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Study on the Impact of eHMI on the Interaction between Cyclists and Autonomous Vehicles

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ABSTRACT
Autonomous vehicles (AVs) have the potential to improve road safety, reduce traffic congestion and lower emissions, but scepticism remains due to the absence of drivers. To address this, an external human-machine communication interface (eHMI) can be employed to communicate with other road users. However, the impact of eHMI on cyclists' self-protective behaviour is still unclear. This study aimed to investigate the effects of eHMI technology on cyclists' behaviour and safety awareness. Data on demographics (gender, age, education level), road behaviour (violations, errors, positive behaviours) and acceptance of AVs (social norms, attitudes, behavioural intention) were collected through online surveys. Six scenarios were designed to simulate potential collision risks and analyse the impact of eHMI on cyclists' self-protective behaviour (e.g. braking, lane changes). A total of 895 respondents participated in the survey. The findings indicated that male and younger cyclists exhibited a higher acceptance of AVs. Cyclists who had experienced an accident within the past two years were more willing to share the road with AVs. Younger cyclists demonstrated better responsiveness and understanding of eHMI signals compared to older cyclists. Additionally, cyclists with higher education levels showed enhanced ability to utilise eHMI information and displayed more self-protective behaviour. This research provides significant theoretical and practical insights for advancing human-machine interactions between AVs and cyclists.

KEYWORDS
external human-machine interfaces; autonomous vehicles; cyclist behaviour; cognitive factors; behavioural preferences; self-protective behaviour.

1. INTRODUCTION

Autonomous vehicles (AVs) are advancing rapidly worldwide, with China making particularly notable progress. Companies such as Volvo and Uber are conducting self-driving tests, while businesses like AutoX in Shenzhen are demonstrating the feasibility of autonomous ride-hailing services [1, 2]. With the advancement of core technologies and the improvement of communication performance, Chinese cities now operate fleets of self-driving taxis that can be booked online [3]. Wuhan has constructed 3,379 km of test roads covering 3,000 km². Although autonomous driving systems have enhanced safety and efficiency, challenges remain in integrating AVs into mixed-traffic environments [4]. To maintain traffic flow and safety, effective communication among road users is essential. In traditional traffic, pedestrians and cyclists rely on formal vehicle signals (e.g. turn signals, brake lights) and informal driver cues (e.g. gestures, eye contact) to understand vehicle intentions [5]. Thus, AVs must effectively exchange information with other road users in complex traffic situations. Research highlights that enhanced external eHMIs are crucial for facilitating communication between AVs and other road users, especially pedestrians and cyclists, and are a key requirement for AVs' large-scale deployment [6].

While eHMI technology holds promise for boosting human-vehicle interaction efficiency, its effects on cyclist behaviour and their ability to take protective actions in response to potential risks require further study. In China, electric bicycles have become a significant part of urban non-motorised transport, with numbers rising in recent years. However, existing non-motorised lanes often fail to meet the unique needs of electric bicycles, leading riders to frequently encroach on motor vehicle lanes and increase accident risks. Additionally, the growing popularity of shared bicycles has added to the complexity of urban traffic conditions, raising the likelihood of congestion and accidents. In this study, self-protective behaviour is defined as actions taken by cyclists, such as braking, changing lanes or adjusting speed, to reduce potential risks during interactions with autonomous vehicles. These behaviours are crucial for ensuring safety in complex traffic situations. This study explores how eHMI technology affects cyclist behaviour. Its results could enhance AV-cyclist interaction, boost transportation system safety and efficiency, and increase public trust in autonomous driving. This would promote the technology's widespread use in mainstream transportation.

2. LITERATURE REVIEW

2.1 Public acceptance of AVs

An increasing number of studies have explored public acceptance of AVs, identifying multiple psychological factors as key influencers. Trust, a core variable, directly impacts behavioural intentions and indirectly regulates other perceptions – excessive trust reduces driver monitoring, risking dangerous delays in critical situations [7]. Perceived usefulness/ease of use drives technological attitudes and usage intentions, while anxiety negatively affects acceptance [8]. Decision styles also matter: 'thoroughness'-oriented individuals trust autonomous systems more, whereas 'social resistance'-oriented groups show lower acceptance [9]. Subjective norms, reflecting social pressure, often emerge as the strongest predictor of behavioural intentions [9].

Cultural context profoundly shapes attitudes. For example, China demonstrates high scenario-neutral acceptance of AV decisions, while Germany and the US prefer less obstructive overtaking; Japan, rooted in rule-abiding culture, rejects behaviours that may hinder others [10]. In Europe, social development and gender equality correlate with acceptance: high-GDP countries with strong Gender Equality Indexes show men accepting AVs more than women, a gap linked to social resource distribution and gender roles. This disparity is less pronounced in less developed nations [11].

Demographic factors also play distinct roles. Younger individuals and those with less driving experience embrace AVs, while older adults focus on infrastructure risks [12, 13]. Higher education correlates with greater acceptance [12]. Gender differences vary: some studies find men more positive, with women citing performance concerns and technical anxiety [8, 14], though others report no gender gaps in risk perception [14]. Frequent drivers tend to favour AV-associated driver monitoring systems [8]. Collectively, these factors highlight the need for tailored AV promotion strategies.

2.2 Interaction between AVs and cyclists

The safety of interaction between AVs and cyclists is a key research focus in intelligent transportation. Existing studies analyse this interaction across three dimensions: conflict patterns, psychological perception and behavioural responses. Conflict analysis using multi-source sensor data (over 1,500 hours of driving in Canada, the US and Singapore) and extreme value theory (EVT) shows higher risks for cyclists interacting with left-turning AVs, emphasising the need for enhanced intention recognition [15]. Photo experiments (35 participants) reveal that instruction types and AV markings affect cyclist trust, with longer initial gaze durations indicating the need for adaptive experience [16]. Controlled field tests (29 cyclists in following/overtaking scenarios) confirm higher automatic overtaking risks and interaction-induced behavioural changes (e.g. speeding, roadside proximity), highlighting the need for AV behaviour optimisation [17].

