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Understanding social attitudes towards autonomous driving: a perspective from Chinese citizens

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Abstract

Given the rapid advancement of autonomous driving technology, discerning public willingness to pay and anticipated driving behavior for autonomous vehicles is crucial for their successful promotion, hastened adoption, and enhanced safety in forthcoming mixed autonomy traffic scenarios. This study employs a comprehensive online survey to scrutinize the factors influencing these objectives, encompassing socioeconomic and demographic elements, driving experience, and attitudes towards autonomous vehicles. Leveraging a sophisticated discrete choice model-the mixed logit model with heterogeneity in means and variances-this analysis unveils significant impacts of public social attitudes towards autonomous vehicles and current driving behavior on their willingness to pay for and behavior around autonomous vehicles. This paper's contributions span theoretical modeling, experimental design, and estimation outcomes, offering valuable insights for policymakers and automobile manufacturers.

Keywords Autonomous vehicle · Social attitude · Driving behavior · Mixed logit · Willingness to pay

Introduction

Autonomous driving (AD) technology has made great strides in recent years due to the tremendous efforts of academia and industry (Li et al., 2019; Liao et al., 2023). A widely accepted classification of levels of AD is defined by the SAE (Society of Automotive Engineers), which categorizes the level of vehicle automation into six levels, ranging from 0 (fully manual) to 5 (fully autonomous) Committee et al. (2021). For a detailed understanding of these levels, their characteristics, benefits, and limitations, refer to Table 1.

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Table 1 Classification and implications of SAE levels of autonomous driving

SAE Level	Automation Features	Potential Benefits	Limitations
0	No automation	Driver retains full control	Subject to human error
1	Driver Assistance (e.g., Adaptive Cruise Control)	Aids in reducing driver fatigue	Human monitoring required
2	Partial Automation (e.g., Lane Keeping and Adaptive Cruise Control)	Safety improvements	Operational within certain scenarios
3	Conditional Automation (No driver attention required in specific conditions)	Increased safety and partial autonomy	Complex transition to human control needed
4	High-level Automation (No driver intervention in certain environments)	Enhanced safety; operational without driver in specific conditions	Limited by operational design domain
5	Full Automation (No driver intervention required)	Maximizes safety and full autonomy	Ethical and regulatory complexities

In a narrow sense, only vehicles with an automation level of 4 or 5 are considered autonomous, especially by the media and the community at large. After much media publicity, the masses have generally become aware of some of the findings of academic research on the benefits of AD, such as its ability to improve traffic safety (Kalra and Paddock, 2016; Litman, 2017), smooth traffic flow (Zheng et al., 2020), and improve social equality (Bigman and Gray, 2020). Consequently, a positive outlook on AD has proliferated among social media users, accompanied by an optimistic anticipation of its imminent availability (Das et al., 2019).

However, the jury is still out on whether, in fact, autonomous vehicles (AVs) will actually be beneficial, and if they can reach a high market share. AD indeed still has some intractable hurdles at the moment. For instance, they are very likely to be priced, at least for now, much higher than manually driven vehicles, since they require more sensors and extra computing hardware as well as AD software (Talebian and Mishra, 2018). In addition, as many previous studies predicted, AD technology may worsen traffic congestion since it may induce more vehicle miles traveled (VMT) Harb et al. (2018); Nair and Bhat (2021); Asmussen et al. (2022). Liability determination will also be more challenging in accidents involving AVs. This is because it may be unclear whether the accident was caused by a vehicle passenger, the manufacturer, or a mechanical failure (Yuan et al., 2021). There have also been some media reports that AD companies have already suffered resistance from certain groups because of the potential for job losses in professions such as cab drivers (Cohen and Hopkins, 2019). However, these relatively negative effects of AD are not frequently reported in the media, and many in the community are actually unaware of them (Jelinski et al., 2021).

In light of all these pros and cons, the future development and deployment of AD technology remain uncertain. But what is certain is that AD will co-exist with human driving in the long term. This environment is referred to as the mixed autonomy environment. To better prepare for this forthcoming new environment, understanding public acceptance of and attitudes towards AVs is a valuable starting point for policymakers to make long-term planning and investment decisions. As previous studies have revealed, the most significant barrier to widespread adoption of AD may be psychological, rather than technological

(Shariff et al., 2017; Xu et al., 2018). Therefore, public attitudes towards AD are critical for it to become a realistic component of the future of transportation. If the general public has a positive attitude towards AD, we will be more confident that AD can flourish in the future. Conversely, specific adjustments would be needed to alter public attitudes in order to ensure that AD could be successfully implemented with less opposition. Maintaining a long-term study of the public's attitude towards AD is necessary because their attitude may change significantly with technological advancement or unexpected events.

Prior research in the realm of human-driven vehicle (HDV) environments illustrates that drivers' attitudes significantly influence their driving behavior when interacting with other vehicles (Mohamed and Bromfield, 2017; Hassen et al., 2011; Atombo et al., 2017; Li et al., 2024; Liao et al., 2023). For instance, some exhibit aggressive driving behaviors when confronted with luxury cars due to negative attitudes towards these vehicles. With the advent of AVs, which exhibit distinct appearances and performance characteristics compared to HDVs, a new dynamics is introduced. Particularly, the conservative driving nature of AVs, designed for safety, may incite certain drivers to act aggressively towards them, a behavior that could deter potential AV buyers especially in the early stages of mixed autonomy. It is imperative that in this transitional phase, AVs are adept at safe interactions with HDVs on shared roads. However, the depth of investigation into this aspect has been lacking in previous literature.

On the facet of willingness-to-pay (WTP) for AVs, numerous studies have delved into understanding the public's valuation of this emerging technology. For instance, Hohenberger et al. (2017) elucidated that individuals are willing to pay a premium for AVs due to the anticipated benefits such as increased safety and convenience. Rahimi et al. (2020) explored WTP for AVs across different levels of automation and trip contexts, underscoring the varying valuation of autonomous features among individuals. Haboucha et al. (2017) explored individual motivations and long-term choice decisions regarding AV ownership and usage, revealing significant hesitations towards AV adoption, especially among certain demographics. Liu et al. (2019) explored the willingness to pay for self-driving technology in China, finding it varies with demographic and psychological factors; notably, higher income, education, and positive perception of the technology lead to higher willingness to pay. While these studies provide valuable insights into consumer valuation of AVs, they primarily focus on WTP as a function of individual or vehicle characteristics. These investigations, while valuable, primarily gravitate towards the monetary valuation and initial adoption, leaving a gap in understanding the behavioral adaptation in a mixed autonomy environment, which is the crux of our research.

Our aim is to augment the existing literature by examining how various determinants affect driving behavior amidst AVs in a mixed autonomy setting. We hypothesize that the driver behavior dynamics in mixed traffic conditions with AVs might diverge from the current traffic environment, warranting a deeper exploration to ascertain the safety and efficacy of future urban mobility systems. Our study transcends the conventional WTP analysis to encompass an exploration of how identified factors could modulate driving behavior in mixed autonomy scenarios. This venture is crucial for astute policy formulation, encouraging AV adoption, and safeguarding traffic safety in a rapidly evolving automotive milieu.

This study pivots on survey data to scrutinize the impact factors of WTP and predicted driving behavior towards Level 4 and Level 5 AVs. Unlike preceding studies that limit their scope to WTP predicated on individual or vehicle traits, our study extends the analysis to fathom how these factors, alongside others like socioeconomic and demographic attributes, driving experience, and attitudes towards AVs, might sculpt driving behavior in mixed autonomy scenarios. To the best of our knowledge, this paper is a pioneer in discussing peoples' predicted driving behavior in the forthcoming mixed autonomy environment. In order to acquaint the participants with the prevailing discourse on AVs, an educational video was utilized as a primer before administering the survey. The video, sourced from GCFGlobal-an online educational platform recognized for its self-paced tutorials on various topics including technology, was employed to present a balanced overview of the advantages and disadvantages associated with AVs. The content of the video was translated into Chinese and delineated potential benefits such as reduced accidents and transformed commutes, alongside challenges like technology malfunctions and job displacement, thus aiming to provide a fair and balanced perspective devoid of any commercial or promotional bias towards AVs. The intent behind employing this video was to emulate a scenario where individuals have a well-rounded awareness of AVs, akin to the awareness level anticipated in the near future as AV technology becomes more commonplace. This step was taken to mitigate any preconceived notions or biases the participants might have had, aiming to furnish them with a balanced understanding of the emerging AV technology before gauging their attitudes and predicted behaviors towards AVs in a mixed autonomy environment. The video was followed by a series of identical questions administered before and after viewing the video, aiming to ascertain any shifts in participants' attitudes towards AD technology, their willingness to purchase AVs, and their predicted driving behavior towards AVs. This methodology was designed to, as far as possible, emulate a future environment in which individuals already possess a relatively well-developed understanding of AD, thereby enhancing the practical significance of the questionnaire results.

The rest of the paper is organized as follows: "Literature review" entails a thorough literature review identifying potential contributing factors to our objectives. "Data" delineates the data acquired from the survey. "Methodology" meticulously introduces the mixed logit model with heterogeneity in means and variances. "Estimation results and discussion" unveils the detailed model estimation results. "Conclusion" encapsulates the entire manuscript, proffering countermeasures and recommendations for the impending mixed autonomy environment. "Limitations and future research" discusses the limitations of this paper and future research avenues.

