THE EFFECTS OF RISK PREFERENCES ON CONSUMERS' REFERENCE-DEPENDENT CHOICES FOR AUTONOMOUS VEHICLES

Ya Liang,[1,2] Lixian Qian,[2*] Yang Lu,[2] Tolga Bektas[3]

[1] School of Economics and Management, Tongji University, Shanghai, China.
[2] International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, Jiangsu Province, China.
[3] University of Liverpool Management School, University of Liverpool, L69 7ZH, UK.
[*] Address correspondence to Lixian Qian, International Business School Suzhou, Xi'an Jiaotong-Liverpool University, Suzhou, Jiangsu Province 215123, China; tel: +86(0)512-88161172; Lixian.Qian@xjtlu.edu.cn.

ABSTRACT

Advances in artificial intelligence (AI) are reshaping mobility through autonomous vehicles (AVs), which may introduce risks such as technical malfunctions, cybersecurity threats, and ethical dilemmas in decision-making. Despite these complexities, the influence of consumers' risk preferences on AV acceptance remains poorly understood. This study explores how individuals' risk preferences affect their choices among private AVs (PAVs), shared AVs (SAVs), and private conventional vehicles (PCVs). Employing a lottery experiment and a self-reported survey, we first derive four parameters to capture individuals' risk preferences. Based on a stated preference experiment and the error component logit model, we analyze reference-dependent preferences for key attributes of PAVs and SAVs, using PCVs as the reference. Our analysis reveals that risk-tolerant consumers are more inclined toward PAVs or SAVs. Further, consumers exhibit a greater sensitivity to losses, such as higher purchasing prices and running costs, than to gains, such as reduced egress time. Specifically, for buying a PAV, consumers are willing to pay 3,582 CNY more for 1,000 CNY saving on annual running cost, 3,470 CNY for a one-minute reduction in egress time, 28,880 CNY for removing driver liability for crashes, and 30,710 CNY for the improved privacy data security. For adopting SAVs, consumers are willing to pay 0.096 CNY extra per kilometer for a one-minute reduction in access time and 0.033 CNY extra per kilometer for a 1% increase in SAV availability. Therefore, this study enhances the understanding on risk preferences in AV acceptance and offers important implications for stakeholders in the AI-empowered mobility context.

KEYWORDS: Autonomous Vehicles; Risk Preferences; Prospect Theory; Reference-dependent Choices; Discrete Choice Analysis

1. INTRODUCTION

Artificial intelligence (AI) technologies have significantly advanced in recent years, offering state-of-the-art capabilities in data collection, processing, and analysis across diverse industries (Puntoni, Reczek, Giesler, & Botti, 2021). In the automotive domain, autonomous vehicles (AVs) represent the pinnacle of current AI applications, integrating sophisticated technologies such as an array of sensors and AI algorithms (Padmaja, Moorthy, Venkateswarulu, & Bala, 2023). These technologies (see Appendix 1 in supplementary materials) are essential for AV operation, allowing them to accurately perceive their environment, make informed decisions, and navigate independently with increased precision and safety (Padmaja et al., 2023; Puntoni et al., 2021). The deployment of AVs aims to address multiple societal and economic goals: enhancing vehicle safety, reducing traffic accidents, lowering fuel consumption, freeing up driver's time, tapping into new business markets, and minimizing emissions and particulate pollution (Gkartzonikas & Gkritza, 2019; Huang & Qian, 2021; Taeihagh & Lim, 2019). Currently, there are significant regional differences in AV testing, piloting, and deployment (see Appendix 2), especially for AV ride-hailing. The U.S. and China lead in robotaxi testing, with several years of piloting these AV ride-hailing services. The U.S. is advancing toward driverless robotaxis, with Waymo operating in Phoenix since 2019, while Cruise is also beginning its driverless service in San Francisco (LeBeau, 2018; Lowery, 2023). In China, multiple companies (e.g., Baidu and AutoX) are testing driverless robotaxis, with commercial operations starting in some cities in 2023 (Betz, 2024). Europe excels in roboshuttles owing to its extensive mass-transit systems, and large operators are starting to deploy these to replace fixed bus routes (Juliussen, 2022). Europe also leads in sidewalk AVs for goods delivery, driven by Starship's success in both Europe and the U.S. For on-road goods delivery AVs, China and the U.S. are again the leaders, with Nurolix and Nuro at the forefront in these two countries, respectively (Juliussen, 2023).