While these studies provide critical insights into interaction mechanisms, several unresolved challenges demand attention. Notably, the same EVT-based analysis that identified left-turn risks also underscores AVs' struggle to predict cyclist paths amid rule violations [15]. Concurrently, the photo experiment's findings on trust misalignment are echoed in cyclists' persistent misperceptions of AV behaviour [17], while the field test's demonstration of behavioural adaptation highlights the gap in AV intent interpretation- a capability pivotal for incident avoidance [18]. Addressing these requires a multi-faceted approach: smart infrastructure [19] to bridge perception gaps, optimised bike lane design (spaciousness, clear markings, physical barriers) [20] to mitigate behavioural risks, and precise cyclist behaviour prediction [21] to enhance AV decision-making.

2.3 The impact of eHMI on cyclists' interaction

The interaction safety between cyclists and AVs represents a key research domain in intelligent transportation, particularly as eHMIs develop to facilitate communication and enhance safety. Engineered to convey AV intentions to vulnerable road users like cyclists, eHMIs shape cyclist behaviour and safety perceptions in mixed traffic environments. Studies have shown that eHMIs excel in intent communication: in emergency scenarios (e.g. sudden braking of a front vehicle), eHMIs can prompt cyclists to maintain pedalling rather than braking, demonstrating positive behavioural influence in critical moments [22]. Meanwhile, clear AV intent conveyance significantly improves cyclists' crossing behaviour and boosts their confidence in shared road spaces [23]. Moreover, eHMIs effectively alleviate uncertainties in cyclist-AV interactions, enhancing trust and safety sensations [24].

Regarding eHMI design and functionality, research underscores the need for understandability and reliability – miscommunication via eHMIs may exacerbate cyclists' perceived risk [25], while diverse design approaches yield varying effects on cyclists' willingness to cross intersections, highlighting the necessity of tailored communication strategies [26]. System reliability is equally critical: evidence shows that eHMI malfunctions drastically erode cyclist trust and safety perceptions [27]. In visual design, light-based eHMIs significantly influence cyclists' perception of AV movements, indicating that optimised visual signals enhance communication clarity [28]. Additionally, eHMI design must account for cyclists' specific needs and dynamic variations in transportation modes and interaction contexts [29].

2.4 Research summary

In the field of research on the interaction between cyclists and AVs, existing studies have made significant contributions by exploring physical-level interactions and conducting in-depth research into the design and functions of eHMIs, with a view to optimising communication between AVs and cyclists. However, the absence of a human driver in AVs may lead to discrepancies between cyclists' expectations and those formed through interactions with existing prototype models. Our understanding of cyclists' behavioural intentions, their acceptance of AVs, and the underlying factors influencing these aspects, particularly their current behavioural characteristics, remains extremely limited.

More crucially, existing studies have largely overlooked the impact of psychological latent variables on the interaction process between cyclists and AVs. Psychological latent variables (e.g. attitudes, perceptions) cannot be accurately measured via direct observation, but are instead reflected indirectly through multiple manifest variables. For instance, a cyclist's "attitude" toward AVs is jointly influenced by past driving experiences, public opinion and personal personality traits. To comprehensively evaluate the role of these latent constructs in the interaction dynamics, diverse research methodologies are required.

To address these identified issues, the present exploratory study aims to: (1) investigate cyclists' acceptance of sharing road space with AVs and explore associations between this acceptance and their current riding behaviours and personal characteristics; (2) elucidate the determinants influencing cyclists' intentions to engage in interactive behaviours during encounters with AVs; and (3) examine how eHMI technology modulates cyclists' self-protective behaviours.

3. METHODOLOGY

3.1 Survey design

This study employs an online questionnaire survey, structured into four sections. The first section provided respondents with detailed information about AVs, omitting any commentary on their benefits or issues. Following introductory content, participants answered questions on demographic characteristics, including gender, age, income, education, employment status, family size, household vehicle ownership and traffic accidents experienced in the past two years.

The second section investigated cyclists' riding behaviours, encompassing violations, errors and positive safety behaviours, drawing on established questionnaires that assess these three dimensions [30]. Violations were defined as intentional breaches of traffic rules; errors referred to unintended behavioural inconsistencies or failed planned actions leading to adverse outcomes; positive safety behaviours were conceptualised as actions reducing accident risk. The 12 violations, 13 errors and 12 positive behaviours were measured using a five-point Likert scale (1= "never", 5= "often").

Building on psychosocial models (e.g. Technology Acceptance Model [31], Theory of Planned Behaviour [32], Unified Theory of Technology Acceptance and Use [33]), the third section examined riders' AV acceptance. These frameworks elucidate acceptance by evaluating psychological constructs [34–36]. Here, six latent variables were derived from the Theory of Planned Behaviour and Technology Acceptance Model: perceived ease of use, perceived usefulness, attitude, social norms, perceived behavioural control and behavioural intention. Except for four items measuring perceived usefulness, each construct was assessed via three five-point Likert items (1= "strongly disapprove", 5= "strongly approve").

The fourth section investigated respondents' self-protective behaviours during interactions with AVs. Self-protective behaviour in this study denoted immediate actions taken by cyclists to ensure road safety in specific scenarios. The selected scenarios depicted typical cyclist-motor vehicle interactions in Hubei Province, featuring collision risks that might prompt cyclists to act protectively near vehicles. Six scenarios were designed: three without an eHMI system and three with it. Each scenario illustrated potential crash risks and elicited respondents' behavioural reactions. Before presenting eHMI-integrated scenarios, participants received explanations of eHMI technology as an external human-computer interface, clarifying its role in conveying AV intentions and status to pedestrians and cyclists. A five-point Likert scale was used, with response options like "How likely would you gesture to an AV when turning left?" (1= "very unlikely", 5= "very likely").

Scenario description

The first two scenarios (see *Figures 1-2*) depict a T-junction where a cyclist intends to turn left in front of an oncoming AV. Participants were presented with scenario-specific questions regarding their likelihood of giving a left-turn hand signal. This scenario is common on urban roads in China, particularly at intersections lacking dedicated cycle traffic lights or turning lanes, where many cyclists rely on hand gestures to communicate intentions. Understanding cyclists' behavioural decisions in this context, such as whether they perform a left-turn signal, helps elucidate user psychological and behavioural characteristics during AV interaction.