Literature review

Previous research on understanding public acceptance of AD has provided many worthwhile findings. In these studies, survey methods were widely used. Data obtained from survey questionnaires are used to analyze public attitudes towards AD and as a basis for predicting market share. For instance, Schoettle and Sivak (2014) studied public attitudes towards AVs in China, India, Japan, the United States, the United Kingdom, and Australia. Surveys were conducted in each of these countries, with approximately 500-600 respondents in each country. Results showed that most respondents had heard of AVs before and had generally positive attitudes and high expectations about the benefits they would bring. However, most respondents also expressed concerns about the safety of AVs and the proper functioning of their technology. In addition, most respondents are keen to have smart technology in their vehicles, whereas they are not prepared to pay any additional costs for such technology. Kyriakidis et al. (2015) conducted a comprehensive 63-question Internet survey on people's general attitudes towards AVs. Overall, they received approximately 5,000 responses from 109 countries. The survey results identified cross-country differences and assessed the association of attitudes with individual variables such as age, gender, and personality traits. In addition, the results showed that respondents were primarily concerned about cyber security, traffic safety, legal aspects, and privacy issues. It has also been observed that people from developed countries are less comfortable with transmitting vehicle data to insurance companies or tax and traffic authorities. Anania et al. (2018) employed a two-study approach to examine the impact of positive or negative messages on consumer perceptions of AVs, and the differences in how people of different genders and nationalities (Indian and American) are affected when confronted with the same information. The findings are consistent with the general view that individuals are more likely to ride AVs after hearing positive information about AVs, and less likely to ride them after hearing negative information about AVs. Acheampong and Cugurullo (2019) proposed a comprehensive framework that integrates socio-demographic variables and latent socio-psychological factors, including perceived benefits and ease of use of AVs, public fear and anxiety about AVs, subjective norms, perceived behavioral control, and attitudinal factors covering environment, technology, collaborative consumption, public transportation, and car ownership, to analyze the determinants of user adoption of three different AV modes for adults living in the Greater Dublin Area of the Republic of Ireland. Bernhard et al. (2020) used a questionnaire to collect passengers' attitudes before or after taking an autonomous minibus in Germany in order to explore crucial determinants for the use of the vehicle. Results showed that age, experience, gender, performance expectancy, valence, spaciousness, and other factors are significantly associated with passengers' attitudes towards AD. Nastjuk et al. (2020) employed a qualitative research design in Germany to identify factors attributed to individual acceptance of AD. In addition, a technology acceptance model was proposed and validated with online survey data. The results of the study revealed that subjective norms had a significant effect on perceived usefulness and intention to use AD. In addition, two other variables, including trust in technology and personal innovativeness, were also found to have a significant effect on the intention to use AD. Morita and Managi (2020) found that Japanese consumers' WTP is, on average, lower than estimates for the U.S. market, not enough to allow AVs to take a meaningful share of the existing automotive market. Liljamo et al. (2018) analyzed a survey data from 2,036 Finland citizens to figure out whether people are ready for AVs and what concerns people have that are preventing the adoption of these vehicles. The findings suggested that people's attitudes towards AVs are a good reflection of the general adoption of the technology. The results also showed that men, those with higher education, those living in densely populated areas, and those living in households without cars have more positive attitudes towards AVs than other respondents. There are also quite a lot of related papers focused on other objectives, such as preferred modes of AVs operation, willingness-to-pay for AVs, and perceived benefits/ concerns of AVs. The interested reader is referred to a recent survey by Gkartzonikas and Gkritza (2019) and references cited therein for more detailed descriptions.

A number of contributing factors, such as gender, age, income level, and education level, have been found to have a significant impact on public attitudes towards AD Thurner et al. (2022); Dos Santos et al. (2022); Goldbach et al. (2022). However, we also found some inconsistencies in the results across studies, especially those applying discrete choice models (Shin et al., 2015). For example, some papers found that male drivers and old drivers were more likely to buy AVs, while others discovered completely different results (Jiang et al., 2019; Shabanpour et al., 2017, 2018; Yap et al., 2015). We believe that part of the reason for this phenomenon may be some unobserved heterogeneity in the data. As the data for most previous studies were derived from surveys, the design of the questionnaire led to the possibility of unobserved heterogeneity, that is, the presence of unmeasured (unobserved) differences between study participants or samples related to the (observed) variables of interest. The presence of unobserved variables may lead to erroneous statistical results on the basis of observed data. One successful approach to deal with the unobserved heterogeneity problem is the mixed logit model, which is a highly flexible model that can approximate any random utility model (McFadden and Train, 2000). It avoids the three limitations of standard logit by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time. As a consequence, it is now being employed intensively in the transportation field (Li et al., 2019a, b; Wali and Khattak, 2020; Behnood et al., 2022). For instance, Krueger et al. (2016) adopted a mixed logit model to identify user characteristics who are likely to adopt shared AD services, as measured by willingness-to-pay for induced service attributes. The results revealed that service attributes including travel cost, travel time and waiting time may be critical determinants of the services and the acceptance of dynamic ride-sharing. Daziano et al. (2017) employed a mixed-mixed logit model to analyze the impacts of different contributing factors on the adoption of AVs. They found that this model provides richer estimates of heterogeneity compared to the conditional logit model and the parametric mixed logit model. Given these successful applications and the characteristics of our data, the mixed logit was used to analyze the factors influencing our objectives. In addition, to account for unobserved heterogeneity at different levels and to obtain a better statistical fit, the model allows the mean and variance of the random parameters to vary across observations.

In addition, as we mentioned above, we also found little concern in previous studies about the possible driving behavior of the public towards AD. However, it is of concern that there is a large body of research in purely human driving environments that shows that a driver's behavior is significantly influenced by his attitudes, which in turn are influenced by his own traits (Atombo et al., 2017; Miles and Johnson, 2003; Măirean and Havârneanu, 2018; Abou Elassad et al., 2020; Fountas et al., 2019). In addition, classical social psychological studies also revealed that human attitudes towards technology may have a strong influence on the perceived benefits and risks associated with new technologies (Siegrist, 1999). For these reasons, we assume that drivers' driving behaviors in the face of AD should still be related to their attitudes towards AD and their own traits. This hypothesis, although not proven by relevant data for the time being, makes sense to us because, by nature, people's behavior is often a projection of their perceptions (Clark et al., 2017). Therefore, in this paper, we will use the human characteristics data obtained from the survey to deconstruct the participants' predicted driving behavior when facing AVs in the future mixed autonomy environment.

In conclusion, the existing body of literature extensively explores the monetary valuation and initial adoption of AVs, leveraging various factors such as demographic attributes, technological features, and psychological inclinations. However, a notable gap persists in understanding how these factors translate to driving behavior in a mixed autonomy environment. Our study seeks to bridge this gap by extending the analysis beyond WTP, to explore how various identified factors influence driving behavior amidst autonomous and human-driven vehicles sharing the road. This endeavor is pivotal for a holistic comprehension of the dynamics at play, which in turn, is imperative for effective policy formulation, fostering AV adoption, and ensuring traffic safety as we transition towards a more automated automotive landscape.

Data

In light of the limited proliferation of AVs, garnering real-market data poses a challenge. Hence, a survey was orchestrated to delve into societal attitudes towards AVs. The survey, segmented into four sections, transitioned into a unique phase where participants viewed an instructional video before responding to the latter segment of questions on attitudes and anticipated behaviors towards AVs. The video, meticulously crafted by GCFGlobal, one of the largest online educational websites on technology, elucidates the fundamentals of AD, delving into an overview of advanced sensors and communication devices integral to autonomous systems, accompanied by balanced commentary from experts and academics on both the merits and concerns surrounding AD. A realistic perspective is maintained by highlighting that despite technological advancements, AD does not equate to absolute traffic safety, and AVs may still partake in accidents. This educational intervention aims to provide participants with a more rounded understanding of AD, amending any misconceptions potentially acquired from fragmented or biased media and social network narratives (Talebian and Mishra, 2018). This step is taken to ensure that the derived model results closely align with the realistic social attitudes towards AD technology in prospective traffic scenarios.

Conducted on China's renowned online questionnaire platform, WenJuanXing, from December 2021 to March 2022, the survey predominantly engaged Chinese citizens due to the language employed. The data cleaning process was meticulously carried out to ensure the reliability and validity of the analysis, given the substantial reduction in data points from 1,243 initial responses to 482 responses post-cleaning. Initially, incomplete responses or those with missing values in crucial questions were segregated and excluded. This was followed by an examination to identify and remove any duplicated entries, ensuring the uniqueness of data points. Statistical techniques were employed for outlier detection to eliminate data points that could skew the analysis. Consistency checks were performed to identify and rectify contradictory responses within the same questionnaire. The duration taken by participants to complete the questionnaire was also taken into account, with responses completed in an extremely short duration being flagged and reviewed for credibility. Furthermore, demographic information was cross-verified to ascertain the authenticity of the responses. To incentivize completion, a subsidy was provided to participants who completed the survey, which was communicated to them at the outset. This rigorous data cleaning methodology ensured a robust and reliable dataset for achieving the objectives of the study. Detailed delineations of the survey design and video are accessible in the Supplementary Materials. The final survey results are presented in Table 2.

Table 2 encapsulates a range of demographic attributes including gender, age, education level, income, living area, and driving experience. From the data, it is evident that there is a balanced gender distribution with 43.98% male and 56.02% female participants. A notable portion of the respondents, 53.53%, falls within the age bracket of 21-40 years, reflecting a segment of the active driving population. The educational background predominantly tilts towards a higher education level with 73.65% of participants having attained a Bachelor's degree. The urban-rural divide is skewed towards urban areas, with 88.59% of respondents residing in urban settings, potentially indicating a higher exposure to congested traffic conditions and possibly a greater readiness or awareness towards AVs. The diversity in driving experience, frequency of driving, and history of accidents among the respondents provides an insight into their driving behavior and interactions on the road. The demographic distribution outlined and the driving experience shared by the respondents offer a rich context for analyzing the attitudes and behavioral tendencies towards AVs. Although the sample was obtained through an online medium, efforts were made to ensure it reflects a diverse cross-section of the population within the study area. The survey was distributed through broad channels to minimize selection bias and aim for a more representative sample. The data collection period was meticulously chosen to sidestep any temporal biases such as major traffic incidents or policy announcements related to AVs that might skew the perceptions of the respondents.