Recently, a growing body of literature on AV acceptance has emerged, focusing on how consumer beliefs and perceptions, such as perceived usefulness and ease of use, influence their attitudes and use intentions (Choi & Ji, 2015; Kapser & Abdelrahman, 2020; Panagiotopoulos & Dimitrakopoulos, 2018). However, research on the impact of individual risk preferences on AV acceptance remains limited. Risk preferences are crucial in technology acceptance decision-making (Feder, 1980; Liu, 2013). Studies have shown the importance of risk attitudes or preferences in adopting innovations such as agricultural technologies, electric vehicles, and rooftop photovoltaic systems (e.g., Hensher, Ho, & Knowles, 2016; Kagaigai & Grepperud, 2023; Liu, 2013; Wu, Ge, & Li, 2023). As a transformative technology, AVs prompt significant changes in driving habits, causing public apprehension because of safety, privacy, and control concerns (Fagnant & Kockelman, 2015; Gkartzonikas & Gkritza, 2019). While existing research primarily focuses on AV-specific risk perceptions (e.g., Chikaraishi, Khan, Yasuda, & Fujiwara, 2020; Liu, Yang, & Xu, 2018; Xu et al., 2018), there is a need for more studies on how individual risk preferences affect AV acceptance.

To the best of our knowledge, Wang and Zhao (2019) present the only empirical study that has examined how consumers' risk preferences affect their choice of AVs. Building on this seminal work, we extend their investigation in two aspects. First, we include loss aversion in risk preference assessment, a parameter that has not been considered in the domain of AV adoption. We employ a tripartite risk preference evaluation rooted in Prospect Theory (PT) (Kahneman & Tversky, 1979), including non-linear probability weighting, risk aversion, and loss aversion. Second, we incorporate reference dependence, considering that consumers may use conventional vehicles as a

reference point when evaluating AVs. This perspective accounts for choices based on perceived gains and losses relative to the reference alternative.

To address the research gaps identified above, our study employs a two-step analytical process, depicted in Fig. 1. First, we conduct a lottery experiment, adapted from Tanaka, Camerer, and Nguyen (2010), to empirically measure the three risk preference parameters derived from PT (Kahneman & Tversky, 1979), supplemented by a self-reported risk-taking personality parameter (Bao, Zhou, & Su, 2003; Kam, 2012). Second, we undertake a stated preference (SP) experiment [1] across five Chinese cities pioneering AV road testing to discern consumer preferences among private AVs (PAVs), shared AVs (SAVs), and private conventional vehicles (PCVs).[2] Discrete choice modelling (DCM) was employed to analyze the effects of individuals' risk preferences and reference dependence on their choice of AVs.