Question: How likely would you gesture to an AV when turning left?

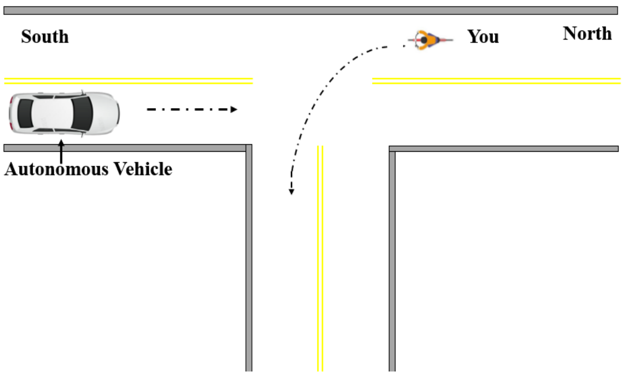

Figure 1 – Cyclist encounters an oncoming AV (without eHMI)

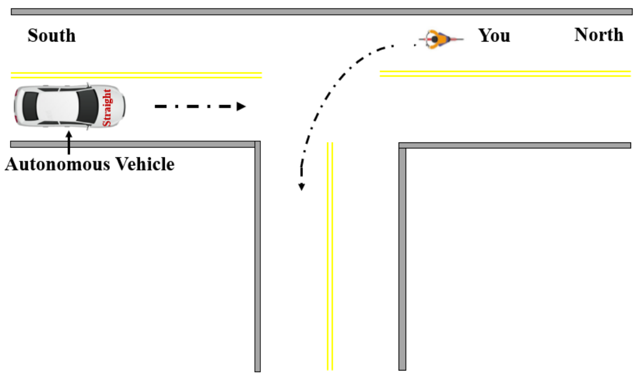

Figure 2 – Cyclist encounters an oncoming AV (loaded eHMI)

The third and fourth scenarios (see *Figures 3-4*) depict a cyclist passing a parked AV, with participants asked to rate the likelihood of lane-changing or slowing down in such contexts. This scenario represents a prevalent safety hazard for cyclists in China, often leading to sudden dangerous situations that threaten cyclist safety. This situation creates dynamic cycling conditions, complicating risk prediction for cyclists. Sudden door-opening from parked vehicles may leave cyclists unable to dodge in time, increasing collision risks.

Question: How likely are you to actively change lanes or slow down in order to avoid colliding with the door?

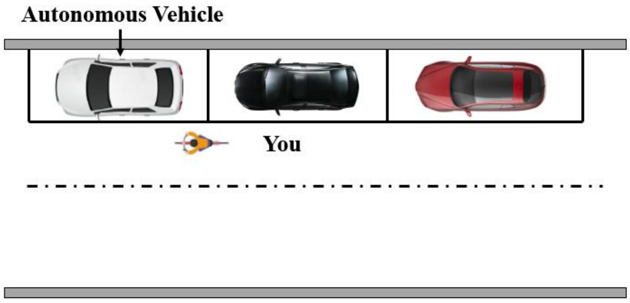

Figure 3 – A cyclist passes by a parked AV (without eHMI)

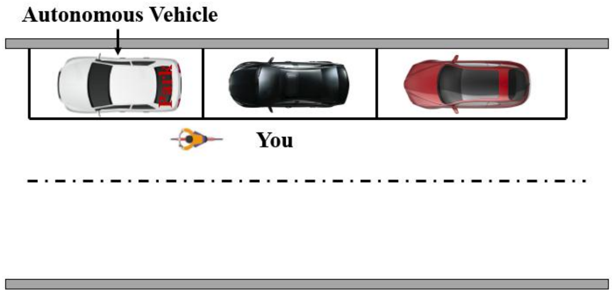

Figure 4 – A cyclist passes by a parked AV (loaded eHMI)

The fifth and sixth scenarios (see *Figures 5-6*) depict an AV driving ahead of another, with the latter accelerating from behind. Participants were asked to assess the likelihood of braking or pulling over in this context. On urban roads in China, non-motorised lanes often run parallel to motorised lanes. When an AV in the motorised lane accelerates past a leading AV, it alters vehicle speed and distance dynamics, which can be perceived by cyclists in adjacent non-motorised lanes. Examining whether cyclists brake or pull over in this scenario helps unpack their interaction intent with AVs.

Question: How likely are you to change lanes or slow down?

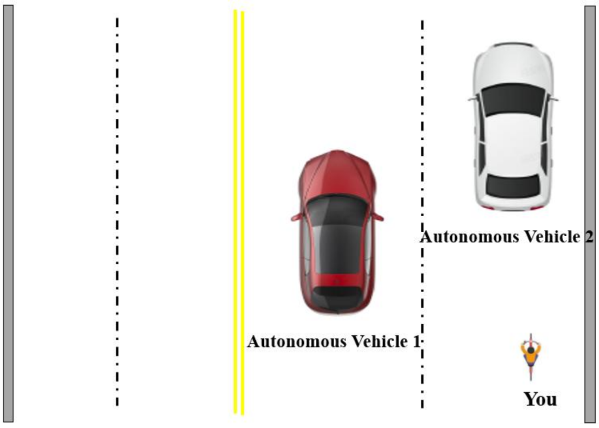

Figure 5 – A cyclist follows the AVs (without eHMI)

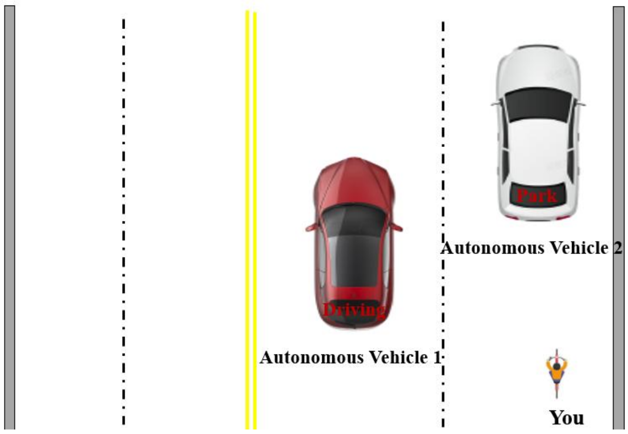

Figure 6 – A cyclist follows the AVs (loaded eHMI)

eHMI design

In the supplementary file, we employed a minimalist, text-based eHMI displayed on an illuminated exterior panel to improve visibility. The message set comprised three states corresponding to the scenarios: straight – the AV intends to proceed ahead; driving – the AV is in motion (with no turning intent); park – the AV is stationary or parked. Messages were shown in a high-contrast, legible sans-serif typeface and appeared only when the vehicle was in the respective state. Before the experiment, participants were informed that the eHMI text described the vehicle's status rather than giving instructions to other road users.

