Navigating the social-technological intersection: Analyzing pedestrian risk perception, trust in autonomous vehicle, and crossing decisions with the ICLV model

Zhongxiang Feng, Ya Gao, Dianchen Zhu, Ho-Yin Chan, Mingming Zhao and Rui Xue

Navigating the social-technological intersection: Analyzing pedestrian risk perception, trust in autonomous vehicle, and crossing decisions with the ICLV model

Zhongxiang Feng
School of Automobile and Traffic Engineering,
Hefei University of Technology, Hefei, Anhui, PR China
Email: fzx@hfut.edu.cn

Ya Gao
School of Automobile and Traffic Engineering,
Hefei University of Technology, Hefei, Anhui, PR China
Email: 2021171035@mail.hfut.edu.cn

Dianchen Zhu (Corresponding author)
School of Automobile and Traffic Engineering,
Hefei University of Technology, Hefei, Anhui, PR China
Intelligent Interconnected Systems Laboratory of Anhui Province,
Hefei University of Technology, Hefei, Anhui, PR China
Email: dianchen.zhu@hfut.edu.cn

Ho-Yin Chan
School of Geography and the Environment,
University of Oxford, Oxford, UK
Email: ho.chan@ouce.ox.ac.uk

Mingming Zhao
State Key Laboratory of Integrated Services Networks,
Xidian University, Xi'an, Shaanxi, PR China
China and Hangzhou Institute of Technology,

Xidian University, Hangzhou, Zhejiang, PR China
Intelligent Interconnected Systems Laboratory of Anhui Province,
Hefei University of Technology, Hefei, Anhui, PR China
Email: zhaomingming@xidian.edu.cn

Rui Xue
Hefei Duowan Information Technology Co., Ltd, Hefei, Anhui, PR China
Email: flyrxue@163.com

Acknowledgements

This paper was supported by the National Natural Science Foundation of China (Grant Nos. 71971073, 52272345, 52302432), the Anhui Provincial Key Research and Development Plan (Grant No. 202304a05020050), the Science and Technology Plan Project of the Housing Urban and Rural Construction in Anhui Province (Grant No. 2023-YF095), the Natural Science Foundation in Anhui Province (Grant No. 23080850E189), and the Fundamental Research Funds for the Central Universities of China (Grant Nos. PA2023IISL0094, JZ2022HGQA0123, JZ2023HGTA0192).

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.

CrediT authorship contribution statement

Zhongxiang Feng: Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Funding acquisition. **Ya Gao:** Conceptualization, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Dianchen Zhu:** Conceptualization, Methodology, Writing - review & editing, Validation, Supervision. **Ho-Yin Chan:** Conceptualization, Methodology, Writing - review & editing. **Mingming Zhao:** Conceptualization, Methodology, Supervision. **Rui Xue:** Supervision, Writing - review & editing.

Navigating the social-technological intersection: Analyzing pedestrian risk perception, trust in autonomous vehicle, and crossing decisions with the ICLV model

Abstract

In the rapidly evolving realm of transportation technology, the dynamic relationship between pedestrians and technological innovations has attained unprecedented importance. The complex social-technological intersection surrounding pedestrian road crossings has emerged as an attention for traffic safety. What distinguishes the contemporary urban environment is the rapid assimilation of intelligent transportation systems (ITS) into the transportation infrastructure, including technological elements such as autonomous vehicles, advanced surveillance systems, and smart infrastructure. To investigate how pedestrians perceive risks, trust technology, and make decisions in this era of technological progress, we designed a video-based questionnaire utilizing the stated preference (SP) methodology. We collected SP data from 589 Chinese pedestrians and employed an integrated choice and latent variable (ICLV) model to quantify the influence of risk perception and trust in autonomous vehicle (trust in AV), treated as latent variables, on their crossing decisions. Our findings indicate that the presence of autonomous vehicles significantly affects pedestrian crossing decisions. Specifically, an increase in the approaching vehicle speed and a decrease in the approaching vehicle distance increase the pedestrians' tendency to choose not to cross the road, and the latent variables of risk perception and trust in AV strongly predict this phenomenon. The results of the scenario analysis show that, compared with overall pedestrians, middle-aged pedestrians and high-risk perception-level pedestrians are more conservative in their crossing decisions, but high levels of trust in AV improve pedestrians' willingness to cross the street. Additionally, the pedestrian-related findings of this study at the social-technological intersection provide better understanding of the decision process and contribute to the planning and development of urban intelligent transportation systems.

Keywords: Pedestrian crossing; Autonomous vehicles; Surveillance cameras; Intelligent transportation systems; Risk perception; Trust

1 Introduction

Pedestrian mobility is experiencing a resurgence as an eco-friendly and health-conscious mode of transportation that contributes to reduced traffic congestion, improved well-being, and environmental sustainability (Bornioli et al., 2019; Ton et al., 2019; Saxena 2023). However, with the accelerated pace of urbanization and the continuous increase in traffic volume, pedestrians, as vulnerable road users, are facing increasingly prominent safety issues in road traffic participation. This is particularly evident in China, whose population has been among the highest in the world (Wang et al., 2020). Evidence shows that 42% of traffic deaths were pedestrians from 2006 to 2016 (Wang et al., 2019), while globally, the percentage is 23% (World Health Organization, 2023). Intersections typically serve as bottlenecks in traffic networks, and the frequency of traffic accidents is very high (Awadallah, 2009; He et al., 2019). Greater emphasis should be placed on ensuring the safety of pedestrians navigating crosswalks within intersections. This has become particularly crucial amidst the rapidly evolving landscape of transportation technology, where intelligent transport systems (ITS), including autonomous vehicles, advanced surveillance systems, and intelligent infrastructure, are being rapidly integrated into the transportation fabric. In this era of technological advancement, pedestrian crossing decision transcends mere random choices and is intricately shaped by factors such as environmental facilities, individual risk perception, and trust in technology (Cœugnet et al., 2019; Soathong et al., 2021; Song et al., 2023). It is crucial to understand how pedestrians perceive risk and trust technology and how these influence their decisions while navigating crossings. This understanding not only has profound implications for enhancing pedestrian safety but also plays a pivotal role in informing policy decisions aimed at creating intelligent and sustainable urban environments.

Technological advancements promise safer and more efficient transportation networks, but they also introduce new variables that influence pedestrian decision behaviors. On the one hand, the development of autonomous vehicles is expected to reduce pedestrian traffic accidents, and China, as the world's largest automobile market, is confident in the development of autonomous vehicles (Wang et al., 2020). Autonomous vehicle technologies have become critical factors in shaping pedestrian crossing decisions (Deb et al., 2017; Velasco et al., 2021; Li et al., 2023). For instance, pedestrians may adjust their behaviors when interacting with autonomous vehicles, trusting their adherence to traffic rules or adapting to their presence on the road (Velasco et al., 2021).

Surveillance systems, on the other hand, may influence perceptions of safety, privacy, and surveillance, all of which can sway pedestrians' decisions at crosswalks and intersections (Li et al., 2023). The ways pedestrians interpret and respond to autonomous vehicles, surveillance systems, and other ITS components profoundly impact their crossing behaviors, safety, and overall urban mobility. Therefore, the importance of investigating the presence of these emerging technologies for pedestrian decision cannot be overstated.

Risk is often used as a key indicator in traffic safety assessments (Zhang et al., 2022). Hansson (2010) clearly points out in the literature that risk is twofold, involving both objective facts of the physical world and statements (of value) that do not include objective facts of the physical world, which contain both objective and subjective components. In the field of transportation, risk can be understood as the combination of both the probability and predicted severity of potential adverse effects resulting from a hazard, which have the potential to cause accidents (Chen and Jou, 2019; Federal Aviation Administration, 2022). Risk perception is an individual's evaluation of the risks associated with potential traffic hazards, involving their perceives of the probability and severity of the consequences of an accident (Deery, 1999). Individual risk perception may influence pedestrians' propensity to take risks (Li et al., 2022). Quantifying the risk perceptions of pedestrians and analyzing the risk factors inherent to pedestrian crossing are challenging tasks. First, different decisions involve different risk levels; for example, obeying traffic signals is considered a safe decision, while running red lights is considered a dangerous decision (Zhu et al., 2021). In addition, situational risk factors, such as vehicle distance (Liu and Tung, 2014), speed (Tian et al., 2022), roadside environment (Zhang et al., 2023a), and potential driver behavior (Fu et al., 2022), need to be accurately quantified and extracted, as these factors have a great impact on the assessment of scene risk. Moreover, differences in societal and cultural backgrounds may also lead to variations in the perception of scenario risks across populations.

In the field of interaction between pedestrians and autonomous vehicles, besides risk perception, trust in autonomous vehicle (trust in AV) is considered as an important factor that affects pedestrians' crossing decision (Velasco et al., 2019; Pal et al., 2022). Generally, the trust is defined as "an attitude in which the agent will help fulfil personal goals in scenarios marked by vulnerability and uncertainty (Lee and See, 2004)." The varying degrees of trust that pedestrians have towards autonomous vehicles will affect their willingness to cross the street (Velasco et al., 2019). Additionally, research by Siegrist (2021) highlights that trust can help better understand the perception of certain risk. Therefore, conducting a thorough investigation into pedestrians' trust in AV will facilitate a deeper understanding of their risk perception and decision process when navigating road crossings.

Previous studies have revealed safety issues faced by pedestrians in complex road crossing scenarios across countries and regions (Zhang et al., 2019; Leung et al., 2021; Osorio-García et al., 2023). However, these studies fail to clearly explain the relationships between various risk factors and pedestrian crossing decisions under the influence of different types of pedestrian risk perceptions and trust in technology, particularly in China. Moreover, establishing a model to explain the factors influencing pedestrian crossing decisions is also a key problem that needs to be solved.

1.1 The current paper

The aim of the paper is to investigate how traffic scenario characteristics, pedestrians' risk perception, trust in autonomous vehicles (AV), and individual characteristics influence pedestrians' decision to cross the street. We achieve this aim by constructing a model that simulates the choice of pedestrians crossing the street. Specifically, a video-based stated preference (SP) questionnaire was designed, and an integrated choice and latent variable (ICLV) model was adopted to integrate multiple factors to comprehensively and accurately explain and predict pedestrian crossing decision.

Through this study, we can reveal the impact of scenario factors on the decisions of different types of pedestrians to achieve targeted design and guidance. By examining the interplay between pedestrians and ITS technologies, we aim to shed light on the factors that influence crossing decisions. Furthermore, we seek to provide valuable insights for policymakers, urban planners, and transportation authorities that can help them craft informed and effective policies to foster the safe coexistence of pedestrians and evolving transport technologies. The relationships between risk perception and trust in AV, as latent variables, and other social-technological factors, as well as decisions, can be revealed, which can serve as a reference for formulating directional guidance and educational intervention to promote the continuous improvement of the urban traffic environment. Our exploration not only contributes to the overarching goal of enhancing pedestrian safety but also advances the vision of ITS for the benefit of all road users and the environment.

The remainder of the paper is structured as follows: Section 2 provides a review of past pedestrian crossing decision studies. Section 3 describes the questionnaire survey, experimental design, model development and specification. Section 4 subsequently describes the collected data and sample situation. Section 5 introduces the estimation results and effect analysis of the ICLV model, followed by the discussion and impact in Section 6. Finally, conclusions and limitations of the study are provided in Section 7.

2 Literature review

2.1 Influencing social-technological factors of pedestrian crossing decisions

In contemporary society, pedestrian crossing choices have become complex multifactor decisions. This complexity is influenced by social-technological factors, which represent the combined impact of social and technological elements. These factors play a vital role in shaping how individuals interact with and adapt to technology, including innovations such as autonomous vehicles and surveillance cameras.

2.1.1 Traffic environment factors

The road traffic environment is one of the factors that affects pedestrian crossing decisions and includes but is not limited to traffic flow, vehicle speed, intersection design, pedestrian flow, traffic lights, and vehicle automation types (Mfinanga 2014; Patra et al., 2020; Theofilatos et al., 2021; Zhang et al., 2023a; Song et al., 2023). A key influencing factor in pedestrian crossing decisions is the crossing time interval, which is determined by the speed and distance of approaching vehicles (Liu and Tung, 2014; Soares et al., 2021; Tian et al., 2022; Ma et al., 2024). For instance, Tian et al. (2022) discussed the influence of vehicle distance and speed on pedestrian crossing behavior and found that pedestrians tend to exhibit more unsafe crossing behavior (e.g., smaller shorter postencroachment times) at given time gaps under higher speed conditions. Therefore, understanding the mechanism of the influence of approaching vehicle speed and distance on pedestrian crossing decisions will help to formulate appropriate countermeasures to reduce the difficulty of pedestrian crossing.

The type of vehicle automation also has an important impact on pedestrian crossing decisions (Rad et al., 2020; Velasco et al., 2021; Zhao et al., 2022). Studies have shown that the impact of this factor on pedestrian crossing varies across countries and regions. A survey study of British pedestrians found that the type of vehicle affected the way participants perceived the risk, but there was no statistically significant difference in their intention to cross. Notably, participants who identified the vehicle as an autonomous vehicle generally had lower intentions to cross (Velasco et al., 2021). In contrast, Zhao et al. (2022) investigated the intention of Australian pedestrians to cross the street through a questionnaire, and the results showed that, compared with human-driven vehicles, pedestrians have a significantly greater willingness to cross the street before approaching autonomous vehicles. Therefore, further research is needed on how the presence of autonomous and human-driven vehicles affects pedestrians' crossing decisions, especially in China, which attaches great importance to the development of autonomous vehicles.