Table 2 Descriptive statistics of survey results

Variable Category	Abbreviation	Percentage
Gender	*Gender*	
Male		43.98%
Female#		56.02%
Age	*Age*	
< 21		11.41%
21-40		53.53%
$41 - 60$#		34.85%
> 60		0.21%
Education Level	*Education*	
High School		19.09%
Bachelor#		73.65%
Master or Higher		7.26%
Income	*Income*	
$< 60,000$ yuan		21.78%
60,000-180,000 yuan#		52.90%
180,000-300,000 yuan		23.44%
$> 300,000$ yuan		1.87%
Living area	*Area*	
Rural		11.41%
Urban#		88.59%
Driving Experience	*Experience*	
Never		14.94%
< 3 years		23.65%
4-7 years #		39.21%
> 7 years		22.20%
Driving Frequency	*Frequency*	
Never		16.18%
< 3 times per week		25.10%
3-6 times per week#		46.68%
Everyday		12.03%
Number of Accidents	*Accident*	
Never		58.92%
1-3 times #		25.31%
4-7 times		12.03%
> 7 times		3.73%
Driving Behavior in Pure HDV Environment	*Behavior*	
Conservative		25.93%
Neutral#		63.12%
Aggressive		10.95%
Prior Knowledge of AV	*Knowledge*	
None		17.63%
Limited#		46.68%

Table 2 continued

Variable Category	Abbreviation	Percentage
Some		35.68%
Attitude Towards AV Technology (Before Video)	*Attitude*	
Believer		25.93%
Neutral#		43.15%
Skeptic		30.91%
Willingness to Relinquish Driving Control (Before Video)	*Relinquish*	
Low		28.42%
Medium#		47.72%
High		23.86%
Willingness to Purchase AV (Before Video)		
Immediately		11.41%
Hesitantly#		73.65%
Never		14.94%
Predicted Driving Behavior When Facing AV (Before Video)		
Cautious		25.73%
Normal#		56.02%
Risky		18.26%
Attitude Towards AV Technology (After Video)	*Attitude*	
Believer		13.28%
Neutral#		46.68%
Skeptic		40.04%
Willingness to Relinquish Driving Control (After Video)	*Relinquish*	
Low		38.38%
Medium#		46.68%
High		14.94%
Willingness to Purchase AV (After Video)		
Immediately		7.26%
Hesitantly#		71.58%
Never		21.16%
Predicted Driving Behavior When Facing AV (After Video)		
Cautious		32.16%
Normal#		45.64%
Risky		22.20%

Notes: # indicates the reference category; bold text indicates the dependent variable

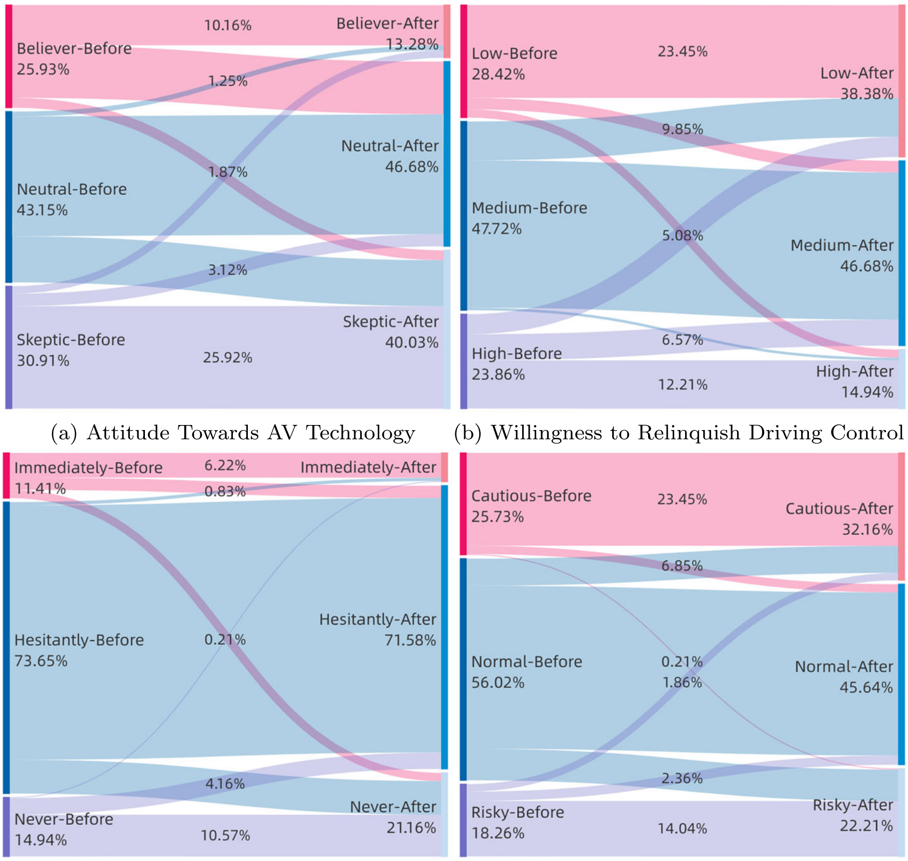
It should be noted that the variable, i.e., *driving behavior in pure HDV environment*, is obtained by aggregating the combined results of the 10 questions (Q9-Q18), including the frequency of awareness of the pedestrians, speeding, etc. The design of these questions was inspired by the Aggressive Driving Scale (ADS) Krahé and Fenske (2002). Each question has five levels, i.e., never, occasionally, sometimes, frequently, and always, and the participants were asked to choose only one. Depending on whether the description of the problem is a risky driving behavior or not, the levels are scored from 1 to 5, or from 5 to 1, with higher scores indicating riskier driving behavior. Participants with less than 20 points were considered to have conservative driving behavior, while drivers with more than 40 points were considered to have aggressive driving behavior and the rest were considered to have neutral driving behavior. The reason for this treatment is due to two major considerations: 1) measuring one's behavior requires consideration of multiple aspects of her driving performance; and 2) to avoid serious multicollinearity problems in the model. In Fig. 1, it is evident that several questions exhibit strong correlations, as indicated by their Spearman's rank correlation coefficients exceeding 0.6 in absolute value, signifying statistical significance at the 0.05 level. In addition, we found that the variance inflation factor (VIF) of the multiple linear regression model reached 17.25 when all variables reflecting these questions were injected into the model. In general, a model is considered to have strong multicollinearity when the VIF exceeds 10. Instead, after replacing all these variables with a combined variable, the VIF of the model becomes 2.34, implying that the multicollinearity problem is solved. These results demonstrate the necessity of this data processing approach. Therefore, we adopted a similar treatment by combining

	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
Q9	1.00									
Q10	0.78	1.00								
Q11	0.73	0.44	1.00							
Q12	0.81	0.28	0.87	1.00						
Q13	0.60	0.43	0.79	0.83	1.00					
Q14	0.57	0.66	0.34	0.48	0.56	1.00				
Q15	0.28	0.64	0.56	0.33	0.34	0.62	1.00			
Q16	0.44	0.33	0.77	0.63	0.49	0.69	0.18	1.00		
Q17	0.37	0.53	0.37	0.69	0.41	0.30	0.54	0.74	1.00	
Q18	0.64	0.75	0.68	0.47	0.64	0.54	0.45	0.23	0.45	1.00

Fig. 1 Spearman's rank correlation coefficient for Q9 to Q18 (results presented in absolute values)

the variables related to future driving behaviors when facing AV into one, namely, *predicted driving behavior when facing AV*.

As demonstrated in Fig. 2, with a more comprehensive understanding of AD, i.e., after watching videos about the pros and cons of AD, there was a significant change in people's choices on questions such as their attitudes, willingness-to-purchase towards AVs. For instance, roughly half and 6% of those who originally believed in AD technology became neutral or even skeptical, respectively. In general, people became more skeptical of AD technology, less inclined to relinquish driving conventional vehicles, less willing to immediately purchase AVs. This may be attributed to excessive trust and expectations in AD technology, which in turn may be caused by one-sided or exaggerated media coverage. As they became more aware of AD, participants became more rational in their attitudes towards AD. These results also clearly indicate the need to design an objective introduction video on AD for respondents in the various current research studies on AD. While participants have become more rational in their attitude towards AD as they have become more aware of its drawbacks. These results also explicitly demonstrated the need to design a video introducing AD. We endeavored to provide participants with a comprehensive understanding of AD in order to



(a) Attitude Towards AV Technology (b) Willingness to Relinquish Driving Control

(c) Willingness to Purchase AV (d) Predicted Driving Behavior When Facing AV

Fig. 2 Sankey diagrams of participant selection shifts before and after watching video enable them to make more rational choices. It is worth noting that this has hardly been considered in previous studies. With this in mind, in the discussion that follows, we will focus more on the choices people make after watching the video.

Methodology

Mixed logit model with heterogeneity in means and variances

Let us first take the study on purchase intentions towards AVs as an example. Assuming that the dependent variable, i.e., willingness to purchase AV, has T levels (in this study T=3, i.e., immediately, hesitantly, and never), the function that determines the nth ($n \in N$) participant's probability of purchase willingness level t ($t \in T$) is given as

$$S_{tn} = \boldsymbol{\beta}_n \boldsymbol{X}_{tn} + \varepsilon_{tn} \tag{1}$$

where N is the total number of participants, $\boldsymbol{X}_{tn}$ is the vector of explanatory variables (e.g., age, education level, etc), and $\boldsymbol{\beta}_n$ is the corresponding vector of parameters to be estimated. ε_{tn} denotes the disturbance term which is assumed to follow independent and identically distributed generalized extreme value distribution, i.e., Type-I Gumbel distribution (Galassi et al., 2022; Li et al., 2023).