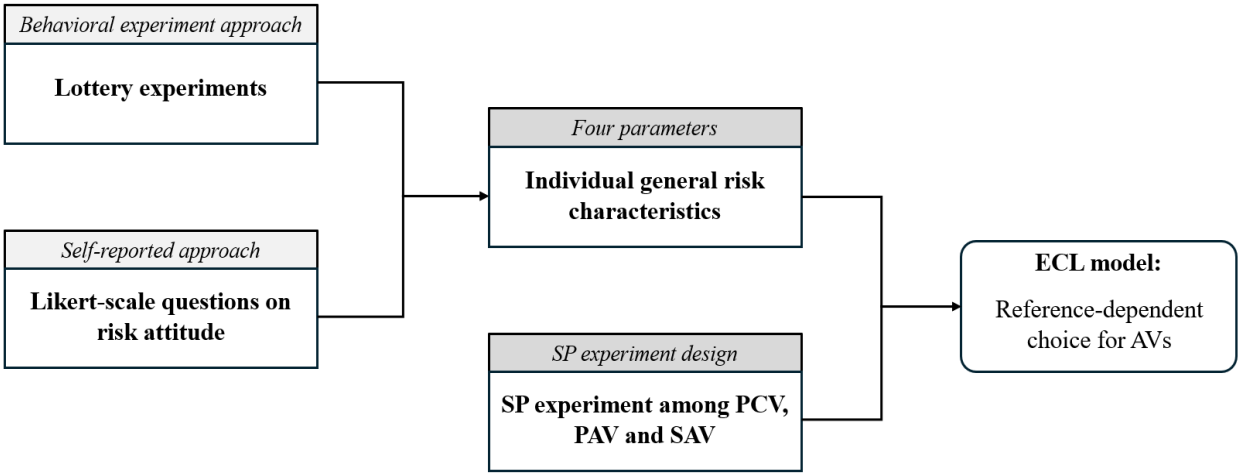


Fig. 1. Structure of models in this study.

Our study makes two contributions to literature. First, by thoroughly measuring individuals' risk preferences and examining their effects on consumers' choice of AVs, this study extends the work of Wang and Zhao (2019) and addresses their call for further investigations into the associations between risk and AV acceptance. Second, this study captures the effect of reference dependence on consumers' choice of AVs. Using PCVs as reference, we assess the relative gains or losses for different attributes of AVs compared to those of PCVs. The reference-dependent DCMs developed in this study demonstrate an improved performance in explaining consumer choices compared to a model that does not consider reference dependence. Consequently, this study shows that relative losses for specific attributes are perceived to be more important than the

[1] We chose the SP approach over the Revealed Preference (RP) approach for several key reasons, especially given the innovative nature of AV technology; further details can be found in Appendix 3.

[2] PCV: Refers to traditional cars that are privately owned and used, representing the reference in our SP experiment.
PAV: Denotes an AV that is purchased, owned, and used by an individual or a household. It is like a traditional car in terms of ownership and usage, with the addition of autonomous driving capabilities.
SAV: These are AVs that are not owned by any individual or household but are available to the public. People can access SAVs as needed through specific channels, such as online rental services or taxi platforms.

general loss aversion preference.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature on AV acceptance and risk preference. Section 3 introduces the data and methodology adopted in this study. The key results are presented in Section 4. Conclusions are given in Section 5, along with a discussion on the main contributions, practical implications, and future research directions.

2. LITERATURE REVIEW

2.1. Consumer Preferences for AVs

As AV development advances, a mixed transportation system that includes both human-driven vehicles and AVs is expected (Tian, Feng, Timmermans, & Yao, 2021). Understanding consumer preferences for different vehicle types, such as AVs and conventional cars, is essential for policy formulation and refining travel demand models. The interest in AVs spans academic researchers, automotive manufacturers, and policymakers, all of whom are keen to grasp consumer preferences for this emerging technology. Given that high-level AVs (e.g., SAE [3] levels 4 and 5; SAE, 2021) are not yet commercially available, researchers frequently use the SP experiment approach to investigate consumer preferences within hypothetical scenarios (e.g., Haboucha, Ishaq, & Shiftan, 2017; Stoiber, Schubert, Hoerler, & Burger, 2019; Tian et al., 2021). These studies examine various AV options, mainly encompassing PAVs and SAVs, and provide valuable insights into how potential users might interact with and adopt AV technology in a future mobility environment (Nair, Astroza, Bhat, Khoeini, & Pendyala, 2018; Stoiber et al., 2019). We conduct a comprehensive review of the prior literature on consumer preferences for AVs, based on the study region, choice alternatives, analytical approach, choice attributes, and individual characteristics.