Mixed-ordered logit model

Mixed-ordered logit models are invaluable in fields such as transportation engineering, economics and marketing. These models allow for random coefficient distributions, capturing respondent heterogeneity and offering a more precise representation of decision-making processes [37–40]. The logit kernel, a variant of mixed logit, can accommodate unobserved factors with correlation and heteroscedasticity, rendering it a robust choice for modelling complex decision scenarios [41].

In the mixed-ordered logit framework, let Y_i be the dependent variable, representing the likelihood that the cyclist makes behaviours such as giving signal gestures, changing lanes or braking, braking or pulling over when interacting with an AV in a specific situation. Define s (s=1, 2, 3, ..., S) as ordinal categories. For example, s=1 represents "extremely unlikely", s=2 represents "unlikely", s=3 represents "neutral", s=4 represents "likely" and s=5 represents "extremely likely".

To explain the modelling process of the mixed-ordered logit model, it is essential to consider individual heterogeneity. In this study, we use random coefficients to capture cyclists' behavioural responses to AVs in different scenarios. Random effects are employed to account for unobserved individual differences, which may arise from cyclists' behavioural habits, trust levels and acceptance of automation. Additionally, the model's estimation is performed using maximum simulated likelihood estimation to ensure accurate parameter estimation while considering the random effects.

Construct the basic linear model:

$$Y_i = \beta_i X_i + \varepsilon_i \tag{1}$$

where β_i is the vector of parameters to be estimated and X_i is the vector of covariates. The included contents are the demographic characteristics of cyclists of cyclists (such as age, gender, which are common demographic factors considered in this type of research), the cycling behaviour of cyclists (error behaviour, violating behaviour and positive behaviour) and potential variables (including perceived ease of use, attitude, etc., which are important potential variables reflecting the acceptability and behavioural tendency of cyclists). ε_i is the heteroscedastic error term, which is assumed to be independent and identically distributed among all observations. This model is employed to account for the unobserved heterogeneity factors in the impact of explanatory variables on the dependent variable, enabling parameters to vary across different respondents.

$$\beta_i = \bar{\beta}_j + \delta_i \tag{2}$$

$$\delta_i \sim Normal(0, v) \tag{3}$$

where $\bar{\beta}_j$ represents the mean of parameters for all respondents. v is the standard deviation of parameters. When v=0, the model degenerates into a regular ordered response model. By introducing random effects, it is possible to capture the impact of individual-specific, time-invariant characteristics such as cyclists' riding habits and attitudes towards AVs on the dependent variable, thus more accurately reflecting the differences in their behavioural responses when interacting with AVs among individuals.

Define a latent variable Y_i^*, which is related to the dependent variable through a linear propensity function. The latent variable Y_i^* is mapped to the actual categories S of the dependent variable through thresholds τ, that is when $\tau^{(s)} < Y_i^* < \tau^{(s+1)}$, $Y_i = S$. This indicates that when the latent variable is between $\tau^{(s)}$ and $\tau^{(s+1)}$, the likelihood that cyclist makes the corresponding behaviour in a specific situation corresponds to category s.

$$E(Y_i^* | X_i) = H_i^s(.) \tag{4}$$

where $0 \leq H_i^s(.) \leq 1$ and $\sum_{s=1}^{s} H_i^s = 1$. $H_i^s(.)$ is the probability density function of category of the dependent variable. In this study, the standard normal probability density function can be adopted (just like in the construction of the mixed-ordered probit model in the reference method), that is, for the ordered probit model, $H_i^s(.)$ is in the standard normal form.

The probability of each category of the dependent variable can be expressed as

$$P(Y_i = s) = \varphi\{\tau^{(s+1)} - (\beta_i X_i)\} - \varphi\{\tau^{(s)} - (\beta_i X_i)\} \tag{5}$$

where $\varphi(.)$ is the standard normal cumulative probability density function.

The probability that cyclist i makes a specific behaviour can be calculated by

$$P(Y_i) = \prod_{S=1}^{S} P(Y_i = S)^I \tag{6}$$

where I is an indicator variable, taking the value of 1 for the selected category and 0 for the non-selected category.

The corresponding likelihood function of the dependent variable over the entire observation is

$$l = \prod_{i=1}^{N} \left(\int_{\beta} P(Y_i) d\beta \right) \tag{7}$$

where N is the number of observation samples.

Use the maximum simulated likelihood estimation technique to estimate the above-mentioned likelihood function to obtain the estimated values of the model parameters.

Adopt the Akaike information criterion (AIC) to compare the goodness-of-fit of different model variants (such as the mixed-ordered model and the regular-ordered model). AIC is defined as

$$AIC = -2\ln(L) + 2K \tag{8}$$

where L is the likelihood value when the model converges, and K is the number of estimated parameters. Generally, a model with a lower AIC value is considered to have a better fit, and this model should be preferentially selected to make inferences about the explanatory variables, and to analyse the likelihood of cyclists making corresponding behaviours when interacting with AVs in specific situations and their influencing factors [42].

3.2 Procedure

Before the formal survey, we conducted a pre-survey by distributing 50 questionnaires via the platform. This pre-survey aimed to provide preliminary insights and inform the research design. The results helped us design the formal questionnaire more effectively, determine the survey's focus and scope, and enhance the survey's reliability and effectiveness. After analysing the pre-survey results, we removed two items that did not meet the required standards. Consequently, 63 items were retained and included in the official questionnaire. The scales used in the questionnaire were derived from authoritative and well-established sources, thereby ensuring a degree of surface and content validity.