In the realm of ITS, it was observed that surveillance systems, such as yielding cameras, are used to enforce traffic laws and improve road safety conditions worldwide, and have a significant impact on driver behaviors. However, this influence was minimal when it came to pedestrians' crossing decisions. This was largely because few pedestrians were aware of the yielding cameras while crossing, as reported by Li et al. (2023). Nevertheless, how speed and distance relate to this perception and the combined effects of surveillance cameras on crossing decisions when considering autonomous vehicles remain unclear.

2.1.2 Demographic factors

Evidence shows that individual factors such as pedestrian age, gender, and behavioral habits (Soathong et al., 2021; Zhu et al., 2023) also play important roles in pedestrian decision. For instance, Soathong et al. (2021) found that compared with men, women's decision intentions regarding crossing are more easily influenced by attitude. In addition, studies have shown that young and elderly pedestrians also exhibit large differences in crossing performance, and elderly pedestrians more likely to make unsafe crossing decisions (Dommes et al., 2014; Luiu 2021). Moreover, pedestrians with different cultural backgrounds also exhibit differences in crossing behaviors (Sueur et al., 2013). Although this literature serves as a basis for future research, few studies have explored pedestrian crossing decisions in depth, and few have considered other socioeconomic characteristics, such as occupation and involvement in accidents. In addition, the influence of the interaction of environmental characteristics created by technological advancements such as autonomous vehicles and surveillance cameras on pedestrian crossing decisions should also be considered.

2.2 Methodology for collecting pedestrian crossing data

The diversity of survey methods for pedestrian crossing data enables researchers to obtain an in-depth understanding of pedestrian behavior and decision from different perspectives, and different data collection methods may also lead to different results on pedestrian behavior (Lanzer et al., 2021). Simulation experiments (Song et al., 2023) and real road experiments (Liang et al., 2022), given their advantages of allowing researchers to highly control experimental conditions and collect reliable data, have been used by relevant scholars to conduct pedestrian crossing studies. In addition, other data collection techniques, such as site observation (Aghabayk et al., 2021) and video analysis (Patra et al., 2020; Zhang et al., 2023b), have also been adopted. Notably, compared to the aforementioned data collection methodologies, the questionnaire survey, as a convenient, efficient, and low-cost data collection methodology (Özkan and Lajunen, 2011), is widely used in studying the behaviors and decisions of pedestrians (Zhu et al., 2021; Esmaili et al., 2021). For instance, Esmaili et al. (2021) investigated the relationship between pedestrian behavior and collisions through the Pedestrian Behavior Questionnaire (PBQ). However, as documented in the literature, there is still a gap between self-report questionnaire data and real-world data. Although this gap may not be eliminated, at least the gap can be greatly reduced through the full use of self-report methods (Reason et al., 1990). However, few studies have comprehensively collected data on pedestrian crossings, such as personal preferences, individual perceptions and trust in technology, and sociodemographic information.

2.3 Risk perception and trust in AV in pedestrian crossing decisions

The travel choice literature increasingly emphasizes the important role of individual perceptions in travel decisions (Wang et al., 2023; Kim and Lee, 2023; Wang et al., 2024). However, studies usually adopt the traditional logit paradigm to conduct discrete choice modeling for pedestrian selection; such as methods include multinomial logit (MNL), mixed logit, and random parameter multinomial logit (RPMNL) models (Zhu and Timmermans, 2009; Liu et al., 2020; Nabipour et al., 2022; Liang et al., 2023), which do not fully consider individual perceptions and trusts.

According to previous studies, risk perception plays an important role in pedestrians' crossing decisions (Salducco et al., 2022; Saxena 2023), and a lower risk perception may lead to more accidents. Scholars have conducted research on the assessment and quantification of pedestrian risk perception. On the one hand, self-report tools, online tasks and surveys are widely used at the subjective level (Dinh et al., 2020; Rankavat and Tiwari, 2020; AlKheder et al., 2022), as these aspects mainly focus on the perceptions of pedestrians. For example, Dinh et al. (2020) found that a higher level of traffic risk perception is associated with safer pedestrian behavior through a questionnaire survey of 835 road users. On the other hand, with the rapid development of eye tracking and virtual reality technology, visual search patterns (Feng et al., 2022) and behavioral performance (Kwon et al., 2022) are used to evaluate pedestrian capacity for risk perception. For instance, eye tracking experiments based on realistic scenes have shown that different visual search patterns affect pedestrian risk perception and thus affect pedestrian decisions (Feng et al., 2022). However, although the risk perception of pedestrians has been quantitatively assessed, the modeling and analysis of pedestrian crossing decisions have not fully considered the impact of individual risk perception factors and the interaction of social-technological factors.

The issue of trust in AV has become an important topic in the research on pedestrian crossing decisions. Relevant scholars have explored the impact of trust in AV on pedestrian crossing decisions during the interaction between pedestrians and autonomous vehicles or human-driven vehicles from the perspective of psychology and behavior by considering external human–machine interactions as the entry point (Deb et al., 2017; Velasco et al., 2019; Jayaraman et al., 2019; Zhou et al., 2021; Faas et al., 2021). For example, Deb et al. (2017) conducted a survey on the acceptance of autonomous vehicles through questionnaires and found that pedestrians' reluctance to cross in front of autonomous vehicles is largely influenced by their mistrust of the unknown associated with this technology. Jayaraman et al. (2019) found that the more trust pedestrians have in autonomous vehicles, the more trust-based behaviors they will exhibit, such as being more willing to cross the street when an AV approaches. However, with the development of autonomous vehicle technology, the level of vehicle automation and the penetration rate of autonomous vehicles are increasing, and the pedestrians' potential trust in AV may also change (Wu et al., 2023). Therefore, it is necessary to further examine the role of trust in AV in the selection of pedestrian crossing patterns.

3 Methods

3.1 Video-based questionnaire survey

An online video-based questionnaire survey was conducted from 18 May 2023 to 8 June 2023 using the Tencent questionnaire platform (https://wj.qq.com/index.html) to investigate pedestrians' crossing decisions. The platform records respondent IP addresses and the user's nickname. The IP address is used only to prevent the same respondent from answering the questionnaire repeatedly, and real information about the respondent cannot be obtained. Prior to completing the questionnaire, the respondents were informed that the survey results were anonymous, that they did not involve private information and that they would be used only for academic research. To increase participation, generous compensation was given for each completed questionnaire.

The video-based questionnaire for this study consisted of four parts: (a) SP experiments on pedestrian crossing choices (including crossing choices and the measures of risk perception). To improve the participants' immersion experience, we produced a visual video of the street crossing scene based on the actual road scene and presented a video with high reproductions of each scene in the questionnaire script. This survey method is helpful for vividly and intuitively displaying street crossing scenes; (b) the issue of trust regarding autonomous vehicles; (c) travel habits (i.e., weekly walking frequency per week, experience of traffic accidents, etc.); and (d) background information (sociodemographics).

3.2 Stated preference (SP) experimental design

SP survey methods can be used to examine individual preferences in a hypothetical setting to allow researchers to conduct surveys in a controlled experimental setting and to assess the effectiveness of policy strategies that have yet to be implemented. Currently, this method is widely applied to travel mode selection (Esztergár-Kiss et al., 2022), pedestrian facility preference (Liang et al., 2023), electric vehicle charging intention (Hoen et al., 2023), and parking intention surveys (Tian et al., 2023). Although the current research explores pedestrian preferences for crossing facilities through SP questionnaires (Zhu et al., 2023), few SP surveys or studies have assessed pedestrian crossing preferences. The influence of the interaction between environmental conditions, personal characteristics, risk perception, and trust in AV on pedestrian crossing decisions needs to be further explored and clarified.

To measure the interactive effects of the combination of approaching vehicle speed, distance, type, and surveillance camera on pedestrian decision at crosswalks, an SP experiment was designed. This will contribute to the understanding of effective enforcement strategies and provide useful insights into future urban traffic planning, policy development, and safety management. The SP choice sets are presented based on a hypothetical scenario involving pedestrian crossing travel. It is assumed that there are three decision patterns (i.e., not cross, quickly cross, and normally cross) for pedestrians to choose from when facing an unsignalized intersection, and they can make crossing decisions under different risk level scenarios according to the given information. Table 1 presents the attributes and levels considered in the experiment. We conducted a pilot study to identify key attributes prior to conducting the choice experiment. Twenty-eight people were recruited through a campaign conducted on university campuses, and these individuals were asked to provide information regarding demographics and socioeconomic issues. However, considering the complexity of choice set generation and the efficiency of parameter estimation models, not all potential attributes could be included. Finally, the pilot survey incorporated the following four attributes: approaching vehicle speed, as represented by three levels accounting for the speed limit and prevailing speed on urban roads (Soares et al., 2021); distance from the approaching vehicle to the crosswalk, as represented by three levels accounting for the approaching vehicle speed and crossing gap time (Liang et al., 2022; Song et al., 2023); types of approaching vehicles, including both autonomous and manual driving vehicle levels; and whether a surveillance camera was installed to reflect the impact of road infrastructure. In addition, after completing the choice of each crossing scenario, participants were also required to complete two risk perception questions to test their perception of the probability and severity of accidents in the scenario (as shown in Table 2).

Table 1 Attributes and levels considered in the SP experiment

SP Attributes	**Levels**
Approaching vehicle speed (km/h)	20, 30, 40
Approaching vehicle distance (m)	20, 35, 50
Types of approaching vehicle	(1) Autonomous vehicle (2) Manual driving vehicle
Is a surveillance camera installed at the intersection	(1) Yes (2) No

Since the experiment has 4 factors (each with 2 to 3 attribute levels), a full factor design would have (3× 3× 2 × 2 =) 36 combinations; however, such a design is not effective or practical for measuring pedestrian perceptions. Therefore, to simplify the participants' choice schemes, an orthogonal fractional factor design was adopted (Tian et al., 2023) to reduce the number of selected scenarios to 9. In addition, a randomized block design approach was used to further divide the choice scenario into 3 blocks, with 3 choice sets divided into each block. According to the levels of the four attributes, each choice set consists of three options. Table 2 shows the choice set used in one of the questionnaires (a combination of text description and video presentation).

Table 2 One of the choice scenes

If you are about to cross the road at a pedestrian crossing and there is a vehicle approaching from the left, what would you choose in the following scene?	
Scene: Assuming the approaching vehicle is an autonomous vehicle, there is a surveillance camera at the intersection, the speed of approaching vehicle is 20 km/h, and the distance to the intersection is 20 meters, among the following three options, which one would you choose?	
Attributes	**Levels**
Speed of approaching vehicle (km/h)	20
Distance of approaching vehicle (m)	20
Types of approaching vehicle	Autonomous vehicle
Is a surveillance camera installed at the intersection	Yes

Choices	Choice 1: not cross	Choice 2: quickly cross	Choice 3: normally cross

(a) What do you think is the probability of an accident when crossing in this situation?

1 (Not at all probable) 2 (Improbable) 3 (Neutral) 4 (Somewhat probable) 5 (Very probable)

(b) If you were to cross the road in this situation and have an accident, how serious do you think the consequences of the accident would be?

1 (Not at all severe) 2 (Not severe) 3 (Neutral) 4 (Somewhat severe) 5 (Very severe)

3.3 Integrated choice and latent variable (ICLV) model design

The ICLV model was selected for this study to explain pedestrian crossing choice at unsignalized intersections while focusing on the influence of pedestrian risk perception and trust in AV factors (Kamargianni et al., 2015; Soto et al., 2018; Irawan et al., 2022; Kavta and Goswami, 2022; Chen et al., 2023; Mohiuddin et al., 2024). The model has the following advantages: it can be used to explore the structural relationship between observable and unobservable variables, as well as the measured relationship between latent and outcome variables (Rossetti et al., 2018). The use of instantaneous estimation methods can measure the additional information provided by latent variables and thus determine the statistical efficacy of parameter estimation (Mahpour et al., 2018). Figure 1 illustrates the conceptual modeling framework used for our analysis. The ICLV model consists of two submodels: a latent variable model and a discrete choice model (Vij and Walker, 2016). In this study, we used Python's Biogeme software programming package (Bierlaire, 2018) to perform a full information estimation of the ICLV model.