We then allow for parameter variations across individuals by introducing a mixed distribution. Consequently, the probability of willingness-to-purchase level t attributed to participant n, $P_n(t)$, can be further written by allowing $\boldsymbol{\beta}_n$ to have a continuous density function, that is

$$P_n(t|\boldsymbol{\varphi}) = \int \frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{2}$$

where $\text{Prob}(\boldsymbol{\beta_n = \beta}) = f(\boldsymbol{\beta}|\boldsymbol{\varphi})$, $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$, and $\boldsymbol{\varphi}$ denotes the vector of mean and variance of the density function. For model estimation, parameter $\boldsymbol{\beta}$ is able to account for individual-specific heterogeneity in the effect of $\boldsymbol{X}_{tn}$ on the probability of willingness-to-purchase, with the density function $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ used to determine $\boldsymbol{\beta}$.

In Eq. 2, $\boldsymbol{\beta}$ can account for individual participant-specific variations of the impacts of variables $\boldsymbol{X}_{tn}$ on the probabilities of willingness to purchase, with the density function $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$. This model becomes different from the standard multinomial logit model since $\boldsymbol{\beta}_n$ is not a fixed parameter and can be randomly distributed with various mode and skeness, and therefore is named as the mixed logit model or random parameter model. If random parameters are identified, the mixed logit weights are determined by the density function $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$, and by integration the probability of a specific participant purchase willingness can be calculated (Li et al., 2024).

When we allow for heterogeneity in both the mean and variance of the random parameters, $\boldsymbol{\beta}_n$ can be further written as

$$\boldsymbol{\beta}_n = \boldsymbol{\beta} + \boldsymbol{\Delta} \boldsymbol{z}_n + \boldsymbol{\Gamma} \boldsymbol{\Omega}_n \boldsymbol{v}_n \tag{3}$$

or

$$\beta_{nk} = \beta_k + \boldsymbol{\delta}'_k \boldsymbol{z}_n + \sigma_k e^{\boldsymbol{\omega}'_k \boldsymbol{h}_n} \upsilon_{nk} \tag{4}$$

where $\boldsymbol{\beta}$ is the constant term in the distribution of the random parameters, β_{nk} is the random coefficient for the kth attribute faced by the individual n. z_n is the observed attribute vector describing the heterogeneity in the mean, $\boldsymbol{\Delta}$ is the corresponding vector of parameters that enter the heterogeneous means of the distributions of the random parameters, and $\boldsymbol{v}_n$ is primitive random vector. The term $\boldsymbol{\beta} + \boldsymbol{\Delta} z_n$ is the heterogeneous means of the distributions of the random parameters. Then, the last part of the right-hand side of the equal sign of Eq. 3 is related to the variance of $\boldsymbol{\beta}_n$. Since the model can capture for the heterogeneity in the variance, the heterogeneous standard deviations in the distributions of the random parameters σ_{nk} is assumed to be equal to $\sigma_k \omega_{nk}$, where $\omega_{nk} = e^{\boldsymbol{\omega}'_k \boldsymbol{h}_n}$ is heterogeneity in the variances of the distributions of the random parameters, ω_k is the vector of parameters in the variance heterogeneity of the random parameters, and $\boldsymbol{h}_n$ is the vector of observed variables that measure the heterogeneity in the variances of the random parameters. $\boldsymbol{\Gamma}$ is a specific diagonal matrix, $\boldsymbol{\Omega}_n$ is the diagonal matrix of individual specific variance terms, and $\boldsymbol{\Omega}_n = \mathrm{diag}(\omega_{n1}, \omega_{n2}, \ldots)$.

Accordingly, the unconditional choice probability of this mixed logit model can be given as

$$
\begin{aligned}
P_n(t|\Theta, \boldsymbol{X}_{tn}, z_n, \boldsymbol{h}_n) &= \int_{\boldsymbol{\beta}_n} P_n(\boldsymbol{\beta}_n|\Theta, \boldsymbol{X}_{tn}, z_n, \boldsymbol{h}_n, \boldsymbol{v}_n) f(\boldsymbol{\beta}_n|\Theta, z_n, \boldsymbol{h}_n) \mathrm{d}\boldsymbol{\beta}_n \\
&= \int_{\boldsymbol{v}_n} P_n(\boldsymbol{\beta}_n|\Theta, \boldsymbol{X}_{tn}, z_n, \boldsymbol{h}_n, \boldsymbol{v}_n) f(\boldsymbol{v}_n|\boldsymbol{W}) \mathrm{d}\boldsymbol{v}_n
\end{aligned}
\tag{5}
$$

where $\boldsymbol{W}$ denotes the matrix of known variances of the random draws, Θ is the component structural parameters of $\boldsymbol{\beta}_n$, and is given as $\Theta = (\boldsymbol{\beta}, \boldsymbol{\Delta}, \boldsymbol{\Gamma}, \boldsymbol{W})$. The log-likelihood functions used to estimate the structural parameters are constructed from these unconditional probabilities, which are aggregated over all the possible choices for the nth individual. Mathematically, it can be given as

$$
\log L = \sum_{n=1}^{N} \log \int_{\boldsymbol{v}_n} \prod_{t=1}^{T} P_n(\boldsymbol{\beta}_n|\Theta, \boldsymbol{X}_{tn}, z_n, \boldsymbol{h}_n, \boldsymbol{v}_n) f(\boldsymbol{v}_n|\boldsymbol{W}) \mathrm{d}\boldsymbol{v}_n \tag{6}
$$

As $\boldsymbol{v}_n$ may have multiple components, the integral in Eq. 6 is very likely to be a multidimensional integral which will have no closed form in general. However, it can be approximated by simulation since the integral is an expected value. The simulated log likelihood function of $\log L$ can be given as

$$
\log L_s = \sum_{n=1}^{N} \log \frac{1}{R} \sum_{r}^{R} \prod_{t=1}^{T} P_n(\boldsymbol{\beta}_{rn}|\Theta, \boldsymbol{X}_{tn}, z_n, \boldsymbol{h}_n, \boldsymbol{v}_{rn}) \tag{7}
$$

where R is the number of draws in the simulation, and $\boldsymbol{v}_{rn}$ is a random draw from the population generating $\boldsymbol{v}_n$. The elements of $\boldsymbol{v}_{rn}$ are obtained by the Halton draws approach with 1,000 draws.

Moreover, as discussed in previous studies, many distribution forms can be considered for $\boldsymbol{\beta}_n$, such as normal, uniform, lognormal, exponential, etc. However, the use of the normal distribution in the estimation of the random parameters has been broadly reported to provide a better fit compared to other distributions and, consequently, was selected in this study. In order to better interpret the estimated results, the direct marginal effects η are calculated for each significant variable, and is given as,

$$
\eta_{x_{tn}}^{P_n(t)} = \frac{\mathrm{d}P_n(t)}{\mathrm{d}x_{tn}} = \frac{\mathrm{d}}{\mathrm{d}x_{tn}} \int \frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{8}
$$

The integral in Eq. 8 can be calculated by Leibniz rule, that is

$$\int \frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} = \int \beta \frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}} f(\beta) \mathrm{d}\beta - \int \beta \left[\frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}} \right]^2 f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta}$$
$$= \int \beta L_n(t)(1 - L_n(t)) f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{9}$$

where $L_n = \frac{e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}{\sum_{\forall t \in T} e^{\boldsymbol{\beta}_n \boldsymbol{X}_{tn}}}$. Similarly, the simulation approach is used to calculate this direct marginal effects. Finally, the marginal effects of a variable are averaged across individuals and are reported in the following section.

Goodness-of-fit statistics

In order to evaluate the performance of the model, two parsimony indices are used in this study, including the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), and they are given as

$$\mathrm{AIC} = -2\ln(L) + 2p \tag{10}$$

$$\mathrm{BIC} = -2\ln(L) + p \times \ln(N) \tag{11}$$

where $\ln(L)$ is the log-likelihood of the model, p is the number of total estimated parameters, and N is the number of participants in the overall dataset. Generally, lower AIC and BIC values indicate a better model fit.

Besides, the McFadden's pseudo R^2 index is also used to evaluate the goodness-of-fit of the model, that is

$$R^2 = 1 - \frac{\ln \hat{L}_{M_{Full}}}{\ln \hat{L}_{M_{Constant}}} \tag{12}$$

where $\hat{L}$ is the maximized likelihood, M_{Full} means the current fitted model with all variables and constant terms, and $M_{Constant}$ denotes the model with only intercepts but no covariates. The ratio of $\ln \hat{L}_{M_{Full}}$ and $\ln \hat{L}_{M_{Constant}}$ measures the extent to which the full model improves on the intercept model, and a larger R^2 indicates a better fit of the full model.

Estimation results and discussion

The estimation of model parameters within the mixed logit models was conducted using simulation-based maximum likelihood estimation methods, specifically employing the NLOGIT 6 software. A simulation approach, entailing 1,000 Halton draws, was utilized in each model to strike a judicious balance between computational efficiency and model fit, thereby ensuring accurate and valid estimation results. It's pertinent to highlight that multiple iterations were conducted to test the models, and the ones exhibiting the lowest values of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were selected as the final models. The resultant model estimations concerning the willingness to purchase AVs and the predicted driving behavior when encountering AV are delineated in Tables 3 and 4, respectively. The models have demonstrated commendable performance, as evidenced by the pseudo R^2 values of 0.44 and 0.47, respectively, thereby affirming the robustness of the analyses conducted within the NLOGIT 6 framework.