The survey was created on the So Jump online survey platform (https://www.wjx.cn) and disseminated via social media platforms (WeChat and Weibo). Respondents were required to be residents of China, aged 18 or above, and to have cycled within the past week. The survey was conducted from 15 December 2023 to 29 January 2024. A total of 1,100 questionnaires were collected, of which 895 were valid, resulting in an effective recovery rate of 81.36%.

3.3 Participants

Table 1 demonstrates a relatively balanced distribution of socioeconomic attributes in the sample. Concerning gender, prior research indicates that females exhibit higher rates of problematic internet use than males [43], which may explain why female respondents slightly outnumbered males in this survey. The age distribution was skewed toward respondents under 29 years, likely due to the study's reliance on online platforms and social media, which typically attract younger, low-to-middle-income participants. In terms of educational background, over one-third of respondents held a bachelor's degree, while those with master's degrees or higher were less prevalent. Family structures predominantly comprised three or four members, with single-person households and large families (⩾5 members) being less common. Most households reported owning at least one vehicle. Concerning traffic accident history, over half of the participants had no accidents in the past two years, with only a minority experiencing 1–2 incidents.

Table 1– Proportion distribution of socioeconomic attributes

Variable name	Variable description	Frequency	Percentage
Gender	Male	429	47.93%
	Female	466	52.07%
Age	18-29	316	35.31%
	30-39	182	20.34%
	40-49	213	23.80%
	50-59	113	12.63%
	60-69	71	7.93%

Variable name	Variable description	Frequency	Percentage
Education	High school or technical school	279	31.17%
	College degree	237	26.48%
	Bachelor's degree	283	31.62%
	Graduate degree	96	10.37%
Family size	Alone	35	3.91%
	Two people	103	11.51%
	Three people	288	32.18%
	Four people	287	32.07%
	Five people and above	182	20.34%
Accident	0 times	458	51.17%
	1-2 times	333	37.21%
	3-4 times	71	7.93%
	Five or more times	33	3.69%
Car	Owns the car	669	74.75%
	Does not own the car	226	25.25%
Income	≤ 3,000 CNY	232	25.92%
	3,001 CNY- 5,000 CNY	185	20.67%
	5,001 CNY -10,000 CNY	248	27.71%
	10,001CNY -20,000 CNY	173	19.33%
	≥20,001CNY	57	6.37%

Table 2 indicates that 64%+ of respondents selected "often" to "almost always" for positive behaviours, reflecting a general trend of safe cycling practices compliant with traffic regulations. By contrast, violation and error behaviours showed notably higher occurrence frequencies, with the "hardly ever" and "sometimes" categories warranting particular attention. This suggests that while some cyclists do not consistently violate rules, intermittent risky behaviours still pose significant accident risks.

Table 2– Proportion distribution of cycling behaviour

Variables	Never	Hardly ever	Sometimes	Almost always	Often
Violations	27.37%	22.65%	18.49%	18.30%	13.18%
Errors	26.11%	23.15%	17.87%	17.37%	15.50%
Positive behaviour	7.23%	9.03%	19.33%	33.19%	31.21%

4. RESULTS

4.1 Data analysis

Reliability analysis of the questionnaire scales is a crucial prerequisite for ensuring measurement quality. Accordingly, we first assessed the reliability of the adapted scales. Next, to measure cyclists' behavioural intentions during AV interactions, this study employed scenario-specific questions (e.g. "How likely would you make a left-turn hand gesture?"). Responses, ordered as "extremely unlikely" to "extremely likely", necessitate an ordered discrete response model. Using an unordered model would introduce biases in parameter estimation. Traditional ordered models assume homogeneous behavioural patterns, overlooking individual heterogeneity. To address this, random effects were incorporated to capture individual-specific, time-invariant effects on the dependent variable. Thus, a mixed-ordered response model was adopted for analysis.

Principal component analysis (PCA) was also applied to cleanse data and reduce collinearity. This method distils complex information into key components, laying a solid foundation for subsequent mixed-ordered probit modelling.

Reliability of measures

Cronbach's α coefficients were computed for all adapted scales in the current sample (N = 895). All α values met or exceeded the conventional threshold of 0.800, indicating acceptable to good internal consistency for subsequent analyses. The coefficients for each subscale are reported in *Table 3*.

Table 3 – Reliability of adapted scales in the current sample (Cronbach's α, N = 895)

Construct	Items	Cronbach's α
Violations	12	0.968
Errors	13	0.973
Positive behaviour	12	0.939
Perceived usefulness	4	0.914
Perceived ease of use	3	0.882
Attitude	3	0.860
Social norms	3	0.875
Perceived behavioural control	3	0.832
Behavioural intention	3	0.871

Principal component analysis

Principal component analysis (PCA), a widely used dimensionality reduction technique, was initially developed for non-random variables and later extended to random variables [44]. Its core principle involves transforming original n-dimensional features into k-dimensional orthogonal components, known as principal components, which are reconstructed from the input dataset. In this study, PCA was applied to multiple variables, including violations, errors, positive behaviours, perceived ease of use, perceived usefulness, attitudes, social norms, perceived behavioural control and behavioural intentions. The first principal components derived from these variables were employed as explanatory factors to comprehensively assess the influence of underlying latent constructs on model performance.

$$PC_i = U_j W_j \tag{9}$$

where PC_i is the ith principal component, U_j is the standardised form of the original variable and W_j is the factor loading.

Correlation analysis

This study examined the correlations among cyclists' personal characteristics, road behaviours and AV acceptance via Pearson correlation analysis, with results summarised in *Tables 4-5*. Age demonstrated a significant negative correlation with educational attainment, positive behaviours and all AV acceptance-related variables, indicating lower AV acceptance among older individuals. Educational attainment correlated positively with positive behaviours and AV acceptance variables, but negatively with violation and error behaviours, suggesting that better-educated cyclists, who commit fewer road violations, exhibit higher AV acceptance.

Notably, violation and error behaviours showed a strong positive correlation, highlighting their interrelatedness. Both behaviours were significantly negatively correlated with all AV acceptance constructs in the questionnaire. For example, violation behaviours had high negative correlations with perceived usefulness and ease of use, a pattern mirrored in error behaviour.