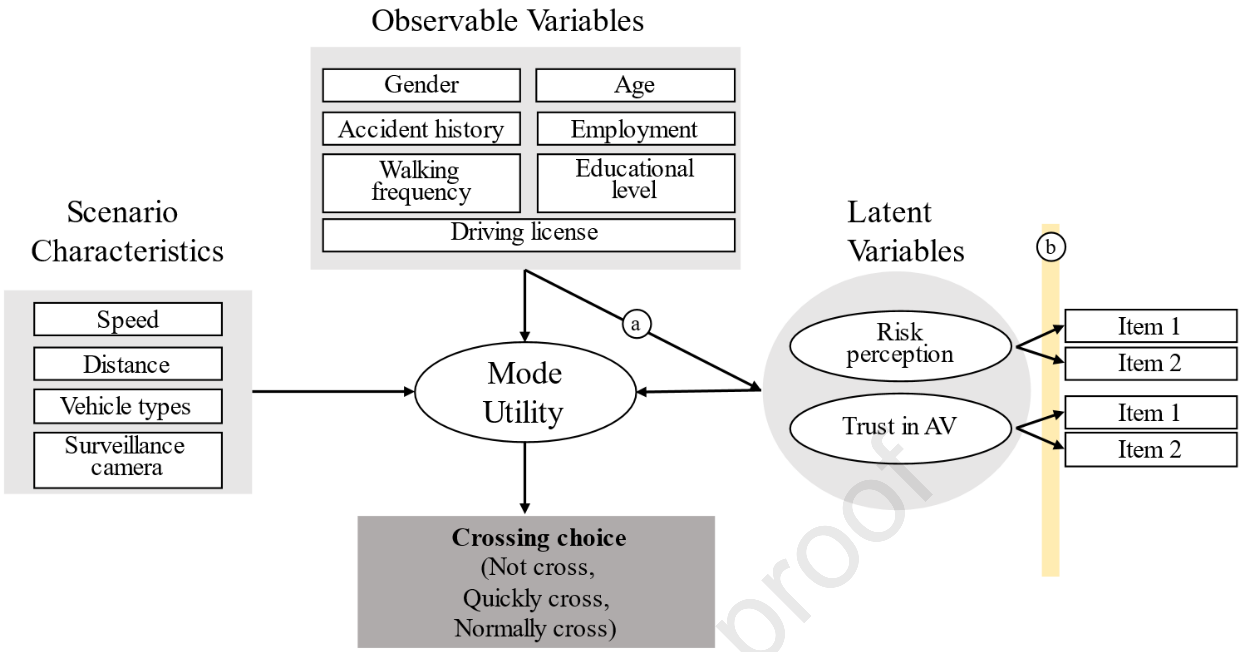


Figure 1 Conceptual modeling framework of the ICLV model

3.3.1 Latent variable part of the ICLV model

Latent variable models were introduced to estimate the structural relationship between sociodemographic characteristics, risk perception characteristics, and trust in AV. The structural equation is used to evaluate the latent variables of risk perception and trust in AV, as shown in equation (1); the measurement equation is shown in equation (2). The former equation is used to identify the reasons for the different levels of risk perception and trust in AV among individuals, and the latter equation is used to identify the relationships between the test indicators and latent variables.

$$Z_l^{n*} = \lambda_l X_n + \omega_l^n \quad (1)$$

where Z_l^{n*} is the lth latent variable vector, and there are two latent variables in this study, namely, risk perception and trust in AV; X_n represents the observed variable of individual n; λ_l is the coefficient to be evaluated; ω_l^n is the error term whose mean is 0, $\omega_l^n \sim N(0, \sigma_\omega)$, and σ_ω is the standard deviation.

$$I_r^{n*} = d_r^n Z_l^{n*} + \nu_r^n \quad (2)$$

where I_r^{n*} represents the *r*th measure of individual *n*, d_r^n is the factor load coefficient, v_r^n is the measurement error, $v_r^n \sim N(0, \sigma_v)$, and σ_v is the standard deviation.

3.3.2 Choice model part of the ICLV model

The discrete choice model is used to estimate the utility of each alternative crossing choice mode relative to different scenario variables, sociodemographic characteristics, risk perception, and trust in AV. The ICLV model is explained as follows: each individual *n* (*n* = 1, 2,... 589) has three choice attributes *i* (*i*=1: not cross (Choice 1); *i*=2: quickly cross (Choice 2); and *i*=3: normally cross (Choice 3). For the crossing choice *i* of individual *n*, its utility ($U_{n,i}$) can be expressed as:

$$U_{n,i} = V_{n,i} + \varepsilon_{n,i} = ASC_i + \beta_i X_n + \beta_i^* Z_l^{n*} + \varepsilon_{n,i} \tag{3}$$

where $U_{n,i}$ is the utility of crossing choice *i* of individual *n*, $V_{n,i}$ is the observable component of utility, ASC_i is the specific constant for choice *i*, X_n is the observable variables, Z_l^{n*} is the latent variables, β_i and β_i^* are the corresponding coefficients of the above variables, and $\varepsilon_{n,i}$ is the random disturbance term, $\varepsilon_{n,i} \sim N(0, \sigma_\varepsilon)$. Note that equation (3), unlike the traditional MNL model, has an additional term $\beta_i^* Z_l^{n*}$.

In addition, the measurement equations in the hybrid choice model assume utility maximization, as shown in equation (4).

$$y_{n,i} = \begin{cases} 1, if\, U_{n,i} = \max_j \{U_{n,j}\} \\ 0, otherwise \end{cases} \tag{4}$$

The probability of individual *n* choosing crossing mode *i* is expressed by equation (5):

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j^J e^{V_{n,j}}} \tag{5}$$

where *J* is the maximum number of alternatives, and there are three alternatives in this experiment.

3.3.3 Likelihood function estimation of the ICLV model

In this study, the maximum likelihood function was used to estimate the ICLV model (Soto et al., 2018; Aaditya and Rahul, 2021). Using full information estimation, the discrete choice model and the latent variable model can be estimated simultaneously. As shown above, the structural random error term ω_l^n and the measurement random error term v_r^n both assume a standard normal independent distribution. Therefore, the probability density function for the latent variable part of the model is shown in equations (6) and (7):

$$f_z(Z_l^{n*} \mid X_n; \lambda_l, \sigma_\omega) = \prod_{l=1}^{2} \frac{1}{\sigma_\omega} \phi\left(\frac{Z_l^{n*} - \lambda_l X_n}{\sigma_\omega}\right) \tag{6}$$

$$f_I(I_r^n \mid Z_l^{n*}; d_r^n, \sigma_v) = \prod_{r=1}^{4} \frac{1}{\sigma_v} \phi\left(\frac{I_r^n - d_r^n Z_l^{n*}}{\sigma_v}\right) \tag{7}$$

where ϕ is the standard normal density function and σ_ω and σ_v are the standard deviations of the error terms ω_l^n and v_r^n, respectively.

Then, the likelihood function is shown in equation (8):

$$L = \int_{Z_l^{n*}} f_Y(y_n \mid X_n, Z_n^*; \beta_i, \beta_i^*, \sigma_\varepsilon) f_I(I_r^n \mid Z_l^{n*}; d_r^n, \sigma_v) f_Z(Z_l^{n*} \mid X_n; \lambda_l, \sigma_\omega) d Z_l^{n*} \tag{8}$$

4 Data and sample description

4.1 Participants

A total of 589 participants submitted valid questionnaires. Table 3 summarizes the characteristics of the participants. Overall, there were 957 males for every 1000 females, which is consistent with the Chinese population (equivalent to 1048 males for every 1000 females) (National Bureau of Statistics, 2022). In terms of age, more than one-third (37.18%) of the participants were aged 25 years or younger, which is much larger than that proportion in the general Chinese population that is aged 15-24 years (10.49%), and 12.40% of the participants were older than 60 years, which is slightly smaller than that proportion in the general Chinese population (18.94%) (National Bureau of Statistics, 2022). Regarding educational level, the majority of participants had an education level of a college degree or above (72.84%), which is higher than that of the Chinese population (18.86%) (National Bureau of Statistics, 2022). Regarding occupation, 38.71% of the participants were full-time workers, 32.26% were students, and 29.03% were engaged in other jobs or retired, which is not consistent with the proportions in the Chinese population (National Bureau of Statistics, 2022). Regarding monthly income, 51.10% of the participants had a monthly income below 4000 RMB, which may be caused by the large proportion of students in the group of participants. For marriage status, the numbers of unmarried and married participants were roughly equal (Esmaili et al., 2021). In terms of travel habits, 31.07% of the participants went out almost every day, more than half of the participants crossed the street an average of 1-5 times per outing, 65.87% of the participants held driver licenses, and 10.19% of the participants had been involved in at least one traffic accident in the past two years.

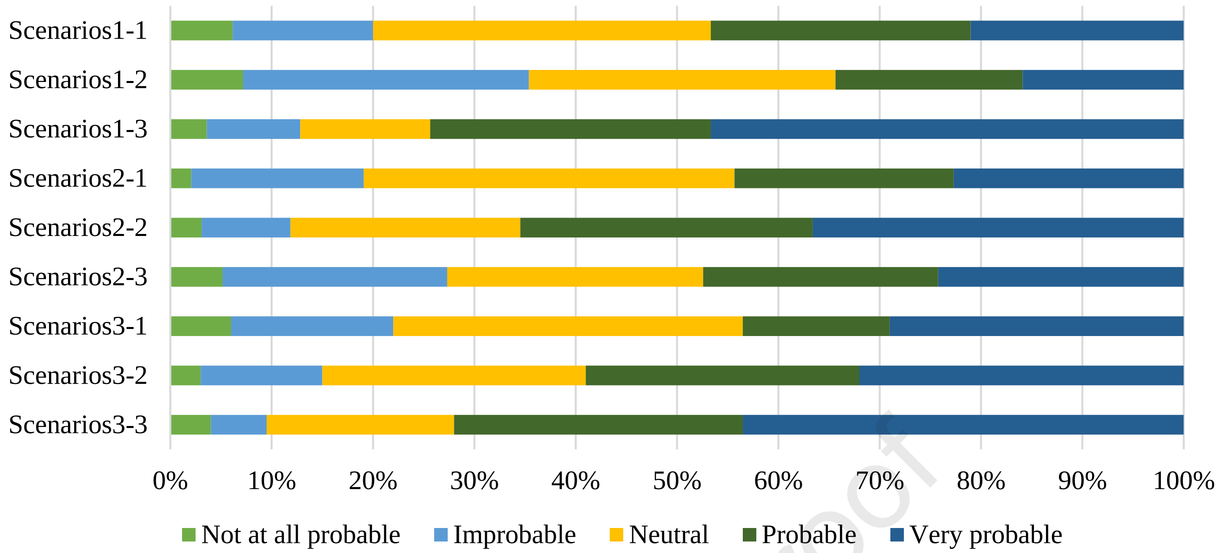
Table 3 Sample distribution

Variables	**Attribute level**	**Count**	**Percentage**
Gender	Male	288	48.90%
	Female	301	51.10%
Age	≤25	219	37.18%
	26-45	165	28.01%
	46-60	132	22.41%
	>60	73	12.40%
Education	Primary	25	4.24%
	Secondary	135	22.92%
	Tertiary	429	72.84%
Employment	Full-time	228	38.71%
	Part-time	26	4.41%
	Self-employed	21	3.57%
	Retired	70	11.88%
	Student	190	32.26%
	Unemployed	54	9.17%
Monthly income	< 4,000 RMB	301	51.10%
	4,000-5,999 RMB	125	21.22%
	6,000-7,999 RMB	63	10.70%
	8,000-8,999 RMB	40	6.79%
	≥ 10,000 RMB	60	10.19%
Accident history	Yes	60	10.19%
	No	529	89.81%

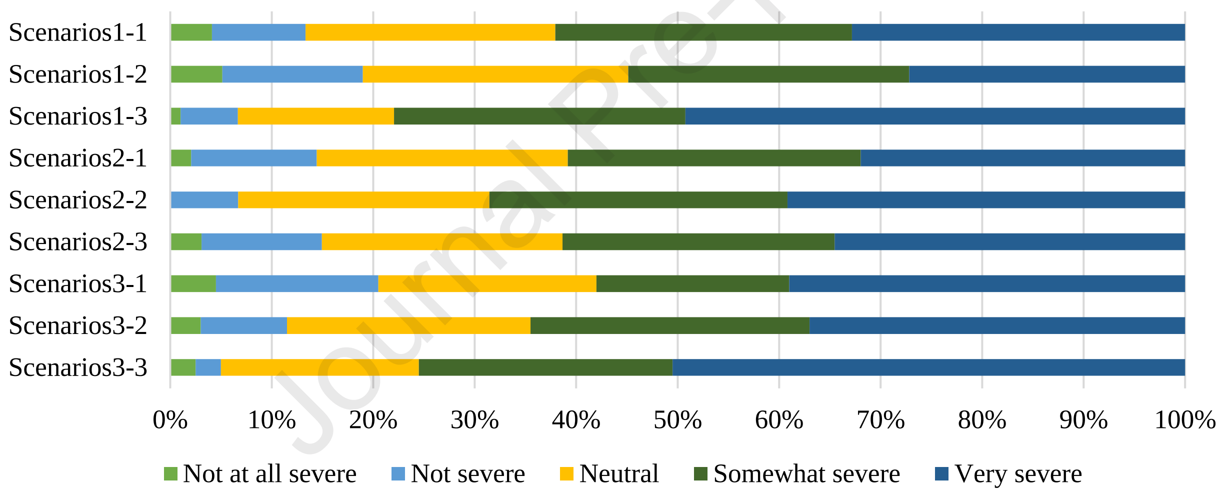
Driving license	Yes	388	65.87%
	No	201	34.13%
Walking frequency (per week)	0 days	47	7.98%
	1-2 days	180	30.56%
	3-5 days	179	30.39%
	6-7 days	183	31.07%
Crossing frequency	0 times	117	19.86%
	1-2 times	186	31.58%
	3-5 times	185	31.41%
	≥6 times	101	17.15%
Marriage Status	Unmarried	290	49.24%
	Married with no children	31	5.26%
	Married with children	268	45.50%

4.2 Latent variables

The latent variables considered in this study were risk perception (AlKheder et al., 2022) and trust in AV (Jing et al., 2021; Deb et al., 2017). Participants' responses to the accident probability and severity questions for each scenario are shown in Figure 2. Since three versions of the questionnaire were adopted in this study, each containing similar levels of risk across three scenarios, the values of accident probability and severity questions for each participant are the mean of their responses across the three scenarios. Table 4 shows the descriptive statistics of the latent variables and their measurement items (mean and standard deviation of all participants for each measurement item). In addition, the Cronbach's alpha (internal consistency or reliability) values of the two latent variables, risk perception and trust in AV, were 0.817 and 0.845, respectively. This indicates that the measurement items associated with the latent variable have sufficient internal consistency.