Table 3 Mixed logit model results of willingness to purchase AV

Variable	Category Abbreviation	Para.	t-Stat.	Marginal effects		
				Immediately	Hesitantly	Never
Willingness to Purchase AV=Immediately						
Constant		-0.07	-5.20			
Male	Gender	0.37	5.83	0.0021	-0.0008	-0.0014
Standard deviation of Male		0.72	4.86			
< 21	Age	1.37	5.57	0.0080	-0.0049	-0.0031
Standard deviation of < 21		1.25	2.46			
Master or Higher	Education	0.21	2.21	0.0012	-0.0009	-0.0003
< 60, 000 yuan	Income	-0.48	-4.55	-0.0066	0.0037	0.0028
180,000-300,000 yuan	Income	-0.18	-5.26	-0.0019	0.0005	0.0014
Rural	Area	-1.89	-3.53	-0.0199	0.0077	0.0121
Standard deviation of Rural		1.42	3.39			
< 3 years	Experience	-0.16	-3.64	-0.0013	0.0007	0.0006
> 7 years	Experience	-0.44	-2.32	-0.0060	0.0046	0.0014
< 3 times per week	Frequency	-0.40	-4.96	-0.0028	0.0007	0.0021
Everyday	Frequency	0.63	4.60	0.0058	-0.0018	-0.0040
4-7 times	Accident	0.78	5.44	0.0046	-0.0032	-0.0014
Aggressive	Behavior	-0.43	-2.36	-0.0023	0.0007	0.0016
Some	Knowledge	0.31	2.69	0.0028	-0.0010	-0.0018
Skeptic	Attitude	-2.33	-2.72	-0.0229	0.0167	0.0062
Low	Relinquish	-1.60	-5.14	-0.0090	0.0019	0.0071
Heterogeneity in the mean						
Male × Everyday	Gender × Frequency	1.24	4.29			
Male × High	Gender × Relinquish	1.33	5.22			
Rural × Never	Area × Experience	-0.92	-2.45			
Willingness to Purchase AV=Never						
Constant		1.12	2.36			
Male	Gender	-1.33	-4.25	0.0059	0.0093	-0.0152
21-40	Age	-0.42	-2.53	0.0012	0.0012	-0.0024
Standard deviation of 21-40		0.52	3.39			
< 60, 000 yuan	Income	1.64	2.17	-0.0037	-0.0056	0.0093
Rural	Area	0.66	5.88	-0.0027	-0.0055	0.0082
Everyday	Frequency	-1.17	-3.24	0.0016	0.0045	-0.0060
Never	Accident	1.04	3.75	-0.0035	-0.0023	0.0059
Standard deviation of Never		1.97	5.65			
4-7 times	Accident	-1.31	-5.58	0.0078	0.0112	-0.0189

Table 3 continued

Variable	Category Abbreviation	Para.	t-Stat.	Marginal effects		
				Immediately	Hesitantly	Never
Standard deviation of 4-7 times		2.42	3.10			
Conservative	Behavior	-0.45	-5.72	0.0015	0.0025	-0.0040
Standard deviation of Conservative		0.57	2.78			
Aggressive	Behavior	0.73	5.72	-0.0052	-0.0038	0.0089
Believer	Attitude	-1.13	-2.99	0.0028	0.0084	-0.0112
Skeptic	Attitude	1.63	2.36	-0.0040	-0.0062	0.0102
High	Relinquish	-1.24	-2.65	0.0035	0.0057	-0.0092
Heterogeneity in the mean						
Male × 21-40	Gender × Age	-0.79	-4.82			
Never × 180,000-300,000 yuan	Accident × Income	-0.65	-4.59			
4-7 times × Believer	Accident × Attitude	-1.08	-5.22			
Believer × Conservative	Attitude × Behavior	-0.22	-2.42			
Model Statistics						
Number of observations		462				
Log-likelihood at zero		-2628.14				
Log-likelihood at convergence		-1476.33				
pseudo R^2		0.44				

Willingness to purchase AV model

Random parameters and heterogeneity in their means

As shown in Table 3 and Fig. 3, seven variables produce significant random parameters in the willingness to purchase AV model in both two levels, three of which are in the Immediately level and four of which in the Never level. In the Immediately level, *Gender: Male* is found to be randomly distributed with a mean and a standard deviation of 0.37 and 0.72, respectively. As demonstrated in Fig. 3a), this variable increases the likelihood of immediately purchasing AV for 69.6% of the respondents while decreasing the likelihood of immediately purchasing AV for 30.4 % of the respondents. In addition, the mean of *Gender: Male* is also found to be significantly affected by *Frequency: Everyday* and *Relinquish: High*. Both variables increase the mean of *Gender: Male*, implying that eligible participants are more willing to purchase AV immediately.

Age: <21 is another parameter found to be randomly distributed across individuals in the Immediately level. As shown in Fig. 3, the variable is found to increase the likelihood of immediately purchasing AV for 86.4% of the respondents, while decreasing the likelihood of immediately purchasing AV for others. The results also reveal that the heterogeneity of the mean of this variable is not significantly influenced by the other variables.

Table 4 Mixed logit model results of predicted driving behavior when facing AV

Variable	Category Abbreviation	Parameter	t-Stat.	Marginal effects		
				Cautious	Normal	Risky
Predicted Driving Behavior When Facing AV=Cautious						
Constant		-0.12	-2.74			
Male	Gender	-0.36	-2.43	-0.0027	0.0009	0.0017
< 21	Age	-1.15	-3.98	-0.0093	0.0043	0.0050
High School	Education	-0.88	-5.78	-0.0051	0.0026	0.0025
Standard deviation of High School		1.44	2.13			
Master or Higher	Education	0.75	2.25	0.0053	-0.0028	-0.0025
180,000-300,000 yuan	Income	0.79	2.19	0.0130	-0.0070	-0.0060
Rural	Area	-0.44	-5.60	-0.0073	0.0042	0.0032
Standard deviation of Rural		0.27	5.09			
Never	Experience	0.61	5.96	0.0070	-0.0024	-0.0046
Never	Accident	1.16	5.77	0.0098	-0.0047	-0.0051
4-7 times	Accident	0.47	3.56	0.0060	-0.0031	-0.0029
Conservative	Behavior	3.64	4.84	0.0236	-0.0102	-0.0135
Standard deviation of Conservative		2.47	5.15			
Aggressive	Behavior	-0.94	-3.48	-0.0107	0.0040	0.0067
Skeptic	Attitude	0.45	4.77	0.0034	-0.0018	-0.0016
Standard deviation of Skeptic		1.18	5.71			
Heterogeneity in the mean						
High School × < 60,000 yuan	Education × Income	-0.66	-3.14			
Rural × 4-7 times	Area × Accident	-1.15	-3.19			
Conservative × Believer	Behavior × Attitude	0.44	4.56			
Predicted Driving Behavior When Facing AV=Risky						
Constant		1.15	2.36			
Male	Gender	0.98	5.23	-0.0041	-0.0030	0.0071
Standard deviation of Male		3.41	5.32			
< 21	Age	1.76	4.85	-0.0036	-0.0068	0.0104
High School	Education	2.09	4.70	-0.0067	-0.0088	0.0155
180,000-300,000 yuan	Income	-0.63	-5.62	0.0024	0.0042	-0.0066
Never	Experience	-0.76	-5.03	0.0026	0.0025	-0.0051
Everyday	Frequency	0.45	5.33	-0.0009	-0.0014	0.0023
Standard deviation of Everyday		1.41	2.43			
Never	Accident	-1.16	-5.86	0.0031	0.0033	-0.0064

Table 4 continued

Variable	Category Abbreviation	Parameter	t-Stat.	Marginal effects		
				Cautious	Normal	Risky
Conservative	Behavior	-1.71	-4.40	0.0074	0.0173	-0.0248
Aggressive	Behavior	4.63	2.81	-0.0147	-0.0212	0.0359
Believer	Attitude	-1.31	-5.93	0.0056	0.0074	-0.0130
Standard deviation of Believer		1.97	3.79			
Skeptic	Attitude	-1.72	3.48	-0.0029	-0.0065	0.0095
Standard deviation of Skeptic		3.26	4.63			
Heterogeneity in the mean						
Male × < 21	Gender × Age	1.77	2.59			
High School × Everyday	Education × Frequency	0.45	5.45			
Never × Believer	Experience × Attitude	-0.77	-4.07			
Aggressive × Skeptic	Behavior × Attitude	1.25	3.76			
Model Statistics						
Number of observations		482				
Log-likelihood at zero		-2370.09				
Log-likelihood at convergence		-1254.88				
pseudo R^2		0.47				

The last randomly distributed parameter in the Immediately level is *Area: Rural* with a mean and a standard deviation of -1.89 and 1.42, respectively. Therefore, the variable can decrease the likelihood of immediately purchasing AV for 90.84% of the participants while increasing the likelihood for the others. The mean of this variable is also found to be significantly impacted by *Experience: Never*. More specifically, *Experience: Never* decreases

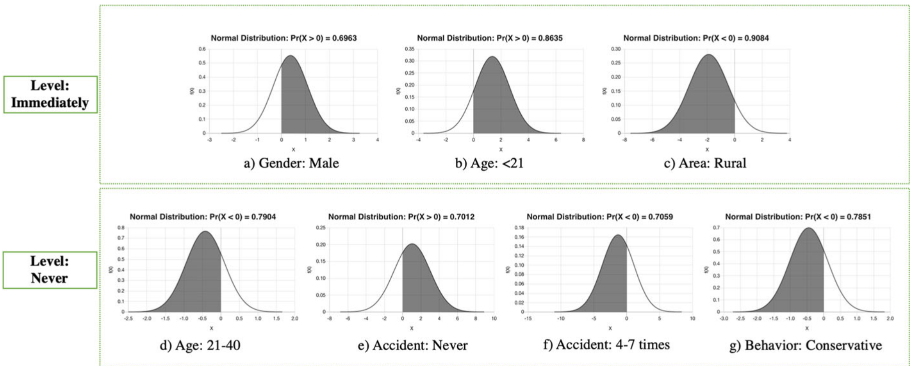


Fig. 3 Random parameters in willingness to purchase AV model

the mean of this random parameter, indicating that the people who live in rural and have no driving experience are less likely to purchase AV immediately.