Table 4 – Correlation coefficient table of basic demographic and behavioural variables

	Gender	Age	Car	Income	Education	Families	Accident	Violations
Gender	1.000							
Age	-0.048	1.000						
Car	-0.004	0.162***	1.000					
Income	-0.117***	0.261***	0.030	1.000				
Education	0.051	-0.382***	-0.045	-0.087	1.000			
Families	0.038	-0.197***	-0.172***	-0.156***	0.058	1.000		
Accident	-0.023	0.118***	0.007	-0.010	-0.138***	-0.004	1.000	
Violations	-0.024	0.439***	0.231***	0.191***	-0.254***	-0.261***	0.141***	1.000

*** represent P value< 0.01; *represent P value< 0.05*

Table 5 – Correlation coefficient table of psychological cognitive variables

	Errors	Positive behaviours	Perceived usefulness	Perceived ease of use	Attitude	Social norms	Perceived behavioural control	Behavioural intention
Errors	1.000							
Positive behaviours	-0.208***	1.000						
Perceived usefulness	-0.580***	0.213***	1.000					
Perceived ease of use	-0.617***	0.192***	0.756***	1.000				
Attitude	-0.539***	0.197***	0.734***	0.712***	1.000			
Social norms	-0.570***	0.209***	0.743***	0.723***	0.747***	1.000		
Perceived behavioural control	-0.260***	0.062	0.293***	0.306***	0.315***	0.349***	1.000	
Behavioural intention	-0.509***	0.216***	0.747***	0.711***	0.738***	0.739***	0.342***	1.000

*** represent P value< 0.01; *represent P value< 0.05*

4.2 Model selection

This study compared the goodness-of-fit of the ordered logit (OL) and mixed ordered logit (MOL) models. Each respondent provided repeated responses across six scenarios, resulting in panel data. Ignoring within-respondent correlation would bias standard errors and fail to account for unobserved heterogeneity. As shown in *Tables 6–7*, although the difference in AIC was small in Scenario 4 (ΔAIC = –1.22), the MOL was still preferred due to its ability to capture between-respondent variation. Likelihood-ratio tests for zero random-effects variance showed a significant improvement in Scenario 1 ($\chi^2(1)$ = 14.00, p = 0.00018), while for Scenarios 2–6 the LR statistic was 2.00 ($\chi^2(1)$, p = 0.157), indicating directional support, albeit without statistical significance. Moreover, the standard deviation (σ) of the random effect for erroneous behaviour was greater than zero in all models (e.g. σ = 0.202–0.505; 95% CI lower bounds 0.029–0.061 > 0; *Tables 8–13*), demonstrating considerable heterogeneity in how error-prone cyclists respond to risk. These results support the use of MOL even when AIC improvements are marginal.

During model construction, we first assessed multicollinearity among explanatory variables via Pearson correlation analysis, eliminating variables with coefficients exceeding 0.7 to ensure model robustness [45]. A stepwise variable selection method was then employed to incrementally incorporate explanatory variables into the mixed-ordered probit model, constructing an optimal predictive framework.

Table 6 – Comparison of goodness of fit between models (part 1)

Scene name	Scenario 1		Scenario 2		Scenario 3	
	OL	**MOL**	**OL**	**MOL**	**OL**	**MOL**
Estimate parameter values	11	12	7	8	8	9
Log-likelihood at convergence	-1199	-1192	-1159	-1158	-1133	-1132
AIC	2427.21	2425.99	2340.22	2339.16	2291.86	2290.22
ΔAIC (MOL – OL)	-1.22		-1.06		-1.64	
LR test for random effects (χ^2, p)	14.0, 0.000183		2.0, 0.157299		2.0, 0.157299	

OL: Ordered logit model; MOL: Mixed-ordered logit model

Table 7 – Comparison of goodness of fit between models (part 2)

Scene name	Scenario 4		Scenario 5		Scenario 6	
	OL	**MOL**	**OL**	**MOL**	**OL**	**MOL**
Estimate parameter values	8	9	12	13	16	17
Log-likelihood at convergence	-1187	-1186	-1152	-1151	-1149	-1148
AIC	2427.21	2425.99	2340.22	2339.16	2291.86	2290.22
ΔAIC (MOL – OL)	-1.22		-1.06		-1.64	
LR test for random effects (χ^2, p)	2.0, 0.157299		2.0, 0.157299		2.0, 0.157299	

OL: Ordered logit model; MOL: Mixed-ordered logit model

4.3 Model analysis

Cyclist encounters oncoming AV

Using the developed model (see *Table 8*), the study reveals that in AVs without an eHMI system, variables such as violations, positive behaviours, attitudes, age and family size are found to be statistically significant. The analysis indicates a negative correlation between violation and positive behaviours: cyclists who frequently violate rules are less likely to make turning gestures, whereas those displaying more positive behaviours tend to gesture. Additionally, parameters associated with error behaviours show random effects and achieve statistical significance.

Table 8 – Comparison of results when a cyclist encounters an oncoming AV (AV without eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.357	0.034	10.610	0.000
Positive behaviours	0.059	0.026	2.300	0.022
Attitude	0.186	0.066	2.820	0.005
Age	0.704	0.269	2.620	0.009
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.223	0.198	0.039	1.269

As shown in *Table 9*, when AVs are equipped with eHMI systems, variables including violations, positive behaviours, attitudes, perceived behavioural control and household vehicle ownership among cyclists are found to be statistically significant. Compared with scenarios without eHMI, the negative correlation with violations is amplified, as indicated by changes in the correlation coefficient. Meanwhile, the positive correlation between positive behaviours and attitudes weakens. Perceived behavioural control exhibits a significant negative relationship, while cyclists from vehicle-owning households are more inclined to use hand signals when turning left, suggesting a positive correlation.

Table 9 – Comparison of results when a cyclist encounters an oncoming AV (AV loaded eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.447	0.047	9.560	0.000
Positive behaviours	0.064	0.028	2.320	0.020
Attitude	0.163	0.062	2.640	0.008
Perceived behavioural control	0.116	0.051	2.260	0.024
Car	0.471	0.167	2.860	0.004
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.505	0.577	0.054	4.761

Cyclists pass by parked AVs

Model analysis (see *Table 10*) reveals that in AVs without an eHMI system, violations, positive behaviours, perceived ease of use and cyclists' educational attainment are statistically significant. Specifically, violations and educational attainment show negative correlations with cyclists' likelihood of taking protective actions. This indicates that cyclists with frequent rule violations or lower education levels are less inclined to slow down or change lanes in situations requiring such actions. By contrast, positive behaviours and perceived ease of use exhibit positive correlations with action-taking, suggesting that cyclists who demonstrate safe riding habits and perceive AV technology as reliable are more proactive in adjusting their routes when necessary.