(a) Probability



(b) Severity

Figure 2 Responses to the accident probability and severity questions for each scenario

Table 4 Descriptive statistics of the indicators of latent variables

Latent variables	**Items**	**Mean**	**Standard deviation**
Risk perception	(a) What do you think is the probability of an accident when crossing in this situation? ("1= not at all probable" to "5= very probable")	3.61	0.99
	(b) If you were to cross the road in this situation and have an	3.88	0.96

	accident, how serious do you think the consequences of the accident would be? ("1= not at all severe" to "5= very severe")		
Trust in AV	(a) I believe autonomous vehicles are safe. ("1 = strongly disagree" to "7 = strongly agree")	3.78	1.46
	(b) When crossing the road, I trust autonomous vehicles to detect and avoid collisions. ("1 = strongly disagree" to "7 = strongly agree")	3.67	1.49

5 Model results and analysis

5.1 Descriptive analysis

Since there were 3 options for each version of the questionnaire, the total number of response options for this study was 1767. Among the 1767 choices, 1308 (74.02%), 315 (17.83%), and 144 (8.15%) were pedestrian choices to "not cross (Choice 1)", "quickly cross (Choice 2)" and "normally cross (Choice 3)", respectively. Figure 3 shows the distribution of choice frequencies for crossing modes, for all cases, the option of "not cross (Choice 1)" always have the highest share in the sample, as it offers greater safety benefits compared to crossing. This also reflects the overall crossing tendency of pedestrians. Moreover, as expected, there is an increasing trend in the frequency of participants choosing "not cross (Choice 1)" as the approaching vehicle distance decreased. However, for the approaching vehicle speed, although the highest number of responses for "not cross (Choice 1)" is observed at 40 km/h, the number of "not cross (Choice 1)" answers at 20 km/h is higher than the number at 30 km/h. This probably occurred because, the scenario cases are the combination of factors (speed, distance, vehicle types, and surveillance cameras) and if it had been only the speed, a steady increase in the number of "not cross (Choice 1)" options with increasing speed might be observed (Ma et al., 2024).

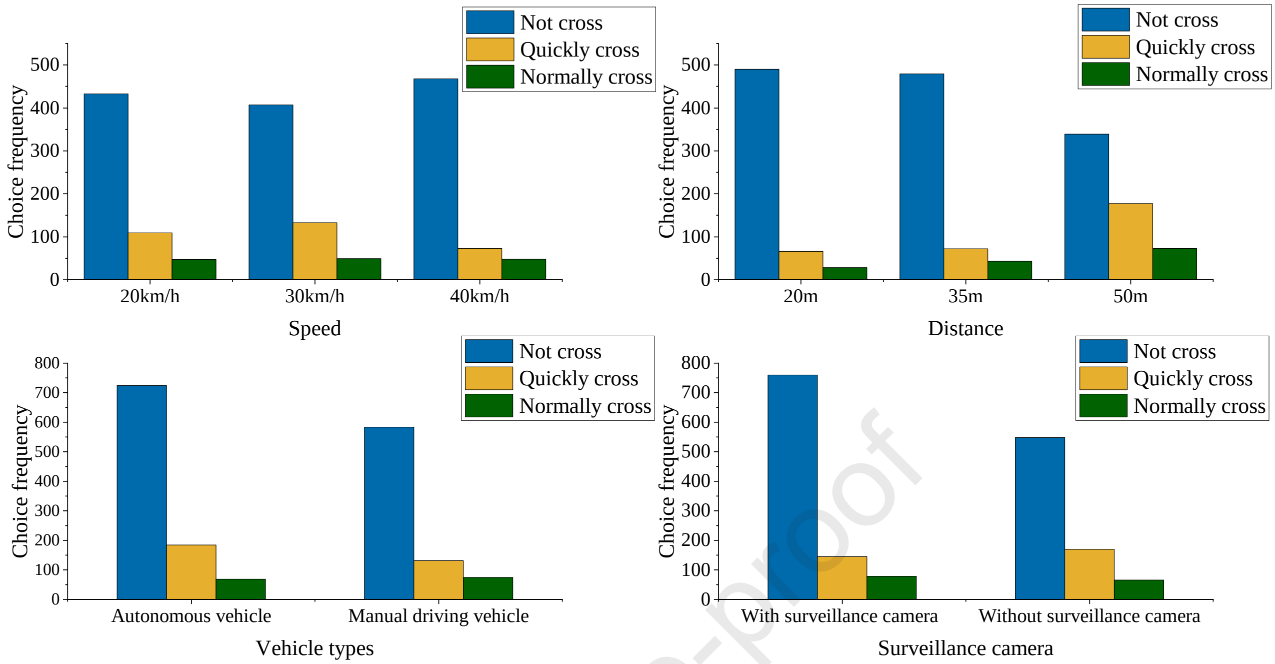


Figure 3 Distribution of the choice frequency for crossing modes

5.2 Correlation analysis of variables

The interdependency between variables might influence coefficient estimates. Therefore, we used Spearman's rank coefficient to investigate the correlation of variables included in the ICLV model estimates, and the results are shown in Figure 4. Red indicates a positive correlation between variables, while blue indicates a negative correlation. All the correlation coefficients of the variables are less than 0.5. Therefore, these variables can be included in the model analysis. The evidence in the literature indicates that the variables are strongly correlated according to the use of the popular cutoff of 0.6 for the absolute values of the correlation coefficient (Shangguan et al., 2023; Singh et al., 2021).

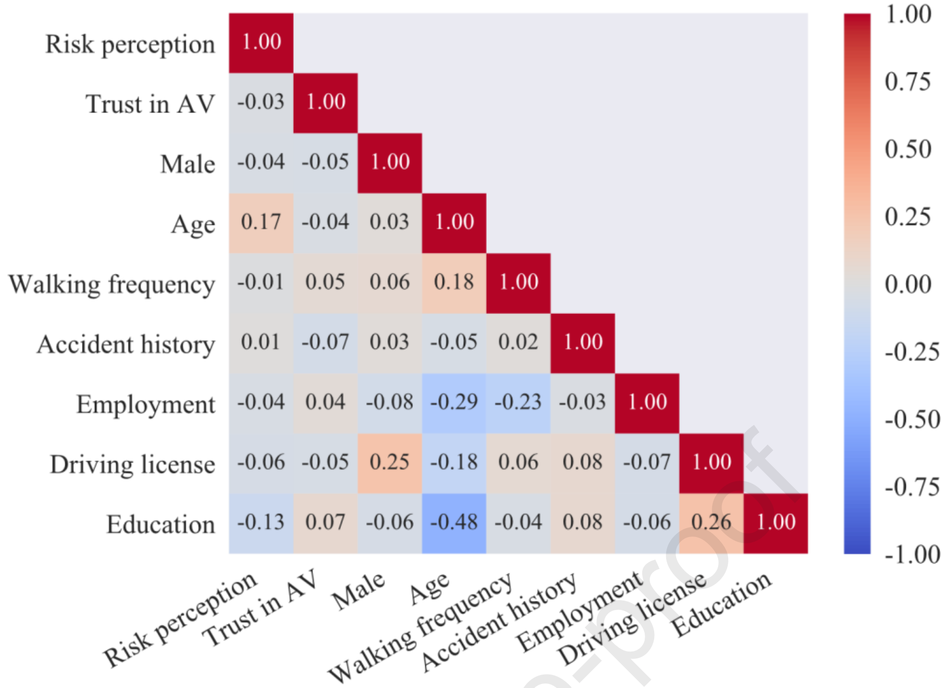


Figure 4 Correlation coefficients of the variables

5.3 ICLV model estimation results

Subsequently, the ICLV model was used to estimate pedestrian choice preferences. To provide a clearer description, the ICLV estimation results are detailed in three parts: the structural model (Equation 1), the measurement model (Equation 2 and 4), and the choice model (Equation 3 and 5).

5.3.1 Structural model

As shown in Table 5, the estimated results of the structural model show that pedestrians' risk perceptions and trust in AV are significantly correlated with their sociodemographic characteristics. Specifically, in terms of risk perception, participants older than 60 years (0.683) had a higher level of risk perception when crossing, and being male (-0.229), full-time employment (-0.499), and student status (-0.784) were significantly negatively associated with risk perception. However, walking frequency, accident history, driving license, and education level were not significantly associated with risk perception. In terms of trust in AV, participants with a high frequency of walking (6-7 days/week) (0.120) and a high level of education (tertiary) (0.344) had a higher level of trust in AV, and being involved in traffic accidents (-0.274), full-time employment (-0.350), student status (-0.163), or holding a driver's license (-0.106) were significantly negatively associated with trust in AV, but gender and age were not significantly associated with trust in AV.

Table 5 Structural model estimation results

Variables	**Risk perception**		**Trust in AV**	
	Estimate	***t* −statistic**	**Estimate**	***t* −statistic**
Male	**-0.229***	-1.87	0.014	0.26
Age (25-60)	0.284	1.58	0.032	0.44
Age (>60)	**0.683****	2.37	-0.015	-0.08
Walking frequency (6-7days/week)	-0.099	-0.82	**0.120****	2.08
Accident history	0.159	0.87	**-0.274*****	-3.04
Full-time employment	**-0.499****	-2.35	**-0.350*****	-5.15
Student status	**-0.784*****	-3.66	**-0.163***	-1.93
Driving license (Holding)	0.057	0.44	**-0.106***	-1.78
Education (Tertiary)	-0.192	-1.27	**0.344*****	4.55

Note: *** p<0.01; ** p<0.05; * p<0.10

5.3.2 Measurement model

In this study, there are two latent variables, each of which has two factors, for a total of four factors; thus, eight parameters had to be estimated (four factor load coefficients *d*, four standard deviations σ). The factor load coefficient refers to the parameter representing the relationship between a factor (measurement item) and a latent variable, while the standard deviation refers to the standard deviation of measurement errors, used to measure the variability of measurement indicators (see equation 2). Since four of these parameters needed to be constrained to one for identification (Irawan et al., 2022; Chen et al., 2023), only four parameters were estimated, and the estimated results of the measurement equation are shown in Table 6. It can be seen from the results that the latent variables are positively correlated with the selected index; that is, a higher level of accident perception probability leads to better risk perception ability (0.928), and a higher level of technology trust leads to greater trust in AV. Moreover, the standard deviation σ_{RP} (1.11) and σ_{AV} (1.03) were also significantly positively correlated with the corresponding latent variables. Neglecting these standard deviation estimates could introduce bias into factor load coefficient estimates and potentially distort the influence of latent variables in the choice model (Chen et al., 2023).

Table 6 Measurement model estimation results

Latent variables	Indicator	d −Estimate	t −statistic	σ −Estimate	t −statistic
Risk perception	1. Probability	**0.928*** **	14.8	**1.110*** **	4.52
	2. Severity	1.000	Fixed	1.000	Fixed
Trust in AV	1. Trust-1	1.000	Fixed	1.000	Fixed
	2. Trust-2	**0.808*** **	6.13	**1.030*** **	66.60

Note: *** p<0.01; ** p<0.05; * p<0.10

5.3.3 Choice model

The estimation results of the choice model are shown in Table 7. In this study, the ICLV model was used to identify the significant influence of social-technological variables and latent perceptions on certain pattern choices. Overall, the constants in the model capture the intrinsic preferences of crossing patterns in the studied pedestrian population, although they are also used to adjust for the presence of other variables in the model's utility.

For the scenario variables, approaching vehicle speed (0.031) was significantly positively correlated with "not cross (Choice 1)" at the 1% level, and approaching vehicle distance (-0.071) was significantly negatively correlated with "not cross (Choice 1)" at the 1% level. In other words, with increasing speed and decreasing distance, pedestrians are more inclined to choose to "not cross (Choice 1)". In addition, there were significant negative correlations between autonomous vehicle type and "not cross (Choice 1)" (-0.407) and "normally cross (Choice 3)" (-0.394), indicating that the presence of autonomous vehicles increases pedestrians' willingness to cross and favors "quickly cross (Choice 2)" with relatively lower risk levels; however, the presence of a surveillance camera had no significant effect on pedestrian crossing decisions.

In terms of the observed variables, the age range 25-60 (0.552) and education (tertiary) (0.776) were significantly positively correlated with "not cross (Choice 1)". Male gender (Choice 1: 0.327;

Choice 3: 0.618) were significantly positively correlated with "not cross (Choice 1)" and "normally cross (Choice 3)", with "normally cross (Choice 3)" showing a larger correlation coefficient, indicating that male pedestrians exhibit a greater tendency for risk-taking behavior when crossing. Furthermore, accident history (Choice 1: -0.983; Choice 3: -0.669), full-time employment (Choice 1: -0.641; Choice 3: -0.693), and holding a driving license (Choice 1: -0.529; Choice 3: -0.912) were significantly negatively correlated with "not cross (Choice 1)" and "normally cross (Choice 3)". This suggests that pedestrians with history of accidents, full-time employment, and possessing a driving license are more inclined to choose the "quickly cross (Choice 2)".

Furthermore, the latent variable of risk perception showed that risk perception (0.393) was significantly positively correlated with "not cross (Choice 1)" at 1%; that is, individuals with higher risk perception levels were more inclined to choose "not cross (Choice 1)" than "quickly cross (Choice 2)". The latent variable of trust in AV is significantly negatively correlated with both "not cross (Choice 1)" (-2.490) and "normally cross (Choice 3)" (-1.940) at 1%; that is, individuals with a higher level of trust in AV are more inclined to choose the "quickly cross (Choice 2)" than "not cross (Choice 1)" and "normally cross (Choice 3)", which not only saves crossing time but also has relatively lower risk.