In the Never level, *Age: 21-40*, *Accident: Never*, *Accident: 4-7 times*, and *Behavior: Conservative* are found to have random effects across the participants. It should be noted that an accident is defined as any form of collision with results ranging from minor damage to a vehicle to the death of a person, whether at fault or not. Detailed effects of these parameters are presented in Fig. 3 d) to g), respectively. In addition, all the four random parameters are found to be significantly impacted by other variables. In particular, *Gender: Male* is observed to decrease the mean of *Age: 21-40*, *Income: 120,000-300,000 yuan* is identified to lower the mean of *Accident: Never*, and *Attitude: Believer* is found to decrease the mean of *Accident: 4-7 times* and *Behavior: Conservative*, respectively.

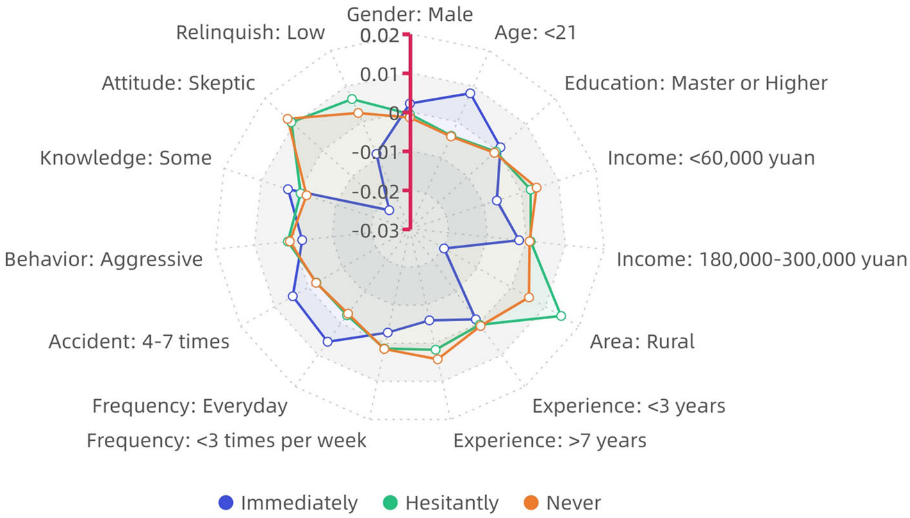
Detailed effects of variables

As presented in Table 3 and Fig. 4, in both Immediately and Never levels, *Gender: Male* has a positive marginal effect on the Immediately outcome and a negative effect on the Never outcome. The results indicate that male participants, compared to their female counterparts, are more willing to purchase AV immediately and less likely to never purchase AV. This finding is consistent with previous research, which found that men are less reluctant to adopt AD technology and have a higher willingness to pay for automated driving systems than women (Cartenì, 2020; Morita and Managi, 2020). This may be attributed to the fact that men generally tend to have more positive attitudes towards new technologies than women, and that they typically have higher levels of sensation-seeking, an important factor related to intention to use AV Payre et al. (2014); Kyriakidis et al. (2015).

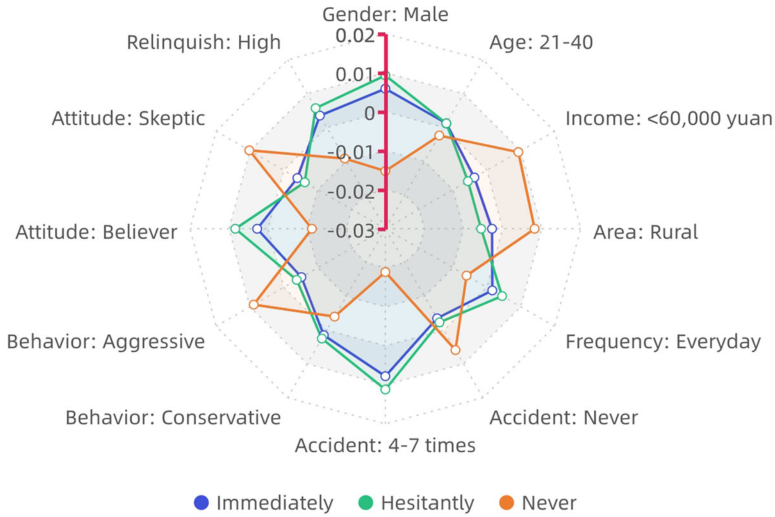
In the Immediately level, *Age:* < 21 is found to have a positive effect on the likelihood of immediately purchasing AV and a negative effect on the likelihood of never purchasing AV, indicating teenagers are more likely to purchase AV immediately, compared to middle-aged individuals (41-60 years old). On the other hand, as shown in Fig. 4, *Age:* $21-40$ is also found to have a similar effect on AV purchasing decisions, since this variable has a negative marginal effect on the Never outcome and a positive marginal effect on the Immediately outcome. Similar findings have been found in studies conducted in other countries, such as Israel and North America (Haboucha et al., 2017). Some studies suggest that the higher likelihood of young people immediately purchasing AVs may be due to their greater acceptance of novel technologies and may also be related to the fact that they currently own fewer private vehicles than the reference age group (Megens et al., 2015; Menon et al., 2019). Although the mixed effects of age and car ownership are not examined, our data also provide some support for the assertion as the younger cohort had significantly lower driving experience and frequency compared to the middle-aged group.

As shown in Table 3, *Education: Master or Higher* is found to significantly increase the likelihood of immediately purchasing AV in the Immediately level. Some previous studies also reported similar findings (Jiang et al., 2019; Howard and Dai, 2014). For instance, Haboucha et al. (2017) found that people with higher levels of education were supportive of the widespread use of AVs. The authors also claim that this may be because those with higher levels of education are more familiar with the concept of AVs and are more open to novel ideas and technologies.

In both levels, *Income:* <60,000 (per year, about 10,000 dollars, could be considered as low-income) is found to have significant impacts on respondents' AV purchasing likelihoods. It demonstrates the implications of reducing people's willingness to purchase AV immediately and increasing their willingness to never purchase AV. In addition, in the Immediately level,



(a) Marginal effects of variables in Immediately level



(b) Marginal effects of variables in Never level

Fig. 4 Marginal effects of significant variables in willingness to purchase model

Income: 180,000-300,000 yuan (per year, about 30,000-50,000 dollars, could be considered as upper-middle-income) shows a negative marginal effect on the willingness to purchase AV immediately. These results indicate that both low-income and upper-middle-income cohorts tend not to purchase AVs immediately compared to the middle-income cohort (*Income: 60,000-180,000 yuan*). For the low-income group, their relatively weak purchase intentions may be due to the fact that AVs tend to be more expensive, in addition to the fact that they use public transportation more often than private vehicles to get around (Litman, 2017). For the upper-middle-income group, the reason they do not have a strong desire to purchase AV immediately may be related to the fact that most of them are more mature (about 62.8% are over 40 years old) and prefer stable and well-established systems. Previous studies have also shown that they have certain concerns about the safety of current AVs Wadud (2017).

Area: Rural is found to significantly influence respondents' purchasing choices in both levels. As shown in Table 3, compared to participants from the urban area, rural respondents' are more likely to not purchase AV immediately, and they are more likely to never purchase AV. This finding is in line with some previous studies (Nastjuk et al., 2020). This may be related to the lower average purchasing power of rural residents and the fact that traffic congestion is less likely to occur in rural areas. It could also be related to the greater lack of EV charging stations in rural areas at the moment, as most people believe that AVs will be electric.

As shown in Table 3, both *Experience:* <3 *years* and *Experience:* >7 *years* show significant impacts on respondents' purchasing choices in Immediately level. As can be evidenced by the results of marginal effects, these two variables can decrease the likelihood of participants' willingness to purchase AV immediately, while on the other hand, the two variables are found to increase the probability of participants' willingness to choose to never purchase AV. This means that both novice and experienced drivers do not have a higher appetite for purchasing AVs compared to drivers with 4-7 years of driving experience. Previous studies have also shown that participants with various driving experiences have significantly different enthusiasm and concerns about AD systems (Qu et al., 2019).

The examination results show that the participants who drive every day are more likely to choose to buy AV immediately, as the variable *Frequency: Everyday* is found to increase this likelihood in both levels. Previous studies also have similar findings, for instance, Kyriakidis et al. (2015) demonstrated that people who drive more will be willing to pay more for an AV. In addition, the authors also suggested that past driving frequency is an excellent predictor of future purchasing behavior.

As shown in Fig. 4, respondents' who have had 4-7 times accidents have a heightened intention to purchase AV once this technology is available on the market since *Accident: 4-7 times* is found to increase this likelihood in both levels. This may be due to the fact that drivers with more accidents have developed some doubts about their driving abilities and therefore prefer more advanced and safer AD technology. Not much research has been done on the impact of this factor on the likelihood of purchasing AVs, but we can get some validation from the research on ADAS adoption (Reimer, 2014; Hagl and Kouabenan, 2020). These studies also suggested that drivers who had more accidents and violations are more likely to purchase vehicles with ADAS.