As shown in Table I, previous studies span multiple regions globally, mainly including Asia (Abe, 2021; Ding, Li, Wang, & Schmid, 2021; Maeng, Jeon, Park, & Cho, 2021; Mo, Wang, Moody, Shen, & Zhao, 2021; Sun & Wong, 2023; Tian et al., 2021; Wang & Zhao, 2019; Wang, Safdar, Zhong, Liu, & Xiao, 2021), North America (Asmussen, Mondal, & Bhat, 2020; Gurumurthy & Kockelman, 2020; Haboucha et al., 2017; Nair et al., 2018; Tu, Jabbari, Khan, & MacKenzie, 2022; Wang, Salehin, & Nurul Habib, 2021), and Europe (Cordera, González-González, Nogués, Arellana, & Moura, 2022; Stoiber et al., 2019; Yap, Correia, & van Arem, 2016), indicating widespread interest in understanding consumer preferences for AVs. Many of these studies incorporated both conventional vehicles and AVs, suggesting a comparative approach to gauge the shift in consumer preferences from traditional to innovative options (Asmussen et al., 2020; Haboucha et al., 2017; Tian et al., 2021; Wang, Salehin, et al., 2021).

[3] The Society of Automotive Engineers.

Table I. Summary of relevant SP experiment research on consumer preferences for AVs

Study	Regions	Alternatives			Data Type	Analytical Model	Choice Attributes			Individual Characteristics	
		PCV	PAV	SAV			Cost-related	Service-related	Policy-related	Demographics	Risk preference
Abe (2021)	Japan	✓	✓		SP experiment	Mixed logit model	✓	✓		✓	
Asmussen et al. (2020)	US	✓	✓	✓	SP experiment	Ranked choice model	✓	✓		✓	
Cordera et al. (2022)	South Europe		✓	✓	SP experiment	Mixed logit model	✓	✓		✓	
Ding et al. (2021)	China	✓	✓		SP experiment	Integrated choice and latent variable model	✓			✓	
Gurumurthy and Kockelman (2020)	US		✓	✓	Survey	Multinomial logit model	✓	✓		✓	
Haboucha et al. (2017)	Canada, US, Israel	✓	✓	✓	SP experiment	Logit kernel approach	✓			✓	
Maeng et al. (2021)	South Korea	✓	✓		SP experiment	Mixed logit model	✓	✓	✓	✓	
Mo et al. (2021)	Singapore	✓		✓	SP experiment	Mixed logit model	✓	✓		✓	
Nair et al. (2018)	US		✓	✓	Survey	Rank ordered probit model				✓	
Stoiber et al. (2019)	Switzerland		✓	✓	SP experiment	Generalized estimating equation ordinal logistic model	✓	✓		✓	
Sun and Wong (2023)	Singapore	✓	✓		SP experiment	Integrated choice and latent variable model	✓	✓		✓	
Tian et al. (2021)	China	✓	✓	✓	SP experiment	Error component logit model	✓	✓		✓	
Tu et al. (2022)	US	✓	✓		SP experiment	Integrated choice and latent variable model	✓	✓		✓	
Wang and Zhao (2019)	Singapore	✓	✓		SP experiment	Mixed logit model	✓	✓		✓	✓
Wang, Safdar, et al. (2021)	Pakistan, China	✓	✓	✓	SP experiment	Mixed logit model	✓	✓		✓	
Wang, Salehin, et al. (2021)	Canada	✓		✓	SP experiment	Mixed logit model	✓	✓		✓	
Yap et al. (2016)	Netherland	✓		✓	SP experiment	Multinomial logit model	✓	✓		✓	
The current study	China	✓	✓	✓	SP experiment	Error component logit model, with reference dependence	✓	✓	✓	✓	✓