Table 7 ICLV model estimation results

Variables	**ICLV**			
	Choice 1: Not cross		**Choice 3: Normally cross**	
	Estimate	***t*−statistic**	**Estimate**	***t*−statistic**
Constant	**2.230*****	4.05	-0.641	-0.89
Speed	**0.031*****	2.68	0.018	1.14
Distance	**-0.071*****	-8.20	-0.014	-1.21
Vehicle types (0 - manual driving vehicle, 1 - autonomous vehicle)	**-0.407****	-2.49	**-0.394***	-1.71
Surveillance camera (0 – No, 1 - Yes)	-0.304	-1.43	-0.024	-0.08
Male	**0.327***	1.72	**0.618****	2.53
Age (25-60)	**0.552****	2.00	0.400	1.21
Age (>60)	-0.603	-1.06	-0.329	-0.52

Walking frequency (6-7days/week)	0.296	1.45	0.131	0.52
Accident history	**-0.983*****	-3.26	**-0.669***	-1.70
Full-time employment	**-0.641*****	-2.83	**-0.693****	-2.47
Student status	-0.448	-1.40	-0.313	-0.81
Driving license (Holding)	**-0.529****	-2.54	**-0.912*****	-3.49
Education (Tertiary)	**0.776*****	3.45	0.442	1.61
Risk perception	**0.393*****	4.07	-0.024	-0.32
Trust in AV	**-2.490*****	-15.70	**-1.940*****	-10.10
LL (start)	-20895.850			
LL (final)	-11667.820			
Rho-square	0.442			
Rho-square-bar	0.439			
AIC	23463.630			
BIC	23814.160			

Note: *** p<0.01; ** p<0.05; * p<0.10

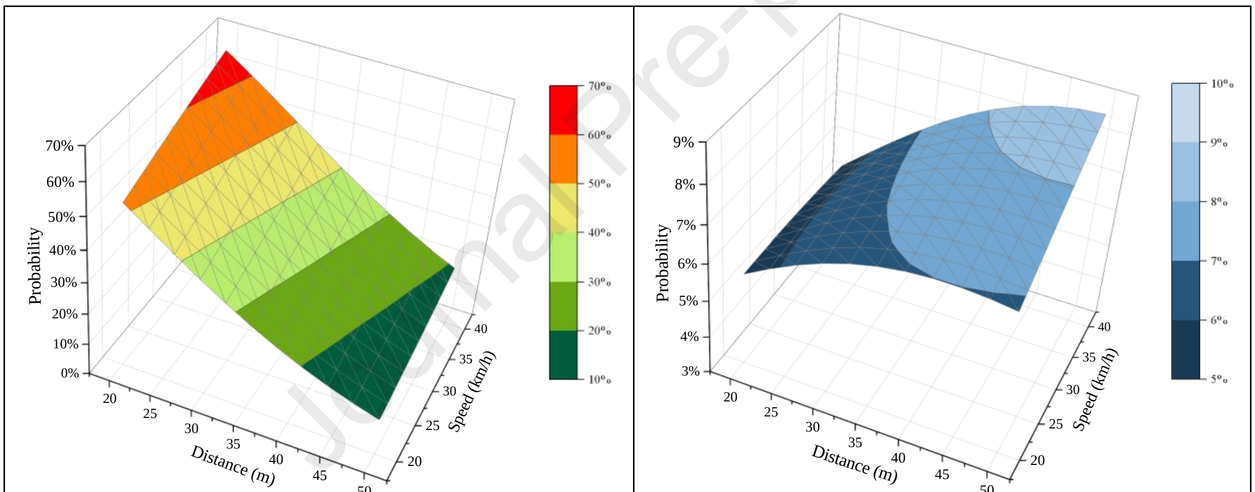
6 Discussion and influence

6.1 Scenario analysis

The estimates of all the parameters in the ICLV model do not directly describe the extent of their impact on the probability of existing alternative choices. Therefore, we assess the influence of a specific variable on pedestrian choice by manipulating the variables and recalculating the shares under these manipulations. For continuous variables (such as speed with a range of 20 to 40 km/h), we evaluate the impact of a specific variable on probability by transforming the values of the continuous variable within the specified range. For categorical variables, we set the values to 1 or 0 to evaluate the impact of a variable on the probability (for example, if there is a surveillance camera in the scenario, the value of the dummy variable for the surveillance camera can be taken as 1 for all individuals).

6.1.1 Individual preferences for speed and distance combinations

There is a negative correlation between the approaching vehicle speed and pedestrian crossing tendency and a positive correlation between the approaching vehicle distance and pedestrian crossing tendency. Figure 5 shows the prediction results of pedestrian decision probabilities for different combinations of approaching vehicle speed and distance under the ICLV model. Figure 5a shows that the probability of pedestrians choosing “not cross (Choice 1)” is sensitive to changes in approaching vehicle speed and distance. As expected, when the distance of the approaching vehicle at the crosswalk decreases and the speed of the approaching vehicle increases, the tendency of the pedestrian to choose “not cross (Choice 1)” increases, while the tendency to choose “normally cross (Choice 3)” gradually decreases. This confirms the findings of Liang et al. (2022), who claimed that when pedestrians cross the street, they allocate more their visual attention to interacting motor vehicles than to other types of stimuli, and they pay special attention to the speed and distance of approaching vehicles. In addition, when the approaching vehicle speed ranges from 20 km/h to 40 km/h and the approaching vehicle distance ranges from 20 m to 50 m, the probability of pedestrians choosing “normally cross (Choice 3)” is low (5.37% to 8.71%), as shown in Figure 5b, which indicates that the participants are more prudent when crossing.



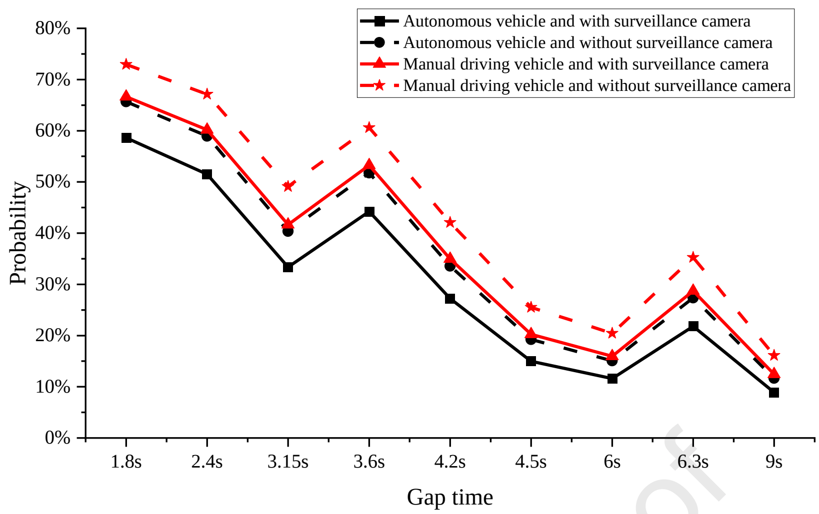
(a) Choice 1 (Not cross) (b) Choice 3 (Normally cross)

Figure 5 Prediction results of pedestrian decision probability with respect to approaching vehicle speed and distance

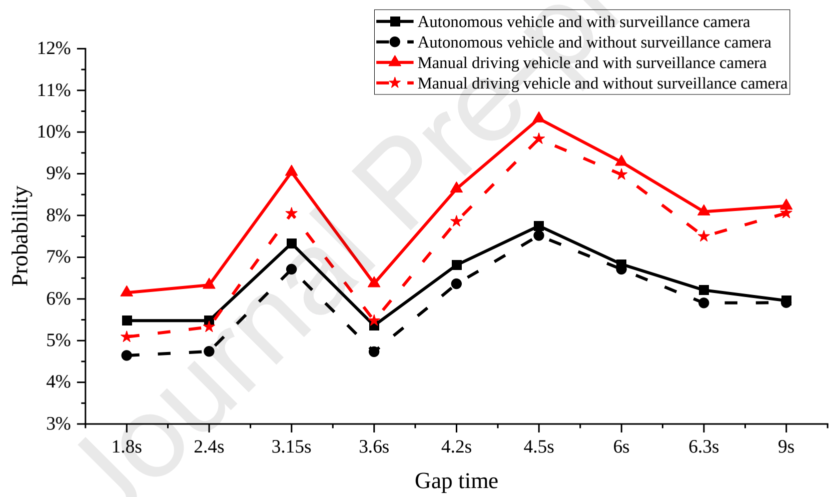
6.1.2 Interaction of gap time with autonomous vehicle and surveillance camera

Pedestrian gap acceptance theory states that each pedestrian has a critical acceptable gap threshold that they use to decide whether to cross the street; therefore, the gap acceptance of pedestrians often affects their crossing decision (Theofilatos et al., 2021). In this study, the crossing gap time used is calculated based on the approaching vehicle speed and distance in 9 scenarios, which include 9 gap times ranging from 1.8 s to 9 s. Next, the presence of autonomous vehicles affects pedestrians' crossing behaviors and decisions (Hulse 2023); therefore, the impact of autonomous vehicles on pedestrians' crossing choices should be considered. Regarding the impact of surveillance cameras, the presence of surveillance cameras makes people feel safer than their absence (Li et al., 2022).

Therefore, in terms of the crossing gap time, the type of approaching vehicle and the presence of surveillance cameras, based on the analysis results of the ICLV model, the influence of different combinations of vehicle types and whether surveillance cameras are installed are predicted based on pedestrians' choice of crossing under increasing gap times. Specifically, Figure 6 shows the change in the probability of pedestrians choosing "not cross (Choice 1)" or "normally cross (Choice 3)" relative to the gap time under different environmental conditions (autonomous vehicle and surveillance cameras, autonomous vehicle and no surveillance cameras, manual driving vehicle and surveillance cameras, and manual driving vehicle and no surveillance cameras). As shown in Figure 6a, with increasing gap time, pedestrians' choices of "not cross (Choice 1)" shows an overall decreasing trend. Moreover, whether in the scenario involving a combination of autonomous vehicles or manual driving vehicles, the presence of surveillance cameras results in a lower probability of choosing "not cross (Choice 1)" than in the scenarios without surveillance cameras. As mentioned earlier, this can be attributed to the fact that the lack of surveillance cameras makes pedestrians uncomfortable (Li et al., 2022), while the presence of such cameras increases drivers' yield behaviors, making pedestrians more inclined to cross the road (Li et al., 2021). In contrast, the impact of gap time on pedestrians' decisions to choose "normally cross (Choice 3)" is relatively small, as shown in Figure 6b. Furthermore, there is an interesting phenomenon. When using a combination of scenarios with manual driving vehicles, the probability of pedestrians choosing "not cross (Choice 1)" or "normally cross (Choice 3)" is higher than in scenarios with autonomous vehicles. This phenomenon can be understood as follows: as the presence of autonomous vehicles in traffic flow increases, pedestrians may be more inclined to choose to "quickly cross (Choice 2)" with shorter waiting times and relatively lower risk.



(a) Choice 1 (Not cross)



(b) Choice 3 (Normally cross)

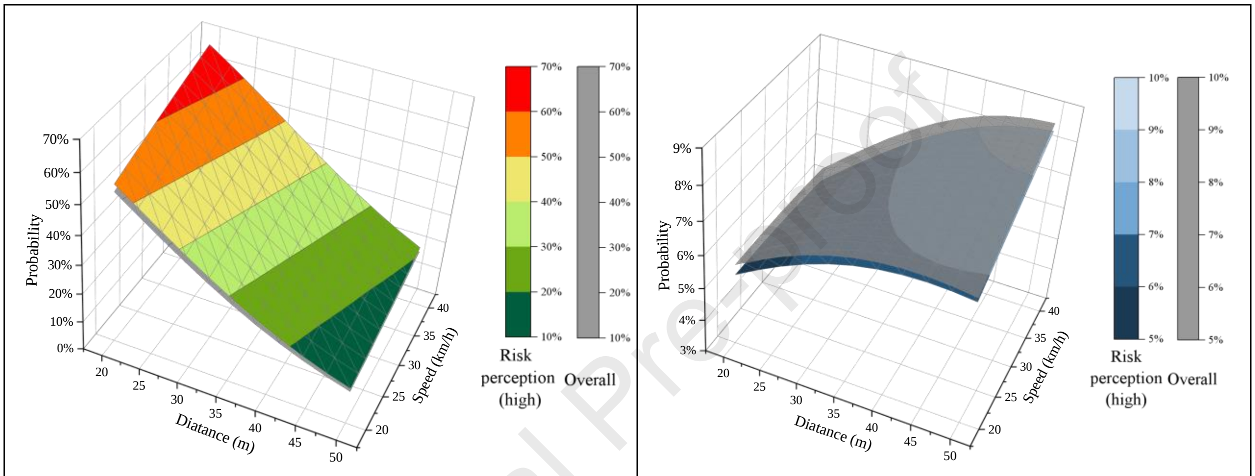
Figure 6 Pedestrian crossing choice probability as influenced by the interaction among gap time, vehicle type and the presence of a surveillance camera

6.2 Influence of latent variable utility

6.2.1 Influence of risk perception utility

Risk perception is an important psychological variable that can explain why people choose to act in a particular way, including the travel choices of road users (Breakwell 2007; Rankavat and Tiwari, 2020). Therefore, this study incorporates the ICLV model with the addition of a latent variable related to risk perception. The research results indicate that the introduced latent variable related to risk perception has a significant impact on pedestrian crossing decisions for "not cross

(Choice 1)". Specifically, we explored the change trends in choice patterns with respect to the speed and distance of approaching vehicles for both overall pedestrians and pedestrians with a high level of risk perception. As shown in Figure 7, compared with that of the overall pedestrians, the probability of pedestrians with a high risk perception level choosing "not cross (Choice 1)" increases, while the probability of choosing "normally cross (Choice 3)" decreases. The risk perceptions of pedestrians have an important positive impact on the process of pedestrian crossing choice.

