theta = \{\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \delta_{CT}, \delta_{SP}\}$ as the decision variable and the loglikelihood (LL) as the objective function. We also include interaction of e-biker's demographics and meeting indicator in the mean specifications of Eq. (6). These interaction effects can potentially account for the personal characteristics of an e-biker such as cycling experience and general risk aversion, among others. We use the traditional Fisher Information matrix (inverse of the Hessian) for inference. We wrote our code in Python programming language for the estimation and inference. It is worth noting that the loglikelihood function is not concave, and therefore, the parameter estimates are sensitive to initial values. We estimate the model using different starting values and choose the one resulting in the maximum value of the converged loglikelihood. At the same time, we also ensure that magnitude of the all elements of the Jacobian at the convergence are at least below 10^{-3}. In the Monte Carlo integration, we test the sensitivity of results relative to the number of draws and find that $R = 200$ draws are sufficient to get the robust parameter estimates.

5. Results and discussion

5.1. Statistical significance

Table 1 shows the parameter estimates of the base specification. The absolute value of the gradient of all parameter estimates is below 10^{-3}, which indicates the convergence of the model. The results show that the lagged pedestrian count has a negative effect on the latent variable (i.e., comfort). We can go beyond interpreting this effect as an "association" and can treat it as the "causal effect" because pedestrians count is the only exogenous variable in the controlled experiment. High t-value of -13.6 indicates that the causal effect is statistically significant at very low significance level. While controlling for the lagged speed and pedestrians count, the effect of an e-bike rider comfort on her speed is positive. The statistically significant relationship further reinforces our characterisation of the latent variable as the e-bike rider's comfort. The interaction effect of the latent variable and the meeting indicator on speed is not statistically significant, that is, we do not have enough statistical evidence to argue that the effect of comfort on speed is

Table 1
Estimation results of the proposed model (base specification).

		Estimates	Standard error	t-stat	Gradient at Convergence
Comfort (α)	Constant	2.461	0.17	14.4	−8.00E-06
	Lagged pedestrian count	−5.998	0.44	−13.6	−8.00E-06
	Standard deviation (δ_{CT})	1.743	0.37	4.8	−8.00E-06
Speed (β)	Constant	0.118	0.02	6.6	−3.80E-05
	Pedestrian count	0.186	0.04	4.2	−8.00E-06
	Lagged speed	0.574	0.03	20.4	−1.50E-05
	Comfort x Meeting?	0.001	0.00	0.4	−2.30E-05
	Comfort	0.015	0.01	2.7	−1.14E-04
	Standard deviation (δ_{SP})	0.101	0.00	29.5	5.30E-05
Lateral distance (γ)	Constant	1.831	0.28	6.6	−8.00E-06
	Pedestrian count	1.751	0.40	4.3	−1.00E-07
	Comfort x Meeting?	0.231	0.98	0.2	−1.00E-07
	Comfort	0.007	0.13	0.1	−8.00E-06
	Initial Loglikelihood	−1100.5			
	Final Loglikelihood	−545.1			

Note: pedestrian count and speed are normalized by 10.

different during passing (overtaking) and meeting. Effects of the latent variable and its interaction with the meeting indicator on the lateral distance also do not appear to be statistically significant.

After accounting for comfort and pedestrian count, an e-bike rider has positive correlation between speed in the current and lagged segments. Finally, pedestrians count has a positive effect on the speed and lateral distance of e-bikers. The effect of pedestrian crowding on the lateral distance is as expected. However, the effect of pedestrians count on the speed is difficult to guess because an e-biker may speed up at a few instances to avoid near crashes with pedestrians. To investigate this result further, we estimate another specification where we parametrise the mean of the speed with dummies for each pedestrian crowding level. We exclude the result table for brevity, but the parameter estimates on pedestrian dummies indicate that the positive effect of pedestrians count on the e-bike rider's speed is statistically significant only if pedestrians count is less than or equal to 2 per segment.

To evaluate the model performance in retrieving probability distributions of the observed variables, we predict lateral distance and speed using simulation. In this process, we first compute the mean of the latent variable (i.e., comfort) for each observation, and then, take a draw from normally distributed comfort for all observations (i.e., $73 \times 11 = 803$). Using these draws, pedestrian counts, and lagged variables, we compute the mean of speed and lateral distance for each observation. Subsequently, we take a draw from truncated normal and exponential distributions for speed and lateral distance for all observations, respectively. These draws provide the predicated kernel density, which we overlay on the observed ones in Fig. 7. These plots indicate that the proposed model is empirically viable as it could retrieve the empirical distribution of the observed variables on their entire support.