As shown in Table 3, *Behavior: Aggressive* and *Behavior: Conservative* are both found to significantly affect participants' choice to purchase AV. More specifically, aggressive drivers have less willingness to purchase AV immediately, while they are more likely to choose to never buy AV. In the contrast, conservative drivers are more likely to buy AV immediately. However, this new finding is somewhat difficult to ground in support from previous studies. This is because to date, few studies have examined how individual differences in driving behavior affect drivers' trust and acceptance of AVs. A recent study on the effects of AD styles and driver's driving styles may provide some insights (Ma and Zhang, 2021). The authors used the STISIM driving simulator to collect data on drivers' driving in different situations, and then classified drivers as aggressive or conservative based on these data. The relationship between driver trust in AVs, acceptance, and takeover frequency was analyzed using generalized estimating equations. The results show that the effect of driver trust in AVs on takeover frequency is mediated by driver acceptance of AVs. These findings imply that driver trust and acceptance of AVs can increase when the driving style of the designed AVs (aggressive/conservative) is consistent with the driver's own driving style (aggressive/conservative), which in turn can reduce undesired takeover behavior. As most media create the image that AVs need to be more conservative to achieve a high level of safety, our results, therefore, become not difficult to understand. That is, aggressive drivers choose not to purchase AVs because AVs are different from their driving behavior, and conversely, conservative drivers have a higher enthusiasm to purchase AVs because AVs are similar to their driving behavior.

As shown in Fig. 4, *Knowledge: Some* is found to have a significant impact on the likelihood of people's AV purchasing choices. Participants who have some knowledge of this technology have a stronger desire to buy AV immediately. The results are consistent with previous research that people who have had some experience with assisted or AD and who are more concerned about AD technology tend to have a higher desire to purchase AVs Payre et al. (2014).

Participants' attitudes to AD technology are also found to have significant effects on their purchasing choices. As the estimated results of *Attitude: Believer* and *Attitude: Skeptic* shown, people who are skeptical about AV technology are more likely to choose not to buy AV at all. While those who believe in this technology are more likely to purchase AV immediately. This result is consistent with common sense that people tend to have a lower desire to purchase things they do not believe in.

The willingness to relinquish control is also found to significantly influence participants' purchasing choices. Results show that people with a high desire to relinquish control are more likely to buy AV immediately, while in the contrast, those with a low willingness to relinquish control are more likely to never buy AV. The results have been proved by other studies, for instance, Weigl et al. (2022) suggested that a higher desire for control may pose a barrier to the willingness to adopt new products. There may be a passive resistance to the adoption of innovations, which implies a fear of losing control.

Predicted driving behavior when facing AV model

Random parameters and heterogeneity in their means

The second dependent variable we focused on is the participant's predicted driving behavior when facing AV. Without causing ambiguity, in the following, we will simply refer to it as predicted behavior. As shown in Table 4 and Fig. 5, four variables are found to be randomly distributed in the Cautious level, including *Education: High School*, *Area: Rural*, *Behavior: Conservative*, and *Attitude: Skeptic*. More specifically, the mean and the standard deviation of *Education: High School* is -0.88 and 1.44, respectively. Overall, this variable decreases the likelihood of holding cautious behavior for 72.9% respondents and increases the likelihood of having risky behavior for 27.1% respondents. In addition, the mean of this variable is found to be reduced by the variable *Income: <60,000 yuan*. The results indicate that participants with lower education levels and income are less likely to have cautious behavior when facing AV.

The random parameter of *Area: Rural* is found to have the mean and the standard deviation of -0.44 and 0.27, respectively. The results imply that 94.8% rural respondents have less probability to have cautious predicted behavior while the other 5.2% rural respondents are more likely to have cautious predicted behavior. Moreover, *Accident: 4-7 times* is identified to decrease the mean of this random parameter.

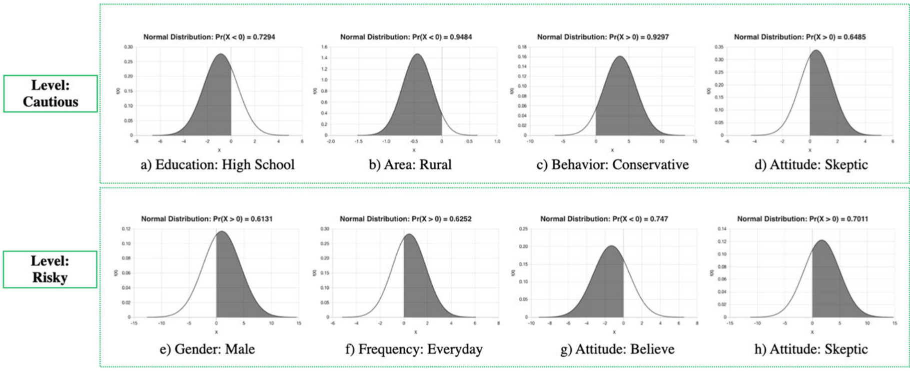


Fig. 5 Random parameters in predicted driving behavior when facing AV model

Similarly, *Behavior: Conservative* is found to increase the likelihood of being cautious when facing AV for 93.0% of the participants, while decreasing the likelihood for the others. The mean of this random parameter is identified to be increased by *Attitude: Believer*. In addition, the mean and the standard deviation of the *Attitude: Skeptic* is 0.45 and 1.18, indicating this variable increases the probability of having cautious predicted behavior for 64.9% of the participants, while decreasing this probability for the other participants.

As shown in Table 4 and Fig. 5, in the Risky level, there are also four variables that lead to significant heterogeneity in the means of the random parameters. *Gender: Male* is found to increase the probability of having risky predicted behavior for 61.3% of the respondents, and decrease this probability for the other 38.7% of the respondents. The mean of this parameter is identified to be increased by *Age: 21*, indicating young male drivers are more likely to have risky predicted behavior.

Figure 5 shows that the variable *Frequency: Everyday* increases the probability of having risky predicted behavior for 62.5% of the respondents. In addition, *Education: High School* is found to increase the mean of this random parameter, implying that low-education participants who drive daily may be more likely to engage in risky predicted behavior.

Attitude: Believer is another variable found to produce significant random parameters with, respectively, a mean and a standard deviation of -1.31 and 1.97. In other words, this variable decreases the probability of having risky predicted behavior when facing AV for 74.7% of the respondents while increasing the probability for the other respondents. As shown in Table 4, the mean of this random parameter decreases by *Experience: Never*, indicating that the participants with no driving experience and believe in AV technology have less probability of having risky predicted behavior.

The last variable that produces random parameter in the Risky level is *Attitude: Skeptic*, which is able to increase the probability of having risky predicted behavior for 70.1% of the respondents while decreasing the probability for the other respondents. In addition, results also show that the mean of this parameter is increased by *Behavior: Aggressive*, indicating participants with aggressive behavior and skeptical attitudes towards AV technology have a higher probability of having risky predicted behavior.

Detailed effects of variables

As shown in Table 4, *Gender: Male* is found to influence participants' predicted driving behavior when facing AV in both levels. The estimation results show that male participants, compared to their female counterparts, are more likely to have risky driving behavior when facing AV. It appears that the predicted behavior of male drivers in the mixed autonomy environment will be similar to their driving behavior in the current traffic environment, i.e., they are more prone to engage in risky driving when confronted with other traffic participants as compared to the females (Moody et al., 2020).

Age: $<$ 21 is another significant variable affecting the participants' predicted driving behavior in both levels. As shown in Fig. 6, the young group is more likely to have risky behavior when facing AV, indicating that in the future mixed autonomy environment young drivers may nonetheless be a target of concern in the future mixed autonomy environment, as they are in the current traffic environment (Scott-Parker and Oviedo-Trespalacios, 2017).

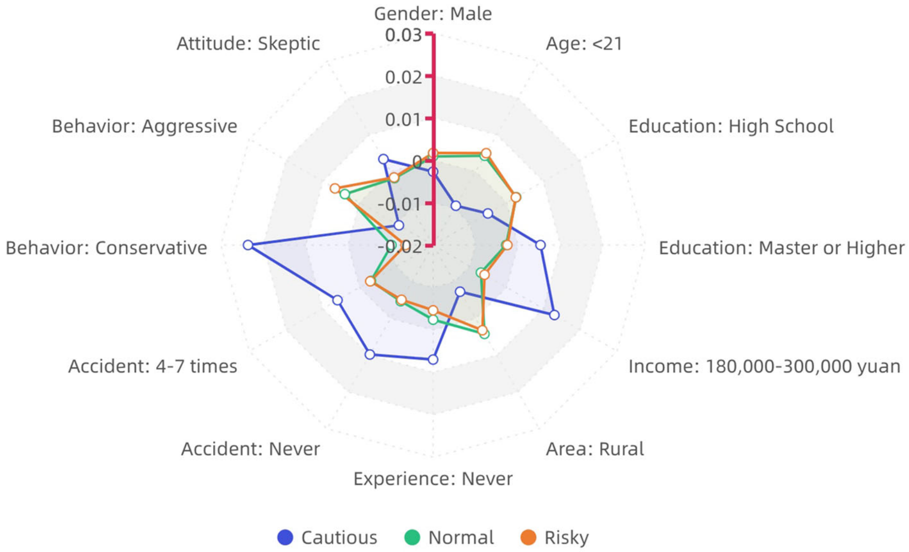
Education: High School is found to significantly influence the participants' predicted driving behavior in both levels. As shown in Fig. 6, this variable increases the probability of people having risky predicted behavior when facing AV. On the contrary, in the Cautious level, *Education: Master or Higher* is found to decrease the probability of people having risky predicted behavior. Research conducted in the current traffic environment may provide insights into this finding. Previous studies suggested the driver's education level can be considered as a key component of socioeconomic status, and has significant association with self-esteem and personal performance (Veselska et al., 2010). Groups with low levels of education may have a heightened likelihood of poverty, drug abuse, illegal activity, etc., and are often found to engage in risky driving behavior (Dursun et al., 2018). For instance, Soliman et al. (2018) figured out that people with low education levels had the most driving violations, lapses and aggressive driving behavior among all the driving groups in the State of Qatar.