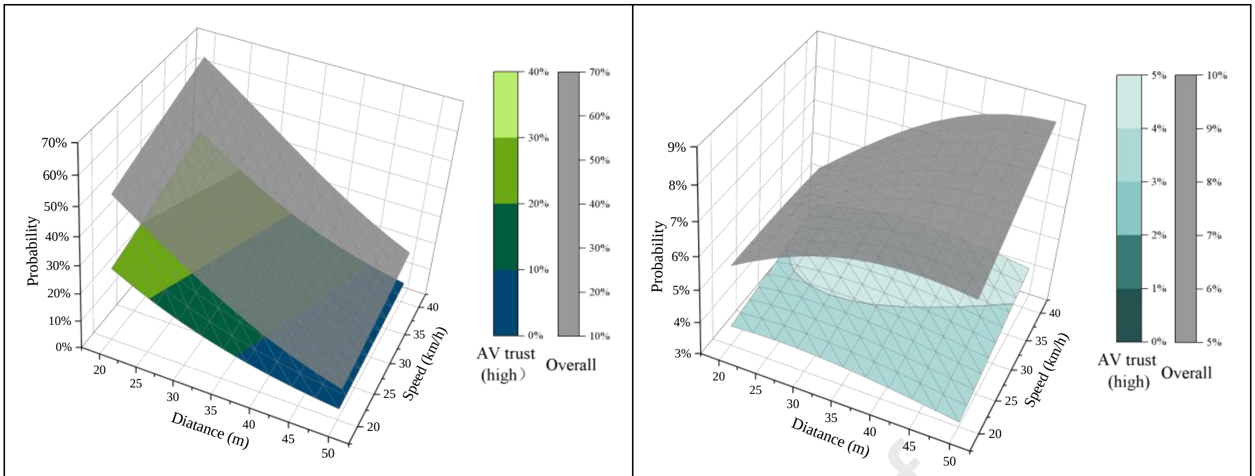


(a) Risk perception - Choice 1 (Not cross) | **(b) Risk perception - Choice 3 (Normally cross)**

Figure 7 Intentions to choose Choice 1 and Choice 3 according to risk perception level

6.2.2 Influence of trust in AV utility

The results of the ICLV model show that the latent variable of trust in AV significantly influences pedestrians' crossing choices. To further explore the dynamic relationship between the variation in trust in AV and pedestrians' crossing decisions, we conducted a similar scenario analysis. Specifically, we investigated the change trends in choice patterns with respect to the speed and distance of approaching vehicles for both overall pedestrians and pedestrians with a high level of trust in AV. As shown in Figure 8, compared to overall pedestrians, those with a high level of trust in AV show a decreased and more sensitive probability of choosing "not cross (Choice 1)" (26.06%), and the probability of choosing "normally cross (Choice 3)" also exhibits a decreasing trend (4.09%). This confirms the statement of Zhao et al. (2022) that trust in autonomous vehicles increases pedestrians' willingness to cross the street.

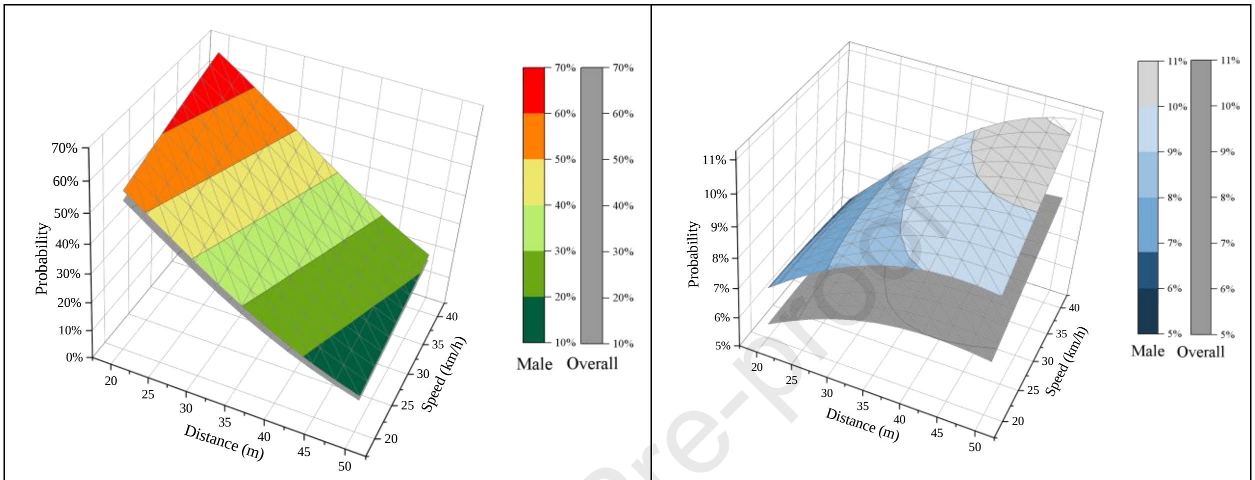


(a) Trust in AV – Choice 1 (Not cross)	(b) Trust in AV – Choice 3 (Normally cross)

Figure 8 Intentions to choose Choice 1 and Choice 3 according to trust level in AV

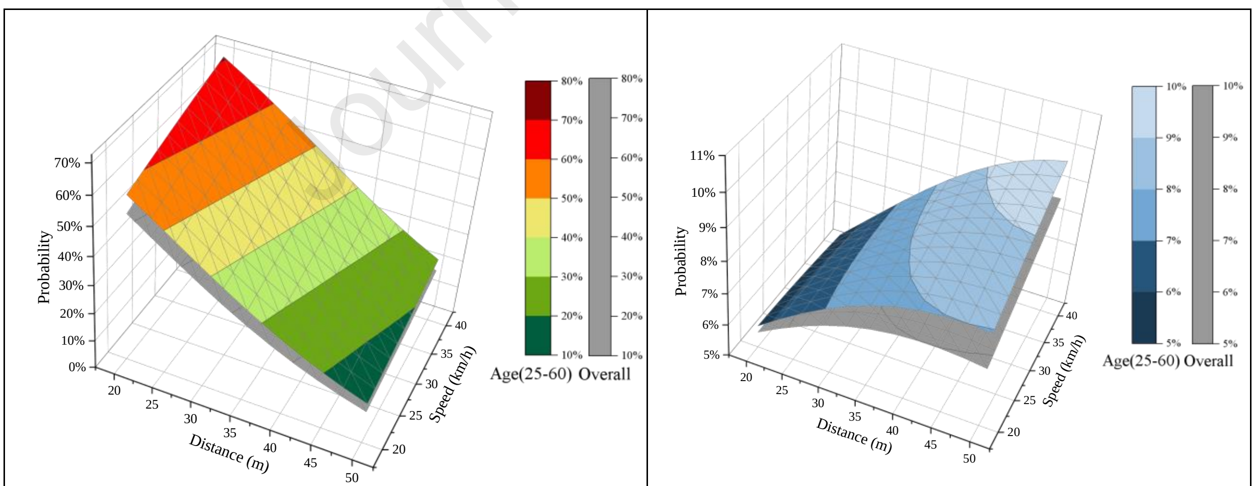
6.3 Influence of individual characteristics

In terms of gender, Figure 9 illustrates the changes in the probability of choosing "not cross (Choice 1)" and "normally cross (Choice 3)" with respect to the speed and distance of approaching vehicle for overall and male pedestrians. Compared with overall pedestrians, male pedestrians had a slightly higher probability of choosing the "not cross (Choice 1)" (2.47%) and "normally cross (Choice 3)" (2.48%) crossing modes. This finding implies that the probability of male pedestrians choosing to "quickly cross (Choice 2)" is lower than that of female pedestrians. This result is consistent with the findings of Yadav and Velaga (2022), where female pedestrians tended to exhibit more conservative behavior when crossing the street. Therefore, female pedestrians may be inclined to choose the "quickly cross (Choice 2)" crossing mode when there is a moderate level of risk. In terms of age, Figure 10 illustrates the changes in the probability of choosing "not cross (Choice 1)" and "normally cross (Choice 3)" with respect to the speed and distance of approaching vehicle for overall and middle-aged (aged 25-60 years) pedestrians. It was found that the probability of middle-aged pedestrians choosing "not cross (Choice 1)" was 5.21% higher than that of overall pedestrians, which is consistent with the findings of previous studies revealing that older pedestrians exhibit less cautious behavior at unsignalized crossings (Aghabayk et al., 2021). This phenomenon is reasonable. It is possible that middle-aged people have more abundant channels to acquire traffic safety knowledge and have received more extensive traffic safety education, so they are more conservative when crossing. Notably, pedestrians who have been previously involved in traffic accidents are less likely to choose “not cross (Choice 1)” (19.72% lower than overall pedestrians), which seems counterintuitive but points to the fact that pedestrians do not improve their crossing decisions after having been involved in traffic accidents and may still make unsafe crossing decisions. As revealed by Cheng et al. (2011), motorcycle drivers involved in traffic accidents engage in more traffic violations.



(a) Male– Choice 1 (Not cross) **(b) Male – Choice 3 (Normally cross)**

Figure 9 Intentions to choose Choice 1 and Choice 3 between gender groups



(a) Age (25-60) – Choice 1 (Not cross) **(b) Age (25-60) – Choice 3 (Normally cross)**

Figure 10 Intentions to choose Choice 1 and Choice 3 between age groups

6.4 Implications

China’s dense population, large-scale transportation development projects, and innovative technological development strategies for autonomous vehicles and surveillance systems have significantly impacted efforts to improve pedestrian crossing safety. In this study, the roles of factors related to the type of approaching vehicle (traditional or autonomous vehicle) and the presence of surveillance cameras in pedestrian crossing decisions (whether or not to cross) were explored, and the influences of individual demographic characteristics, risk perception, and trust in AV were considered. In this section, the impact of technological advancements on traffic safety and policy implications for traffic safety in sociotechnical transport systems are discussed.

6.4.1 Impact of technological advancements on traffic safety

Effective pedestrian crossing decision policies can prompt pedestrians to abide by traffic rules and improve their crossing behaviors, thereby reducing conflicts between pedestrians and vehicles, decreasing the occurrence of traffic accidents, and improving road traffic safety (Zhang et al., 2019; Che et al., 2024; Banerjee et al., 2024). Our study has shown that the existence of autonomous vehicles significantly impacts pedestrian crossing decisions, even though these impacts are based on perceptions rather than traffic rules. This highlights an essential aspect of traffic safety: the role of human perception and psychology in influencing behaviors on the road. On the one hand, traffic safety is governed by a set of well-defined traffic rules and regulations, such as speed limits and traffic signals. These rules are designed to establish clear guidelines for safe behaviors on the road. Violating these rules can lead to accidents and injuries, so law enforcement typically enforces them. Beyond objective rules, individual perceptions and beliefs play a significant role in road safety. People's perceptions of the road environment, the behaviors of other road users, and their own abilities to navigate traffic influence their actions. For example, if pedestrians perceive autonomous vehicles to be safer or more predictable, they may be more inclined to cross streets confidently. Similarly, the presence of surveillance cameras may influence both pedestrians and drivers to adhere to traffic rules due to their perceptions of being monitored. Human factors, including perception, attention, decision, and risk assessment, have a profound impact on road safety. The way individuals perceive risks and make decisions on the road can sometimes override strict adherence to traffic rules. For example, pedestrians may cross the street against a traffic signal if they perceive that there is no immediate danger from approaching vehicles, even if it technically violates the rule. However, changing the level of risk perception of pedestrians may not be an easy or cost-effective task. For example, well-designed interventions have been shown to significantly improve the risk perception involved in pedestrian crossings (Feng et al., 2022). With the gradual increase in the penetration rate of autonomous vehicles, pedestrians' crossing decisions have also been significantly affected. For instance, the form and content of the external human–machine interface (eHMI) of autonomous vehicles are not uniform (De Clercq et al., 2019; Eisma et al., 2019). Future research should further standardize the design of autonomous vehicles to ensure not only materially safer and smoother interactions with pedestrians but also socially acceptable behavior of all road users, including both drivers and pedestrians.

6.4.2 Policy implications for traffic safety in sociotechnical transport systems

Policymakers and safety advocates understand the significance of social perceptions of technological advancements and traffic safety, employing various strategies to shape public perceptions and trusts. These strategies include education campaigns (Goniewicz et al., 2016), public awareness initiatives (Davey and Freeman, 2011), and changes in infrastructure design (Ewing and Dumbaugh, 2009). These measures aim to influence how people perceive and interact with the road environment. First, educational campaigns could be launched to inform pedestrians about technological advancements such as autonomous vehicles and surveillance cameras, including their presence and features. This could empower pedestrians to make more informed decisions, dispel misconceptions, and alleviate fears. Engaging local communities in discussions about the integration of autonomous vehicles and surveillance cameras is crucial for building trust and ensuring that policies align with community needs and expectations. Collaboration among traffic management authorities, autonomous vehicle manufacturers, camera system operators, and pedestrian advocacy groups is essential for addressing concerns and developing best practices. Second, autonomous vehicle manufacturers and operators should actively communicate with the public to elucidate their vehicles' operations and their commitment to pedestrian safety. This entails sharing information about safety features and the technology employed in autonomous vehicles. Authorities should also develop regulatory guidelines that specify the obligations and responsibilities of both autonomous vehicle operators and pedestrians. Although not equivalent to traffic rules, these guidelines provide a framework for safe interactions. Seeking feedback from the public, including pedestrians, on their experiences and concerns regarding autonomous vehicles and surveillance cameras is vital for refining policies and addressing public perceptions.