Considering that the relationship between the latent variable and lateral distance is not statistically significant, we simplify the model for further analysis and focus on only speed and the latent variable. The results of the reduced model are presented in Table 2. We first estimate the base model (specification 1), and subsequently, explore demographic heterogeneity and differences between relationships under meeting and passing (specification 2). The directions of estimates in specification 1 are consistent with those obtained in the full model. Whereas the pedestrian crowing has a highly negative impact on the comfort of young e-bikers under overtaking conditions, there is almost no such negative impact for e-bikers of age 30 years or above under

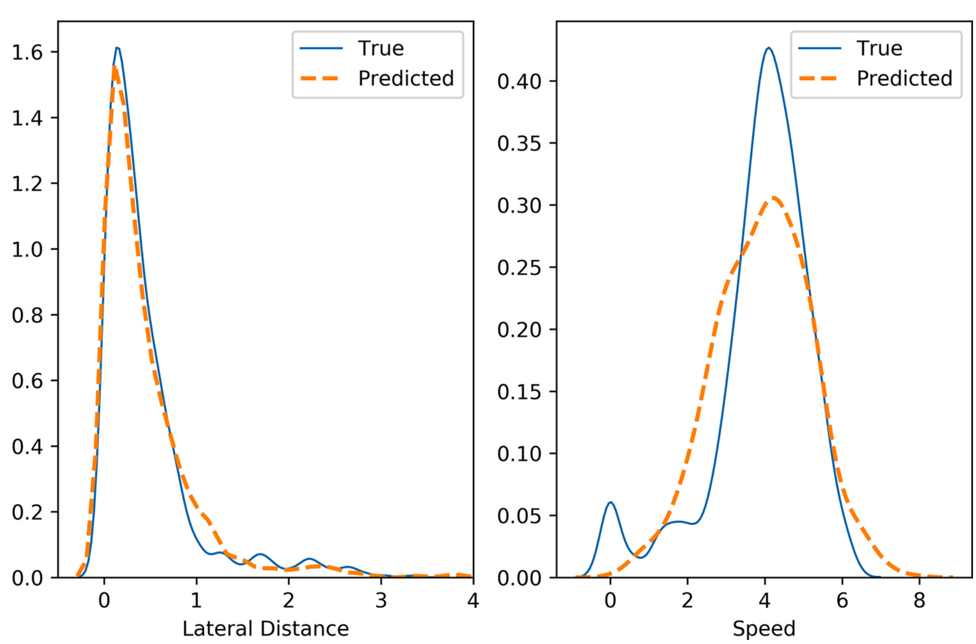

Fig. 7. Comparison of the in-sample predicted distribution with the true distribution.

Table 2
Estimation results of the comfort and speed model.

		Specification 1		Specification 2	
		Estimates	t-stat	Estimates	t-stat
Comfort (α)	Constant	0.468	8.7	0.432	4.5
	Lagged pedestrian count	−0.465	−3.3	−1.129	−5.0
	Lagged pedestrian count x meeting? x (age > 29?)			1.133	3.4
	Standard deviation (δ_{CT})	0.249	7.2	0.515	7.4
Speed (β)	Constant	0.017	0.8	0.096	5.4
	Pedestrian count	0.215	4.7	0.226	3.2
	Pedestrian count x (age > 29?)			−0.164	−2.5
	Pedestrian count x male?			0.154	2.4
	Lagged speed	0.574	18.9	0.565	19.3
	Comfort	0.302	16.6	0.147	18.3
	Standard deviation (δ_{SP})	0.074	8.7	0.073	8.8
	Initial Loglikelihood	−1500.5		−1401.5	
	Final Loglikelihood	−692.4		−687.5	

Note: pedestrian count and speed are normalized by 10.

meeting conditions. Perhaps, older e-bikers are more experienced and meeting further ease down with communication between e-bikers and pedestrians, leading to a negligible effect on the e-bikers' comfort. Consistently, the increase in the speed due to pedestrian crowding is lower for e-bikers of age 30 years or above than that for younger e-bikers. We also find that male e-bikers encounter higher speed increments due to pedestrian crowding as compared to their female counterparts.