Table 10 – Comparison table of results of cyclists passing by and parking AV (AV without eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.445	0.036	-12.500	0.000
Positive behaviours	0.077	0.026	2.930	0.003
Perceived ease of use	0.302	0.070	4.290	0.000
Education	0.434	0.153	-2.830	0.005
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.275	0.246	0.047	1.593

As shown in *Table 11*, when AVs are equipped with eHMI systems, the negative correlation between violations and cyclists' actions is amplified – meaning cyclists with more frequent violations are less inclined to slow down or change lanes, as reflected in the correlation coefficient. Meanwhile, the eHMI system strengthens the association between education level and safety perception. Specifically, cyclists with graduate degrees or higher are more likely to adjust their routes (slowing or lane-changing) with eHMI assistance. This suggests that better-educated cyclists may excel in assessing traffic risks and leveraging eHMI-provided information to take preventive actions.

Table 11 – Comparison table of results of cyclists passing by and parking AV (AV loaded eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.481	0.037	13.080	0.000
Positive behaviours	0.071	0.026	2.700	0.007
Education	0.848	0.243	3.480	0.000
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.202	0.192	0.031	1.298

Cyclist follows AVs

The model results (see *Table 12*) indicate that when AVs lack an eHMI system, variables such as violations, positive behaviours, perceived ease of use and cyclists' age are statistically significant. Specifically, cyclists with more frequent violations were less inclined to slow down or pull over. By contrast, cyclists exhibiting positive behaviours, perceiving AV technology as user-friendly, and aged 29 or below tended to take protective actions in this scenario.

Table 12 – Comparison table of results of cyclists following cars (AV without eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.459	0.038	12.140	0.000
Positive behaviours	0.068	0.026	2.610	0.009
Perceived ease of use	0.204	0.059	3.440	0.001
Age	0.309	0.148	2.090	0.037
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.330	0.284	0.061	1.786

As shown in *Table 13*, when AVs are equipped with eHMI systems, the positive correlation between perceived ease of use and cyclists' behaviours of slowing down or pulling over is diminished. Meanwhile, cyclists with no accident history in the past year were more inclined to enhance safety by braking or pulling over. Furthermore, the eHMI system influenced young cyclists (29 or younger) to be more likely to take safety measures compared with those over 60. These changes are reflected in the fluctuations of correlation coefficients.

Table 13 – Comparison table of results of cyclists following cars (AV loaded eHMI)

Variable name	Coefficient	SE	z-value	p-value
Violations	0.456	0.036	12.510	0.000
Perceived ease of use	0.179	0.059	3.040	0.002
Accident	0.988	0.374	2.640	0.008
Age	0.721	0.213	3.380	0.001
Random effects (SD, σ)	Std. Dev. (σ)	SE(σ)	[95% CI]	
Erroneous behaviours	0.214	0.217	0.029	1.562

5. DISCUSSION

5.1 Analysis of cyclists' road behaviour

The survey revealed that cyclists' road behaviour trended predominantly positively, though violation and error rates were relatively high – a pattern influenced by multifaceted factors. Cyclists' road behaviour represents a complex construct shaped by age, distraction, risk-taking propensities, interactions with other road users and infrastructure. Firstly, China's high traffic density, where non-motorised and motor lanes often lack segregation, along with road congestion, may induce cyclist anxiety and stress, thereby elevating violation and error occurrences. Secondly, insufficient traffic regulation literacy and weak safety awareness among some cyclists lead to frequent disregard. Additionally, imperfect traffic management and lax law enforcement may contribute to non-compliant behaviour.

Thus, there is a need to enhance traffic rule education and awareness campaigns to improve cyclists' safety and regulatory consciousness. Moreover, environmental and infrastructural factors significantly impact cycling behaviour. Studies have underscored the importance of road safety, convenience and public security in shaping such behaviour [46]. Infrastructure and human factors, including age, riding intensity and problematic user-infrastructure interactions, predict self-reported road crashes among cyclists [47]. Furthermore, interactions with other road users, risk anticipation, and coping strategies in hazardous situations are critical determinants of cyclist behaviour [48].

5.2 Cyclists' acceptance of AVs sharing roads

This study provides critical insights into cyclists' acceptance of sharing roads with AVs and associated influencing factors. Research indicates that AV acceptance among cyclists is not only closely linked to their riding behaviour but also to socioeconomic attributes. Socioeconomic background influences AV acceptance, with income, education and social status shaping perceptions [49]. Specifically, cyclists with more frequent violations exhibit lower AV acceptance [50], attributable to two key mechanisms: firstly, their risk-prone behaviours may erode trust in AV interaction capabilities; secondly, they may doubt AVs' adaptability to their riding patterns, fearing safety risks.

Additionally, the study finds that cyclists with lower education levels demonstrate more conservative AV acceptance than their better-educated counterparts. Younger cyclists (aged under 29) show higher AV receptiveness than older groups (aged over 60), as reflected in lower scores for perceived ease of use, usefulness and social norms. This aligns with age-related findings in prior research [50], suggesting older adults are less likely to accept AVs or pay for related services. A plausible explanation is that younger individuals are more optimistic about technological advancement, believing AVs enhance convenience and safety.

Notably, cyclists with crash experiences in the past two years exhibit higher willingness to share roads with AVs. Such experiences may heighten unease about human error, prompting greater trust in technological solutions like AVs to prevent recurrences [51].