Regarding infrastructure design, our scenario analysis results reveal that the speed and distance of the approaching vehicle are important factors influencing crossing decision. Therefore, improving road speed limits, strengthening traffic control, and optimizing signal timing should be considered by policymakers to reduce the risk of traffic accidents by controlling vehicle speed and maintaining a safe distance between vehicles to provide pedestrians with greater crossing gap times (Theofilatos et al., 2021). The results of the scenario analysis also show that the installation of surveillance cameras has a positive effect on improving pedestrian decisions regarding crossing. This provides an important reference for the construction and optimization of traffic infrastructure. Policymakers should consider installing law enforcement cameras at places prone to traffic accidents, such as intersections with no traffic signals (Li et al., 2023), to effectively improve the traffic behaviors of pedestrians and drivers and to enhance the monitoring and management of road safety. In addition, as considered in the literature, strengthening the construction of overpasses, underpasses, and other facilities is an important means of improving the safety of pedestrian crossings (Miśkiewicz et al., 2017; Chandrappa et al., 2021; Chan et al., 2022). The relevant authorities can actively promote the construction and optimization of these facilities to separate the flows of pedestrians and vehicles to ensure that pedestrians can cross the street in a safe environment. Furthermore, considering the characteristics of the elderly pedestrian population in communities with a high concentration of elderly residents by providing shorter crossing distances or longer crossing times can increase the convenience of elderly people's travel and reduce the risks associated with their difficulties in crossing the road. This method can also be applied to other developed countries that are facing aging populations. Nevertheless, in this ever-changing world of technology, continuous monitoring and analysis of pedestrian behaviors and decisions in the presence of diverse technological advancements can provide valuable data to inform infrastructure design for improved safety.

7 Conclusion

In this study, we employed a questionnaire survey with video clips to gather data from 589 Chinese pedestrians for an SP (stated preference) experiment to comprehensively investigate how technological advancements (e.g., the type of autonomous vehicle, presence of a surveillance camera), personal attributes, risk perception, and trust in AV influence pedestrian crossing choice preferences in the context of ITS. The contributions of this research are twofold. First, we estimated the trade-off between approaching vehicle speed and distance for different pedestrians and considered the moderating effect of technological advancements and individual factors. Second, the ICLV model was established, and the influence of the latent variables of risk perception and trust in AV on pedestrian crossing decisions was considered.

The results indicate that, in addition to social-technological factors, individual perception and trust toward relevant issues also significantly influence crossing choice modes. As expected, the latent variable of risk perception increases the probability of pedestrians choosing to "not cross (Choice 1)". In particular, trust in AV has a substantial impact on pedestrians' selection of the "quickly cross (Choice 2)" mode. This finding suggests that improving pedestrians' risk perceptions and enhancing their trust in AV can contribute to improving pedestrians' crossing decisions. Scenario analysis reveals that the tendency of pedestrians not to cross the road increases with increasing approaching vehicle speed but decreases with increasing approaching vehicle distance. In addition, the interactions among vehicle types, roadside facilities, and crossing gap times also affect the propensity of pedestrians to cross the street. Furthermore, middle-aged pedestrians made more conservative decisions regarding crossing the street. The variation in trust in AV is highly sensitive to pedestrians' crossing decisions. The conclusions of this study have important guiding significance for formulating traffic control remedy measures, strengthening road infrastructure construction and optimization, and improving pedestrian crossing safety.

However, there are several limitations as well. One of the limitations of this study is that the sample is skewed toward a younger age group, with approximately one-third of the participants being younger than 25 years, while older pedestrians are underrepresented, which could skew the results of parameter estimation of pedestrian choice. In future research, it is recommended that the sample distribution be consistent with the population distribution to provide more generalizable and convincing results. Another limitation of this study is that the selected scenario variables, such as the speed and distance of the approaching vehicle, are relatively conventional. Future research should further explore the impact of other scenario variables, such as weather conditions, on pedestrian crossing decision.

References

Aaditya, B., & Rahul, T. M. (2021). Psychological impacts of COVID-19 pandemic on the mode choice behaviour: A hybrid choice modelling approach. *Transport policy, 108*, 47-58.

Aghabayk, K., Esmailpour, J., Jafari, A., & Shiwakoti, N. (2021). Observational-based study to explore pedestrian crossing behaviors at signalized and unsignalized crosswalks. *Accident Analysis & Prevention, 151*, 105990.

AlKheder, S., Alkandriy, F., Alkhames, Z., Habeeb, M., Alenezi, R., & Al Kader, A. (2022). Walkability, risk perception and safety assessment among urban college pedestrians in Kuwait. *Transportation Research Part F: Traffic Psychology and Behaviour*, *86*, 10-32.

Awadallah, F. (2009). Intersection sight distance analysis and guidelines. *Transport Policy, 16*(4), 143-150.

Banerjee, A., Das, S., & Maurya, A. K. (2024). Behavioural characteristics influencing walking speed of pedestrians over elevated facilities: A case study of India. *Transport Policy, 147*, 169-182.

Bierlaire, M. (2018). Estimating choice models with latent variables with PandasBiogeme. Rep. TRANSP-OR, 181227.

Bornioli, A., Parkhurst, G., & Morgan, P. L. (2019). Affective experiences of built environments and the promotion of urban walking. *Transportation Research Part A: Policy and Practice, 123*, 200-215.

Breakwell, G. M. (2007). The Psychology of Risk. Cambridge University Press, Cambridge.

Chan, H.Y., Ip, L.C., Mansoor, U. and Chen, A., 2022. Pedestrian route choice with respect to new lift-only entrances to underground space: Case study of a metro station area in hilly terrain in Hong Kong. *Tunnelling and Underground Space Technology*, *129*, p.104678.

Chandrappa, A. K., Bhattacharyya, K., & Maitra, B. (2021). Measures for improving pedestrian crossing facilities based on perceptions of urban commuters: An experience in Kolkata. *Case Studies on Transport Policy, 9*(2), 965-973.

Che, M., Wong, Y. D., Lum, K. M., & Liu, S. (2024). Impact of “keep left” measure on pedestrians, cyclists and e-scooter riders at a crossing of a signalised junction. *Transportation Research Part A: Policy and Practice, 179*, 103942.

Chen, T. Y., & Jou, R. C. (2019). Using HLM to investigate the relationship between traffic accident risk of private vehicles and public transportation. *Transportation Research Part A: Policy and Practice, 119*, 148-161.

Chen, C. F., Fu, C., & Siao, P. Y. (2023). Exploring electric moped sharing preferences with integrated choice and latent variable approach. *Transportation Research Part D: Transport and Environment, 121*, 103837.

Cheng, A. S., Ng, T. C., & Lee, H. C. (2011). A comparison of the hazard perception ability of accident-involved and accident-free motorcycle riders. *Accident Analysis & Prevention, 43*(4), 1464-14

71.

Cœugnet, S., Cahour, B., & Kraiem, S. (2019). Risk-taking, emotions and socio-cognitive dynamics of pedestrian street-crossing decision-making in the city. *Transportation Research Part F: Traffic Psychology and Behaviour, 65*, 141-157.

Davey, J.D. and Freeman, J.E. (2011). Improving road safety through deterrence-based initiatives: A review of research. *Sultan Qaboos University Medical Journal*, *11*(1), 29.

Deb, S., Strawderman, L., Carruth, D. W., DuBien, J., Smith, B., & Garrison, T. M. (2017). Development and validation of a questionnaire to assess pedestrian receptivity toward fully autonomous vehicles. *Transportation Research Part C: Emerging Technologies, 84*, 178-195.

De Clercq, K., Dietrich, A., Núñez Velasco, J. P., De Winter, J., & Happee, R. (2019). External human-machine interfaces on automated vehicles: Effects on pedestrian crossing decisions. *Human Factors, 61*(8), 1353-1370.

Deery, H. A. (1999). Hazard and risk perception among young novice drivers. *Journal of Safety Research, 30*(4), 225-236.

Dinh, D. D., Vũ, N. H., McIlroy, R. C., Plant, K. A., & Stanton, N. A. (2020). Effect of attitudes towards traffic safety and risk perceptions on pedestrian behaviours in Vietnam. *IATSS Research, 44*(3), 238-247.

Dommes, A., Cavallo, V., Dubuisson, J. B., Tournier, I., & Vienne, F. (2014). *Journal of Safety Research, 50*, 27-34.

Eisma, Y. B., van Bergen, S., Ter Brake, S. M., Hensen, M. T. T., Tempelaar, W. J., & de Winter, J. C. (2019). External human–machine interfaces: The effect of display location on crossing intentions and eye movements. *Information, 11*(1), 13.

Esmaili, A., Aghabayk, K., Parishad, N., & Stephens, A. N. (2021). Investigating the interaction between pedestrian behaviors and crashes through validation of a pedestrian behavior questionnaire (PBQ). *Accident Analysis & Prevention, 153*, 106050.

Esztergár-Kiss, D., Tordai, D., & Lizarraga, J. C. L. (2022). Assessment of travel behavior related to e-scooters using a stated preference experiment. *Transportation Research Part A: Policy and Practice, 166*, 389-405.

Ewing, R. and Dumbaugh, E. (2009). The built environment and traffic safety: a review of empirical evidence. *Journal of Planning Literature*, *23*(4), 347-367.

Faas, S. M., Kraus, J., Schoenhals, A., & Baumann, M. (2021). Calibrating pedestrians' trust in automated vehicles: Does an intent display in an external HMI support trust calibration and safe crossing behavior?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1-17.

Federal Aviation Administration. (2022). Risk Management Handbook. U.S. Department of Transportation.

Feng, Z., Chu, C., Zhu, D., Ji, N., Cui, J., & Huang, Z. (2022). Investigation of intervention methods based on different leading roles in family regarding child road safety education: An experimental study. *Accident Analysis & Prevention, 178*, 106874.

Fu, T., Yu, X., Xiong, B., Jiang, C., Wang, J., Shangguan, Q., & Xu, W. (2022). A method in modeling interactive pedestrian crossing and driver yielding decisions during their interactions at intersections. *Transportation Research Part F: Traffic Psychology and Behaviour, 88*, 37-53.

Goniewicz, K., Goniewicz, M., Pawłowski, W. & Fiedor, P. (2016). Road accident rates: strategies and programmes for improving road traffic safety. *European Journal of Trauma and Emergency Surgery, 42*, 433-438.

Hansson, S. O. (2010). Risk: objective or subjective, facts or values. *Journal of Risk Research, 13*(2), 231-238.

He, Y. L., Li, R. T., Li, L., Schwebel, D. C., Huang, H. L., Yin, Q. Y., & Hu, G. Q. (2019). Left-turning vehicle-pedestrian conflicts at signalized intersections with traffic lights: benefit or harm? A two-stage study. *Chinese Journal of Traumatology, 22*(02), 63-68.

Hoen, F. S., Díez-Gutiérrez, M., Babri, S., Hess, S., & Tørset, T. (2023). Charging electric vehicles on long trips and the willingness to pay to reduce waiting for charging. Stated preference survey in Norway. *Transportation Research Part A: Policy and Practice, 175*, 103774.

Hulse, L. M. (2023). Pedestrians' perceived vulnerability and observed behaviours relating to crossing and passing interactions with autonomous vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour, 93*, 34-54.

Irawan, M. Z., Belgiawan, P. F., & Joewono, T. B. (2022). Investigating the effects of individual attitudes and social norms on students' intention to use motorcycles–An integrated choice and latent variable model. *Travel Behaviour and Society, 28*, 50-58.

Jayaraman, S. K., Creech, C., Tilbury, D. M., Yang, X. J., Pradhan, A. K., Tsui, K. M., & Robert Jr, L. P. (2019). Pedestrian trust in automated vehicles: Role of traffic signal and AV driving behavior. *Frontiers in Robotics and AI, 6*, 117.

Jing, P., Wang, W., & Wu, L. (2021). Acceptance of autonomous vehicles for the elderly. *China Journal of Highway and Transport, 34*(06), 158-171. (In Chinese)

Kamargianni, M., Dubey, S., Polydoropoulou, A., & Bhat, C. (2015). Investigating the subjective and objective factors influencing teenagers' school travel mode choice–An integrated choice and latent variable model. *Transportation Research Part A: Policy and Practice, 78*, 473-488.

Kavta, K., & Goswami, A. K. (2022). Estimating mode choice of motorized two-wheeler commuters under the influence of combined travel demand management measures: An ICLV modeling approach. *Transport Policy, 126*, 327-335.

Kim, J., & Lee, B. (2023). Campus commute mode choice in a college town: An application of the integrated choice and latent variable (ICLV) model. *Travel Behaviour and Society, 30*, 249-261.

Kwon, J. H., Kim, J., Kim, S., & Cho, G. H. (2022). Pedestrians safety perception and crossing behaviors in narrow urban streets: An experimental study using immersive virtual reality technology. *Accident Analysis & Prevention, 174*, 106757.

Lanzer, M., Gieselmann, M., Mühl, K., & Baumann, M. (2021). Assessing crossing and communication behavior of pedestrians at urban streets. *Transportation Research Part F: Traffic Psychology and Behaviour, 80*, 341-358.

Lajunen, T., & Özkan, T. (2011). Self-report instruments and methods. *Handbook of Traffic Psychology, Academic Press*, 43-59.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50-80.

Leung, K. Y., Loo, B. P., Tsui, K. L., So, F. L., & Fok, E. (2021). To cross or not to cross: A closer look at children's decision-making on the road. *Transportation Research Part A: Policy and Practice, 149*, 1-11.