5.2. Practical significance

Whereas Table 2 evaluates the statistical significance of various relationships, the practical significance of these estimates is difficult to understand due to inherent uncertainty. In other word, it is important get a sense of the magnitude of these mean marginal effects relative to standard deviations. To visualize these mean marginal effects under uncertainty, we first plot the kernel density of comfort at different pedestrian crowding levels in Fig. 8. We observe that a shift in the mean comfort of the young e-biker due to the change in pedestrian crowding during passing is substantial enough to be relevant even in the presence of inherent uncertainty. Consistent with the estimates, such effect is negligible for older e-bikers under meeting conditions.

Similarly, we plot the changes in kernel density of the e-biker's speed in response to comfort while keeping all observed variables at their

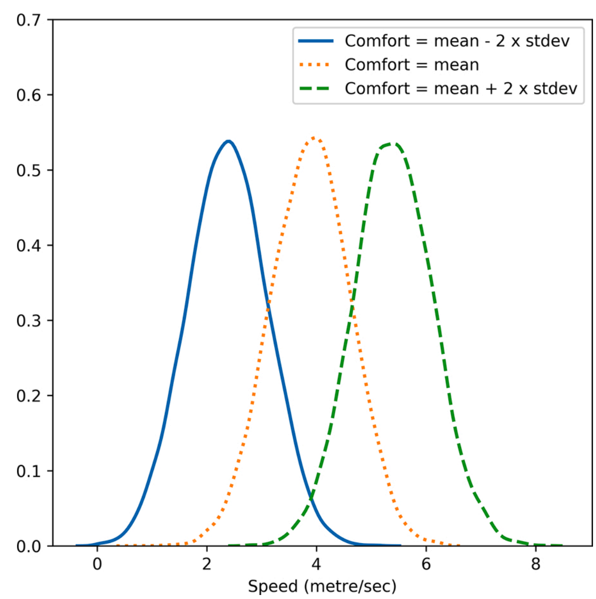

Fig. 9. Effect of comfort on the distribution of the e-biker's speed.

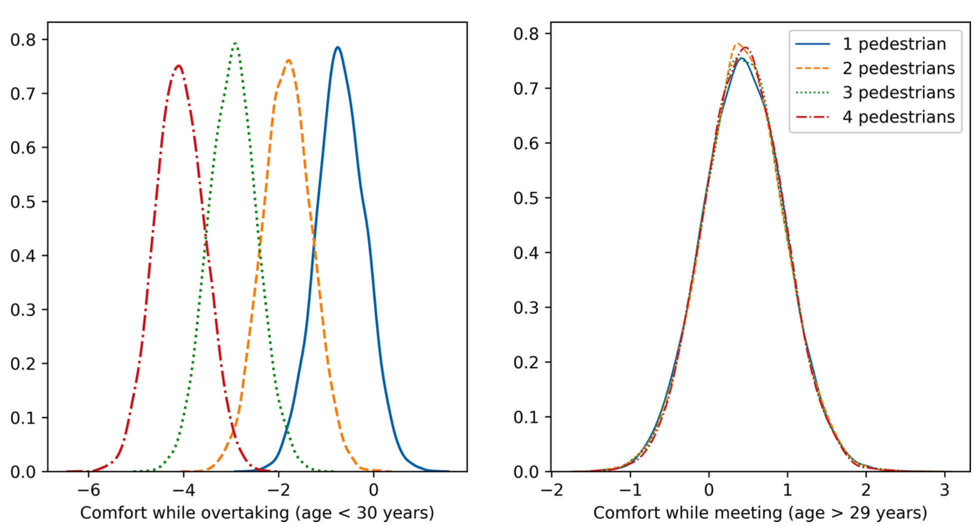

Fig. 8. Effect of pedestrian crowding on the distribution of the e-biker's comfort.