5.3 Self-protective behaviours of cyclists interacting with AVs

The role of road user characteristics

This study reveals that certain socioeconomic attributes influence cyclists' responses to AVs. Prior research has established that socioeconomic status (SES) shapes behavioural responses across diverse contexts. For example, SES, measured via education level and neighbourhood characteristics, affects perceptions of physical activity environments [52]. This study finds that better-educated cyclists are more inclined to perform left lane-changes or slow down when passing AVs with eHMI systems. This may stem from their greater receptiveness to eHMI-provided information and deeper road rule literacy. Additionally, age exhibits a stronger positive correlation with self-protective behaviours in eHMI scenarios, indicating that younger cyclists more readily accept AV information and deploy timely safety measures, highlighting their general openness to new technologies.

Cyclists without recent traffic accidents (past year) also demonstrate a higher propensity to brake or pull over when eHMI provides accurate vehicle information. Clear, intuitive eHMI signals facilitate information comprehension and trust, prompting appropriate safety responses.

Cyclists' road behaviour

This study found that cyclists who frequently violate rules are less likely to slow down or change lanes when encountering AVs. Their low trust in eHMIs can be explained by three factors: (i) a risk-taking tendency, relying more on personal judgment than external cues [53]; (ii) scepticism about automation reliability and accountability [27, 53]; and (iii) the visibility and timing limitations of text-based eHMIs in dense traffic, whereas high-salience light/flashing cues are recognised faster [30, 54, 56]. These factors help explain the negative correlation between violation behaviour and safety measure adoption, which may be further amplified in the presence of eHMIs [27, 54-55].

This is due to high-violation cyclists' preference for self-judgment and caution towards automation, where any ambiguity or inconsistency is likely interpreted as "device unreliability," leading them to ignore eHMI signals and maintain their behaviour [27, 29, 53]. Therefore, the trust and associated benefits observed in this study rely on eHMI functioning normally, promptly and clearly; once high-violation cyclists perceive eHMI failure, trust and acceptance will significantly decrease [29].

Self-protective behaviour of cyclists

Significant variables vary across scenarios. Overall, cyclists with positive attitudes toward AVs were more inclined to use hand signals when turning to oncoming AVs, likely due to higher trust levels. Cyclists trusting AVs to correctly interpret gestures are more willing to communicate via signalling. Nevertheless, eHMI deployment reduces this signalling tendency among positively disposed cyclists, indicating their confidence in AVs' ability to adhere to traffic rules and navigate environments. This trust may prompt reduced gesturing, as they believe AVs can independently interpret their actions. Perceived ease of use and behavioural control emerged as significant in specific scenarios.

When an advancing AV displays a "straight-ahead" message, cyclists with strong perceptual and behavioural control better assess traffic contexts and respond appropriately, managing bicycles effectively to mitigate risks with eHMI support. Thus, they may deem hand signalling unnecessary, as eHMI provides sufficient decision-making information. When following a vehicle, clear "park" messages from ahead reduce additional safety measures among technologically trusting cyclists. Clear, interpretable eHMI signals enable cyclists to rely on AV behavioural cues, thereby diminishing the need for supplementary safety actions.

5.4 Policy suggestion

Based on the study findings, we propose the following policy recommendations. First, government authorities should update existing traffic regulations to better integrate eHMI technology. These updates should clearly define how autonomous vehicles interact with cyclists, specifying rights of way, yielding obligations and liability frameworks to ensure traffic safety and order. A clear delineation of roles and responsibilities for different road users is crucial, particularly regarding yielding obligations, right-of-way rules and accident liability in AV-cyclist interactions.

Second, reflecting China's mixed-traffic conditions – unsegregated non-motorised lanes, high e-bike and delivery volumes and frequent conflicts at bus stops and driveways – local governments may consider adopting corridor-level improvements along AV routes. These could include: (1) physically protected, continuous cycle lanes (using curbs, planters or delineator posts) with coloured surfacing to discourage motor vehicle encroachment; (2) protected intersections with bicycle-specific signal phases (e.g. leading bicycle intervals), set-back crossings at side streets and right-turn channelisation to reduce turning conflicts; and (3) 30 km/h slow-zone designs (raised crossings, narrowed lanes and parking controls) in areas where full separation is not feasible.

Finally, since cyclists' self-protective behaviours are strongly linked to their educational background, targeted public awareness campaigns are necessary. These should educate both cyclists and drivers about eHMI technology, promoting understanding of its functionalities and improving traffic safety literacy among all road users.

5.5 Limitations and further work

This study has some main limitations. First, the online questionnaire method may have introduced sampling bias, as it potentially excluded cyclists without easy internet access or those disinclined to participate in online surveys. This could affect the representativeness of samples across age groups, educational backgrounds and socioeconomic statuses. Future research could adopt mixed-method approaches, such as field observations, in-depth interviews and focus groups, to mitigate such biases and enhance data diversity.

Second, qualitative probing was limited. Targeted interviews or focus groups with high-violation cyclists are needed to examine specific reasons for lower trust in eHMIs and to refine the interpretation of behavioural patterns.

Third, the study's focus on specific regions in China may limit generalisability to other contexts. Traffic environments, regulatory frameworks and cultural norms vary significantly across regions, which could influence cyclists' behaviours and AV acceptance. Expanding the sample to include international contexts would help explore how cultural and infrastructural differences shape AV acceptance, thereby fostering a more universal theoretical framework for autonomous driving technology.

6. CONCLUSION

This study utilises an online questionnaire to explore cyclists' attitudes toward AVs and their road-sharing behaviours. Findings indicate a significant association between AV acceptance, riding behaviours and socioeconomic characteristics. Specifically, cyclists with violation histories exhibit lower AV acceptance, while male and younger cyclists demonstrate more positive attitudes. Notably, those with recent crash experiences (past two years) show higher AV receptiveness.

Six scenarios were designed to examine the impact of eHMI on cyclists, focusing on self-protective measures among high-violation groups. Results show younger cyclists better interpret eHMI signals and adopt safety measures, while educated riders more effectively utilise eHMI information. By contrast, less-educated cyclists may require guidance to leverage eHMI fully. Intriguingly, high-risk riders did not consistently improve safety margins when interacting with eHMI-equipped AVs.

For future eHMI design, recommendations include simplifying information presentation to reduce cognitive load – clear interfaces and concise language facilitate user comprehension. Specialised training for older or less-educated users can enhance system literacy, while continuous feedback collection optimises usability. User surveys and focus groups are advised to inform iterative design improvements.

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