Li, H., Hu, H., Zhang, Z., Ren, G., & Liu, X. (2022). Impacts of enforcement cameras on pedestrians' risk perception and drivers' behaviors at non-signalized crosswalks. *Journal of Safety Research, 81*, 313-325.

Li, H., Hu, H., Zhang, Z., & Zhang, Y. (2023). The role of yielding cameras in pedestrian-vehicle interactions at un-signalized crosswalks: An application of game theoretical model. *Transportation Research Part F: Traffic Psychology and Behaviour, 92*, 27-43.

Li, H., Zhang, Z., Sze, N. N., Hu, H., & Ding, H. (2021). Safety effects of law enforcement cameras at non-signalized crosswalks: A case study in China. *Accident Analysis & Prevention, 156*, 106124.

Liang, G., Fu, H., Wang, B., Yi, Z., & Yang, W. (2022). Evaluating the influence of approaching vehicles on pedestrian's visual patterns and crossing behaviors at an uncontrolled crosswalk. *Transportation Research Part F: Traffic Psychology and Behaviour, 88*, 236-247.

Liang, Z., NG, K. F., Huai, Y., Lo, H. K., & Axhausen, K. W. (2023). A stated preference approach for measuring walking accessibility. *Transportation Research Part D: Transport and Environment, 122*, 103876.

Liu, Y. C., & Tung, Y. C. (2014). Risk analysis of pedestrians' road-crossing decisions: Effects of age, time gap, time of day, and vehicle speed. *Safety Science, 63*, 77-82.

Liu, Y., Yang, D., Timmermans, H. J., & de Vries, B. (2020). Analysis of the impact of street-scale built environment design near metro stations on pedestrian and cyclist road segment choice: A stated choice experiment. *Journal of Transport Geography, 82*, 102570.

Luiu C. (2021). Pedestrian Safety, Older People. *International Encyclopedia of Transportation*, 429-434.

Ma, J., Shen, Z., Wang, N., Xiao, X., & Zhang, J. (2024). Developmental differences in children's ad aptation to vehicle distance and speed in street-crossing decision-making. *Journal of Safety Research*, *88,* 261-274.

Mahpour, A., Mamdoohi, A., HosseinRashidi, T., Schmid, B., & Axhausen, K. W. (2018). Shopping destination choice in Tehran: An integrated choice and latent variable approach. *Transportation Research Part F: Traffic Psychology and Behaviour, 58*, 566-580.

Mfinanga, D. A. (2014). Implication of pedestrians′ stated preference of certain attributes of crosswalks. *Transport Policy, 32*, 156-164.

Miśkiewicz, M., Pyrzowski, Ł., & Okraszewska, R. (2017). Pedestrian and bicycle bridges as examples of safe collision-free road crossings. In *MATEC Web of Conferences*, *122*, 01005.

Mohiuddin, H., Bhuiya, M. M. R., Hasan, M. M. U., & Jamme, H. T. (2024). How individual perceptions of transportation systems influence mode choice for mobility-challenged people: a case study in Dhaka using an integrated choice and latent variable model. *Transport Policy, 147*, 259-270.

Nabipour, M., Rosenberg, M. W., & Nasseri, S. H. (2022). The built environment, networks design, and safety features: An analysis of pedestrian commuting behavior in intermediate-sized cities. *Transport Policy, 129*, 14-23.

National Bureau of Statistics. (2022). National Bureau of Statistics Population Status - 2022 CHINA STATISTICAL YEARBOOK. Last access 22 March, 2023, from http://www.stats.gov.cn/sj/ndsj/2022/indexch.htm

Nasar, J. L., Holloman, C., & Abdulkarim, D. (2015). Street characteristics to encourage children to walk. *Transportation Research Part A: Policy and Practice*, *72*, 62-70.

Osorio-García, D., Hernández-Pulgarín, G., & Escobar, D. A. (2023). Profiles of pedestrian risk behavior while crossing the street. *Safety Science, 163*, 106120.

Pal, S., Sharma, L., & Jangid, M. (2022). Trust and technology acceptance in crossing-decision of pedestrian in automated vehicles. In *2022 8th international conference on advanced computing and communication systems (ICACCS), 1,* 609-614.

Patra, M., Perumal, V., & Rao, K. K. (2020). Modelling the effects of risk factor and time savings on pedestrians' choice of crossing facilities at signalised intersections. *Case Studies on Transport Policy, 8*(2), 460-470.

Rad, S. R., de Almeida Correia, G. H., & Hagenzieker, M. (2020). Pedestrians' road crossing behaviour in front of automated vehicles: Results from a pedestrian simulation experiment using agent-based modelling. *Transportation Research Part F: Traffic Psychology and Behaviour, 69*, 101-119.

Rankavat, S., & Tiwari, G. (2020). Influence of actual and perceived risks in selecting crossing facilities by pedestrians. *Travel Behaviour and Society, 21*, 1-9.

Reason, J., Manstead, A., Stradling, S., Baxter, J., & Campbell, K. (1990). Errors and violations on the roads: A real distinction? *Ergonomics, 33*(10e11), 1315e1332.

Rossetti, T., Guevara, C. A., Galilea, P., & Hurtubia, R. (2018). Modeling safety as a perceptual laten t variable to assess cycling infrastructure. *Transportation Research Part A: Policy and Practice, 111*, 252-265.

Salducco, A., Abati, D., Bina, M., Bertani, B., Calarco, S., Balzarotti, S., & Biassoni, F. (2022). Young pedestrians' behaviours and risk perception: a pilot study with Italian early adolescents. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 512-523.

Saxena, A. (2023). Assessing the factors affecting the perceived crossing speed of pedestrians and investigating the direct and indirect effects of crash risk perception on perceived crossing speed. *Journal of Transport & Health, 28*, 101541.

Shangguan, Q., Wang, J., Fu, T., & Fu, L. (2023). An empirical investigation of driver car-following risk evolution using naturistic driving data and random parameters multinomial logit model with heterogeneity in means and variances. *Analytic Methods in Accident Research, 38,* 100265.

Siegrist, M. (2021). Trust and risk perception: A critical review of the literature. *Risk Analysis, 41*(3), 480-490.

Singh, M., Cheng, W., Samuelson, D., Kwong, J., Li, B., Cao, M., & Li, Y. (2021). Development of pedestrian-and vehicle-related safety performance functions using Bayesian bivariate hierarchical models with mode-specific covariates. *Journal of Safety Research, 78*, 180-188.

Soares, F., Silva, E., Pereira, F., Silva, C., Sousa, E., & Freitas, E. (2021). To cross or not to cross: Impact of visual and auditory cues on pedestrians' crossing decision-making. *Transportation Research Part F: Traffic Psychology and Behaviour, 82*, 202-220.

Soathong, A., Chowdhury, S., Wilson, D., & Ranjitkar, P. (2021). Investigating the motivation for pedestrians' risky crossing behaviour at urban mid-block road sections. *Travel Behaviour and Society, 22*, 155-165.

Song, Y., Jiang, Q., Chen, W., Zhuang, X., & Ma, G. (2023). Pedestrians' road-crossing behavior towards eHMI-equipped autonomous vehicles driving in segregated and mixed traffic conditions. *Accident Analysis & Prevention, 188*, 107115.

Soto, J. J., Márquez, L., & Macea, L. F. (2018). Accounting for attitudes on parking choice: An integrated choice and latent variable approach. *Transportation Research Part A: Policy and Practice, 111*, 65-77.

Sueur, C., Class, B., Hamm, C., Meyer, X., & Pelé, M. (2013). Different risk thresholds in pedestrian road crossing behaviour: A comparison of French and Japanese approaches. *Accident Analysis & Prevention*, 58, 59-63.

Theofilatos, A., Ziakopoulos, A., Oviedo-Trespalacios, O., & Timmis, A. (2021). To cross or not to cross? Review and meta-analysis of pedestrian gap acceptance decisions at midblock street crossings. *Journal of Transport & Health, 22*, 101108.

Tian, Z., Feng, T., Yao, B., Hu, Y., & Zhang, J. (2023). Where to park an autonomous vehicle? Results of a stated choice experiment. *Transportation Research Part A: Policy and Practice, 175*, 103

763.

Tian, K., Markkula, G., Wei, C., Lee, Y. M., Madigan, R., Merat, N., & Romano, R. (2022). Explaining unsafe pedestrian road crossing behaviours using a psychophysics-based gap acceptance model. *Safety Science, 154*, 105837.

Ton, D., Duives, D. C., Cats, O., Hoogendoorn-Lanser, S., & Hoogendoorn, S. P. (2019). Cycling or walking? Determinants of mode choice in the Netherlands. *Transportation Research Part A: Policy and Practice, 123*, 7-23.

Velasco, J. P. N., Farah, H., Van Arem, B., & Hagenzieker, M. P. (2019). Studying pedestrians' crossing behavior when interacting with automated vehicles using virtual reality. *Transportation Research Part F: Traffic Psychology and Behaviour, 66*, 1-14.

Velasco, J.P.N., Lee, Y.M., Uttley, J., Solernou, A., Farah, H., van Arem, B., Hagenzieker, M. and Merat, N. (2021). Will pedestrians cross the road before an automated vehicle? The effect of drivers' attentiveness and presence on pedestrians' road crossing behavior. *Transportation Research Interdisciplinary Perspectives, 12*, 100466.

Vij, A., & Walker, J. L. (2016). How, when and why integrated choice and latent variable models are latently useful. *Transportation Research Part B: Methodological, 90*, 192-217.

Wang, L., Ning, P., Yin, P., Cheng, P., Schwebel, D. C., Liu, J., ... & Hu, G. (2019). Road traffic mortality in China: analysis of national surveillance data from 2006 to 2016. *The Lancet Public Health*, 4(5), e245-e255.

Wang, K., Li, G., Chen, J., Long, Y., Chen, T., Chen, L., & Xia, Q. (2020). The adaptability and challenges of autonomous vehicles to pedestrians in urban China. *Accident Analysis & Prevention, 145*, 105692.

Wang, X., Liu, Y., Yao, Y., Zhou, S., Zhu, Q., Liu, M., & Helbich, M. (2023). Adolescents' environmental perceptions mediate associations between streetscape environments and active school travel. *Transportation Research Part D: Transport and Environment, 114*, 103549.

Wang, Y., Choudhury, C., Hancock, T. O., Wang, Y., & de Dios Ortúzar, J. (2024). Influence of perceived risk on travel mode choice during Covid-19. *Transport Policy, 148*, 181-191.

World Health Organization. (2023). Global status report on road safety 2023. Last access 13 December, 2023, from https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023

Wu, M., Wang, N., & Yuen, K. F. (2023). Can autonomy level and anthropomorphic characteristics affect public acceptance and trust towards shared autonomous vehicles?. *Technological Forecasting and Social Change, 189*, 122384.

Yadav, A. K., & Velaga, N. R. (2022). A systematic review of observational studies investigating the influence of mobile phone distraction on road crossing behaviour of pedestrians. *Transportation Research Part F: Traffic Psychology and Behaviour, 91*, 236-259.

Zhang, Z., Li, H., Sze, N. N., & Ren, G. (2023a). Investigating pedestrian crossing route choice at mid-blocks without crossing facilities: The role of roadside environment. *Travel Behaviour and Society, 32*, 100573.

Zhang, Y., Lu, L., Liu, Q., & Hu, M. (2023b). Modeling of low-risk behavior of pedestrian movement based on dynamic data analysis. *Transportation Research Part A: Policy and Practice, 168,* 103576.

Zhang, J., Tu, Y., Liu, J., Liu, L., & Li, Z. (2022). Regional public transportation safety risk grading assessment under time dimension: A case study of Chinese mainland. *Transport Policy, 126*, 343-354.

Zhang, C., Chen, F., & Wei, Y. (2019). Evaluation of pedestrian crossing behavior and safety at uncontrolled mid-block crosswalks with different numbers of lanes in China. *Accident Analysis & Prevention, 123*, 263-273.

Zhao, X., Li, X., Rakotonirainy, A., Bourgeois-Bougrine, S., & Delhomme, P. (2022). Predicting pedestrians' intention to cross the road in front of automated vehicles in risky situations. *Transportation Research Part F: Traffic Psychology and Behaviour, 90*, 524-536.

Zhou, S., Sun, X., Liu, B., & Burnett, G. (2021). Factors affecting pedestrians' trust in automated vehicles: Literature review and theoretical model. *IEEE Transactions on Human-Machine Systems, 52*(3), 490-500.

Zhu, D., Sze, N. N., & Feng, Z. (2021). The trade-off between safety and time in the red light running behaviors of pedestrians: A random regret minimization approach. *Accident Analysis & Prevention, 158*, 106214.

Zhu, D., Sze, N. N., Feng, Z., & Chan, H. Y. (2023). Waiting for signalized crossing or walking to footbridge/underpass? Examining the effect of weather using stated choice experiment with panel mixed random regret minimization approach. *Transport Policy, 138*, 144-169.

Zhu, W., & Timmermans, H. (2009). Modelling pedestrian go-home decisions: A comparison of linear and nonlinear compensatory, and conjunctive non-compensatory specifications. *Journal of Retailing and Consumer Services, 16*(3), 227-231.

Highlights

- Relationship between intelligent transportation facilities, pedestrian risk perception, trust in AV, and crossing decisions are investigated.
- A video-based SP questionnaire was design.
- The ICLV model was used to predict pedestrians' propensity to cross the street.
- The presence of autonomous vehicles can have a significant impact on pedestrian crossing decision.
- Pedestrians who are middle-aged, and have high levels of risk perception are more conservative in their crossing decisions.