Regarding the data collection method, prior literature often employs the SP experiment method to gather consumer choice data. Louviere, Hensher, and Swait (2000) argue that there are compelling reasons to use the SP approach, which involves hypothetical market scenarios, over the alternative revealed preference (RP) approach. For instance, organizations estimating demand for new products with novel attributes may not have RP data on such products that are not launched in the market yet. Furthermore, even if the companies can access observational data in the market, such data are likely censored because the companies cannot measure what alternatives consumers considered before making the choice decision (Qian, Pang, & Soopramanien, 2022). Moreover, while RP data are invaluable for capturing actual consumer choices, this approach is constrained by existing market conditions and available alternatives. In contrast, SP experiments can include variables and options that do not yet exist, providing richer data on consumer preferences and willingness to pay (Louviere et al., 2000; Train, 2009). In such cases, the SP approach is recommended in the literature to collect primary data on consumer choice preferences (Louviere et al., 2000).

The collected data are then analyzed using various analytical models, among which the mixed logit model is most commonly used (Abe, 2021; Cordera et al., 2022; Maeng et al., 2021; Mo et al., 2021; Tian et al., 2021; Wang, Salehin, et al.; Wang & Zhao, 2019; Wang, Safdar, et al., 2021), followed by other models such as the integrated choice and latent variable model (Ding et al., 2021; Sun & Wong, 2023; Tu et al., 2022), ranked choice models (Asmussen et al., 2020; Nair et al., 2018), and the multinomial logit model (Gurumurthy & Kockelman, 2020; Yap et al., 2016).

Furthermore, the attributes examined across these studies mainly include cost-related factors (e.g., purchase price and running costs) and service-related attributes (e.g., waiting time, enabling multitasks, and vehicle availability), which are crucial determinants of consumer choice (e.g., Asmussen et al., 2020; Gurumurthy & Kockelman, 2020; Stoiber et al., 2019; Tian et al., 2021; Yap et al., 2016). Some studies, such asMaeng et al. (2021), also considered policy-related factors such as exclusive lanes for AVs and infrastructure coverage, indicating a broader scope that encompasses the regulatory landscape's impact on AV adoption.

Additionally, literature frequently examines the impact of socio-demographic characteristics such as age, gender, and education level on AV adoption. For example, Haboucha et al. (2017) found that early AV adopters are typically younger, more educated, and often students, who spend more time in vehicles. However, to the best of our knowledge, among the prior studies on consumer preferences for AVs, only Wang and Zhao (2019) account for risk preference. This is reviewed in detail in the next subsection since it is a critical aspect of consumer behavior toward innovations.

2.2. Risk Preference

Risk preference, which describes how individuals perceive and respond to risk, plays a pivotal role in studying decision-making behavior. Extensive literature has examined how risk preferences shape individuals' choices in uncertain circumstances, such as brand selection, route choice, and investment decisions (e.g., Gao, Sun, Yang, Meng, & Qu, 2021; Hardie, Johnson, & Fader, 1993; Hensher, Greene, & Li, 2011). Risk preference also plays a crucial role in the adoption of emerging technologies, as it governs consumers' responses not only to the technology itself but also to the accompanying policy and market conditions (Wang & Zhao, 2019). For instance, Liu (2013) investigated how farmers' risk preferences influenced their adoption of Bacillus thuringiensis (BT) cotton, a cutting-edge agricultural technology, and found that farmers with higher risk aversion or loss aversion adopted BT cotton later, while those valuing small probabilities did so sooner.