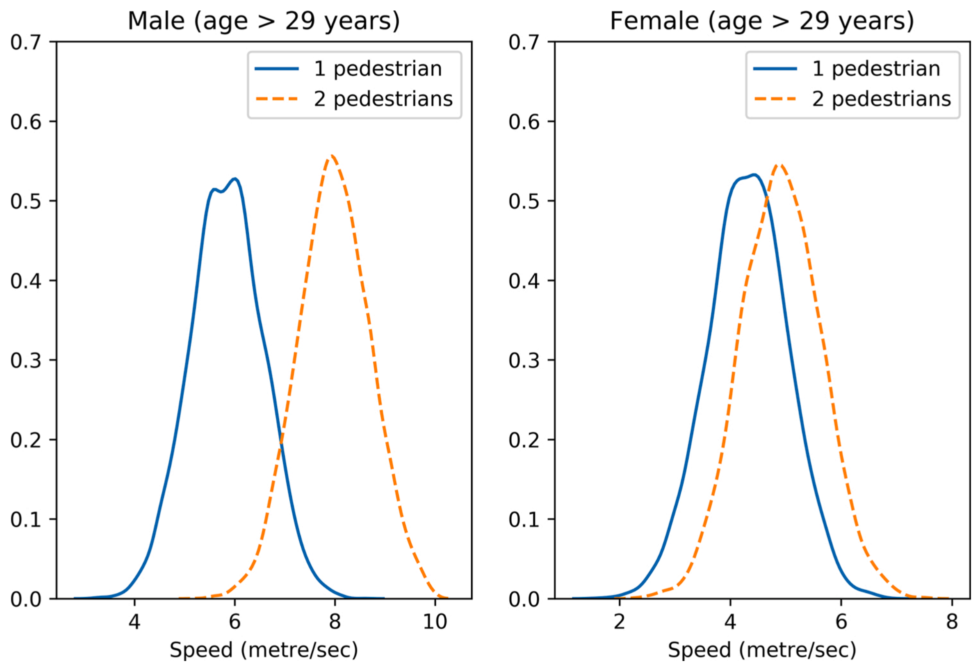

Fig. 10. Effect of pedestrian count on the distribution of the e-biker's speed.

sample mean values. To make these plots, we compute mean comfort by predicting comfort and taking its average across all observations. These plots in Fig. 9 indicate that changes in comfort are practically significant for speed of the e-bike rider. We also present the demographic heterogeneity in the effect of pedestrian crowding on the e-biker's speed in Fig. 10 . These plots indicate that pedestrian crowding affects the speed of male e-bikers more, as compared to their female counterparts.

5.3. Practical relevance

We now discuss the practical relevance of these results. The following four hypotheses are intuitive, and most of them are well-established in the cyclists LOS literature. First, since the bike tracks are relatively narrower and speed regimes of bikes are different from pedestrians, pedestrians are likely to impose significant discomfort on cyclists as they try to avoid any conflict/collision. Second, consequently, the e-bike riders adjust their traffic characteristics such as speed and lateral distance due to hindrance. Third, pedestrian crowding may cause relatively lower discomfort during meeting encounters as the e-bike rider and the pedestrian can communicate nonverbally, and both parties are involved in evasive action. Fourth, the effect of pedestrian crowding on riding behaviour should vary across different demographic groups. We not only validate these hypotheses for "e-bikes" but also empirically quantify all these relationships in reusable mathematical equations. All these results are crucial in advancing the ongoing research on developing LOS index and microsimulation models for e-bikes, which in turn are relevant in the design and management of bike tracks where the presence of e-bikes is prevalent. We put this discussion in perspective below in detail.

5.3.1. E-bike LOS

Different policies and programs have been adopted across the Globe to increase the adoption of e-bikes. For instance, the Swedish government subsidised 25 % of e-bike purchase prices in 2018 to support active and sustainable transport modes ("Swedish Law for e-bike," 2018). Transport network infrastructure is an expensive component of the investment, and therefore, precise evaluation metrics is essential for the effective investment decisions to facilitate the mission towards sustainable mobility. LOS is a powerful tool that can potentially assist in the evaluation of e-bike infrastructure design, and consequently, can help in making effective policies and investment decisions. However, the research in the area of the e-bike LOS is quite limited and is at a very nascent stage (Kazemzadeh, Laureshyn, Winslott Hiselius, & Ronchi, 2020)

The results of this study can help in classifying the e-bike rider's comfort (and LOS) under different pedestrian crowding levels, which can in turn be useful in defining letter-based LOS (e.g., A, B, …, F). As the riding comfort is estimated based on the concept of *hindrance*, these findings are relevant for the development of the LOS index for e-bikes based on the HCM framework. The modelling procedure allows differentiating LOS index under passing and meeting events, which is in line with the existing literature on bike LOS. The model also quantifies the impacts of sociodemographic characteristics of a user on her level of comfort which is useful to understand the diversity of perceived comfort across users.