As shown in Table 4, *Income: 180,000-300,000 yuan* decreases the probability of participants of having risky predicted behavior in both levels. The results indicate the middle-high income group is less likely to intentionally engage in unsuspecting or safety-ignoring predicted behavior, such as blocking an AV attempting to pass or change lanes. Previous studies also show that people in this group are less likely to have risky behavior (Pantangi et al., 2020; Vaughn et al., 2011). Our results imply that the relatively good driving behavior of this group are likely to be maintained in the future mixed autonomy environment.

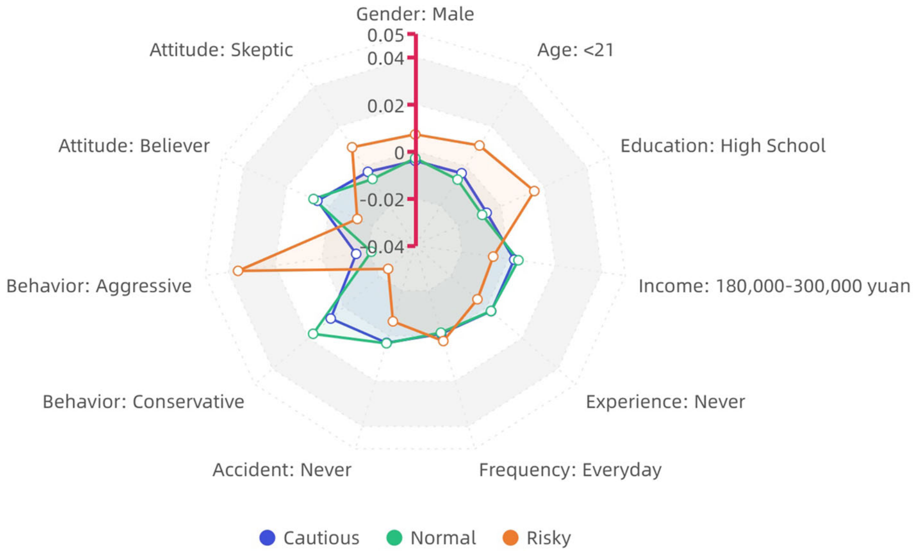
Area: Rural is found to significantly influence the participants' predicted behavior in the Cautious level. As shown in Fig. 6, the participants living in the rural area are more likely to have risky predicted behavior when facing AVs. This finding appears to be consistent with previous studies conducted in the current traffic environment, for example, drivers in rural areas were found to have greater risk-seeking potential and risk tolerance and were more likely to ignore unsafe elements of rural roads (Cox et al., 2017).

The marginal effects of *Experience: Never* show that this variable decreases the probability of participants having risky predicted behavior in both levels. The results indicate that the participants with no driving experiences are more likely to have cautious or normal predicted behavior based on their responses. However, it is worth noting that due to their lack of driving experience, their subjective expressions may not be a realistic reflection of how they will actually perform when driving a vehicle in the future.

Accident: Never is found to have significant effects on participants' predicted behaviors in both levels, with results indicating that the variable can decrease the probability of participants having risky predicted behavior. In addition, *Accident: 4-7 times* is also found to decrease this probability in the Cautious level. These findings suggest that participants who had either no accidents or a large number of accidents would be more likely to have cautious predicted behavior when facing with AVs. Some studies conducted in the current traffic environment have also shown that these two driver groups have fewer driving errors, anger and nervousness



(a) Marginal effects of variables in Cautious level



(b) Marginal effects of variables in Risky level

Fig. 6 Marginal effects of significant variables in predicted behavior when facing AV model

in the Ahwaz aggression inventory, indicating that they are less likely to have risky behavior (Sani et al., 2017).

Both the behavior-related variables, *Behavior: Conservative* and *Behavior: Aggressive* are found to significantly affect participants' predicted behaviors in both levels, and as expected, they had apparently opposite effects. More specifically, drivers who are conservative in the current traffic environment are less likely to have risky predicted behavior when facing AVs, while aggressive drivers are more likely to have risky predicted behavior. In addition, as previously discussed, *Behavior: Conservative* is found to be randomly distributed, indicating some conservative drivers may also engage in risky driving in the future mixed autonomy environment. These findings suggest that people's driving behavior in the current traffic environment may change somewhat in future mixed autonomy environment. It can be expected that these predicted behaviors of people towards AV may render the safety of AD challenging.

In addition, the two variables related to participants' attitudes towards AD technology, i.e., *Attitude: Believer* and *Attitude: Skeptic*, are both found to significantly affect participants' predicted behavior. However, the results show that the effects of these two variables are very complicated, since both of them are found to be randomly distributed across the individuals. In general, the majority of people who believe in AD technology are less likely to have risky predicted behavior when facing AVs. However, the results also indicate that about 30% of these believers are more prone to engage in risky predicted behavior. In addition, *Attitude: Skeptic* was found to be randomly distributed at both levels, making it difficult to determine its effect on participants' predicted driving behavior. This also suggests that participants who are distrustful of AD technology will behave in a highly variable manner when facing with AV in the mixed autonomy environment.

Conclusions

Upon deeper exploration of the study's findings, the comprehensive online survey deployed herein reveals a complex interplay of demographic, socio-economic, and attitudinal factors influencing individuals' propensity to purchase and engage with Level 4 and Level 5 AVs. Employing a mixed logit model with heterogeneity in means and variances via NLOGIT 6 has facilitated a richer comprehension of unobserved heterogeneity across respondents, marking a departure from conventional models frequently referenced in prior literature.

The analytical results underscore the pronounced impact of demographic variables and driving experience on both the immediate AV purchase likelihood and anticipated driving behavior when encountering AVs. Notably, gender, age, and driving experience have emerged as critical factors in shaping the dynamics of interaction with AV technology. The gender variable, particularly 'Gender: Male', unveils a higher inclination among male respondents towards immediate AV adoption. Similarly, the age variable demonstrates a marked propensity among younger cohorts towards immediate AV purchasing, aligning with their generally more positive attitudes towards emergent technologies. The nuanced effects of driving experience further enrich the dialogue, illuminating the diverse attitudes and behavioral tendencies exhibited by individuals with varying driving histories.

Moreover, the study accentuates the significant role of socio-economic determinants, with income levels and educational attainment markedly affecting AV purchase intentions and predicted driving behavior. The delineated effects of income brackets offer a nuanced understanding of economic constraints and preferences across disparate income groups. Furthermore, findings related to education levels underscore the importance of informational awareness and potentially risk perception in forming attitudes towards AVs.

The identification of heterogeneous effects across these variables not only contributes to a more refined understanding of AV adoption and interaction tendencies but also provides invaluable insights for policymakers and automobile manufacturers. The elucidated preferences and behavioral tendencies towards AVs among different demographic and socio-economic groups underscore the imperative for targeted educational and promotional initiatives to nurture a conducive ecosystem for the burgeoning AV industry. Moreover, the insights into the public's disposition towards AVs, as unveiled by this study, lay a robust foundation for strategizing the accelerated adoption and safe operation of AVs, signifying a significant advancement in the collective endeavor towards a safer and more efficient transportation landscape.

In conclusion, the methodological rigor, the broad spectrum of examined factors, and the profound analysis conducted in this study substantially augment the existing literature on AVs. The elucidation of complex determinants influencing AV interactions provides a robust platform for both scholarly inquiry and pragmatic strategies aimed at advancing the AV industry. Consequently, this study stands as a significant contribution to the discourse on AD adoption, fostering a more extensive understanding of the prevailing dynamics, and paving the way for informed strategies to navigate the myriad challenges and opportunities inherent in the transition towards a more automated transportation ecosystem.

Limitations and future research

In acknowledgment of the limitations of this study, several points warrant mention. Firstly, the data collection process, being conducted online, might inherit biases associated with self-selection and accessibility. Despite our efforts to ensure a diverse respondent pool, the online medium inherently may exclude individuals with limited internet access or digital literacy, potentially skewing the sample towards a younger, more educated demographic. Secondly, the sample size and demographic distribution, while robust, may not fully encapsulate the broader societal attitudes towards AVs. The variations between our sample demographics and the actual demographic distribution of the study area may influence the generalizability of our findings. Thirdly, the hypothetical nature of the stated preference survey is a fundamental limitation. The responses collected reflect stated preferences in a hypothetical scenario rather than revealed preferences in real-world settings. This discrepancy could potentially lead to a bias known as hypothetical bias, where individuals might express different preferences when faced with actual decisions as compared to hypothetical scenarios. Furthermore, potential biases might arise from the way questions were framed or the order in which they were presented, which may have inadvertently influenced the respondents' answers. Lastly, the use of a single video as the informational medium about AVs, although carefully chosen and designed, might carry its own set of biases in terms of the information presented and the manner of its presentation. Future studies might consider employing a variety of informational media to mitigate any informational bias and provide a more rounded understanding of public attitudes towards AVs.

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Availability of data and materials Desensitized data that support the findings of this study are available from the authors, upon reasonable request.

Declarations

Conflicts of interest The authors have no conflicts of interest to declare.

Ethical standard The survey of this paper complies with the requirements of the Ethics Committee of the University of Macau.

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