5.3.2. Microsimulation models

Microscopic simulation of the traffic system is a powerful tool to evaluate the impact of transport infrastructure interventions prior to their implementation. Researchers have adopted different methodologies to simulate homogeneous and heterogeneous bike traffic flow. For instance, Jiang, Hu, Wu, and Song (2016) adopted the cellular automata approach to model homogeneous bike flow. Liang, Mao, and Xu (2012) developed a psychological-physiological force model to simulate heterogeneous bike flow. However, there is limited literature on microsimulation models for bike traffic flow, which are validated using empirical data (Twaddle, Schendzielorz, & Fakler, 2014). More importantly, there is no comprehensive study that analyses microscopic interactions of e-bikes with other vulnerable road users to be further used for developing e-bike microsimulation models in shared mobility. The findings of this study reveal the dynamic behaviour of the e-bike rider relative to the change in the level of pedestrian crowding. Incorporating empirically learned parameters of dynamic behaviour models in microsimulations improves their realism. The parametric relationships derived in this study can thus be used as inputs for developing e-bike microsimulation models that can capture the interactions of e-bikes and pedestrians in shared mobility.

6. Conclusions

Little is known about the microscopic characteristics of the e-bike in shared mobility. We take the first step towards the development of a stochastic model to evaluate the comfort of e-bike riding in pedestrian crowds. We adopt Bayesian networks to quantify the causal effect of pedestrian crowding on the e-bike riding comfort. We also estimate how the comfort affects the speed and lateral distance of an e-bike rider. The model is calibrated using the data collected from a laboratory-controlled experiment. The estimated parametric relationships have direct implications in designing cyclists' facilities, LOS evaluation, and developing microsimulation models for e-bikes.

Our study is not without limitations. First, a controlled experiment provides detailed traffic characteristics of pedestrians and e-bike riders, but their behaviour may differ from a naturalistic study in which they do not notice the recording. Second, our experimental setup did not include any environment- and infrastructure-related variables such as complex road geometries, different pavement conditions, different weather conditions, and other variables that may associate with the comfort of the e-bike riders. Whereas this controlled setup enabled us in identifying the *causal effect* of pedestrian crowding on the e-bike rider comfort, consideration of additional variables could yield a more realistic representation of comfort.

Since this is the first study on microscopic characteristics of e-bikes in shared mobility, several avenues of future research emerge. Apart from addressing limitations of this study by improving the experiment to account for the above-discussed influencing variables, this study can be further extended to investigate the comfort of an e-bike rider in the mixed flow of e-bikes, bikes, and pedestrians. Our consideration of the maximum speed differences in shared mobility (e-bike and pedestrians) advances the baseline for further evaluation of different mode combinations (e.g., bike/e-bike and bike/pedestrians). Without loss of generality, the proposed framework is transferrable to all the suggested advancements. Having distribution of riding comfort and parametric relationships between riding characteristics under various infrastructure-related and mixed-traffic conditions would help planners in better evaluation of LOS from the perspective of bike lane users and developing more realistic micro-simulation models of shared sustainable mobility.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A

Table A1
Socio-demographic characteristics of participants.

Participants' ID	Gender	Have you ever ridden an electric bike?	How often do you ride a bike?	age
1	Male	Yes	Everyday	30
2	Male	Yes	Everyday	27
3	Female	Yes	Everyday	24
4	Female	No	Everyday	28
5	Female	No	Everyday	25
6	Female	No	Everyday	25
7	Female	No	Everyday	34
8	Male	Yes	Everyday	25
9	Male	No	Everyday	30
10	Male	No	Everyday	26
11	Male	Yes	Everyday	26
12	Female	No	Everyday	18
13	Female	No	Everyday	34
14	Male	No	Everyday	34
15	Female	Yes	Everyday	30
16	Female	No	Rarely	32
17	Female	No	Rarely	25
18	Male	No	Everyday	38

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