The integration of various AI technologies in AVs introduces multiple risks, such as technical reliability issues from software and hardware malfunctions, increased cybersecurity threats affecting vehicle control and data privacy, and complex ethical dilemmas in decision-making (Awad et al., 2018; Bonnefon, Shariff, & Rahwan, 2016; Fagnant & Kockelman, 2015; Liu, Nikitas, & Parkinson, 2020). Although recent studies (e.g., Liu, Guo, Ren, Wang, & Xu, 2019; Zhang et al., 2019) have started exploring the impact of perceived risks on AV acceptance, there remains a gap in understanding how general risk preferences specifically affect AV adoption decisions. Several recent empirical studies (e.g., Dixit, Xiong, Jian, & Saxena, 2019; Huang & Qian, 2021; Wang & Zhao, 2019) have considered consumers' risk attitudes or preferences in the context of AV research. To the best of our knowledge, Wang and Zhao (2019), in examining the influence of risk preference on prospective consumer choices concerning AVs based on an extensive survey, is the only empirical study to explore the link between risk preference and AV choice. Wang and Zhao (2019) incorporated dual modalities—an economic paradigm and a psychometric stratagem—to gauge individual risk preference parameters. Harmonizing with Kahneman and Tversky (1979), the surveyed populace generally tended to overestimate small-probability events while simultaneously revealing risk averseness. Further, they reported that early enthusiasts for AVs are likely to demonstrate stronger value function-based risk preferences and a heightened psychological risk factor.

Despite the existing work, the current body of research on the effect of individuals' risk preferences on consumer choice of AVs remains limited in several ways. First, previous studies typically used a single approach, providing only a one-dimensional view of risk preferences rather than a comprehensive assessment. Although Wang and Zhao (2019) integrated both a behavioral experiment approach and a self-reported method, they did not incorporate the crucial aspect of risk preference (i.e., loss aversion; Kahneman & Tversky, 1979) into their study. Second, the influence of reference dependence – a key factor in understanding consumer behavior toward AVs – is not largely considered in the relevant literature. The concept of reference dependence, rooted in Kahneman and Tversky (1979), posits that individuals base their decisions on deviations from specific reference points (perceived as gains or losses) rather than absolute values. Such an approach is pivotal for capturing asymmetric effects between potential gains and losses. In the context of mobility choice, when presented with both traditional and novel alternatives, such as conventional vehicles versus AVs, consumers may perceive the conventional alternative as the reference and make their choices based on the deviation in the attribute values of the new alternative from those of the reference option. It therefore becomes imperative to investigate consumers' loss aversion preference by considering reference dependence, deliberating between the acceptance of AVs and conventional vehicles.

Thus, while previous studies have laid a foundational understanding of consumer preferences for AVs from various perspectives, there remain critical gaps that the current study aims to fill. Specifically, the current study differentiates itself from the prior literature by incorporating individuals' risk preference and a wider array of attributes in a mixed logit model that accommodates reference dependence in consumer choice.

3. DATA AND METHODS

3.1. Measure Risk Preference Parameters

Risk preference, as characterized by its trait-like attributes, demonstrates temporal stability and convergent validity across diverse domains (contexts) (Mata, Frey, Richter, Schupp, & Hertwig, 2018), implying that an individual's risk preference tends to remain consistent over the long term and does not exhibit significant variations across different research contexts. It is measured through two primary paradigms: the behavioral experiment method and self-reported approach (Arslan et al., 2020). As in Mata et al. (2018), these paradigms exhibit marginal convergent validity, underscoring the imperative of integrating both approaches for a comprehensive assessment of people's risk preferences. Therefore, in this study, we integrated both an SP [4] and self-reported methods to paint a complete and accurate picture of individuals' risk preferences.

First, based on PT, we used the SP method to capture risk preferences by three non-negative parameters—non-linear probability weighting (α), risk aversion (σ), and loss aversion (γ) (Hardie et al., 1993; Tversky & Kahneman, 1992)—calculating the utility function of an individual i as follows:

$$U(x_i, p_i) = \sum_{i \in D} \pi(p_i) * v(x_i),$$

in which x_i is the payoff with risky prospect in the value function $v(\cdot)$ defined as

$$v(x_i) = \begin{cases} {x_i}^{\sigma} & x_i > 0 \\ -\gamma(-x_i)^{\sigma} & x_i < 0 \end{cases}$$

and p_i is the risk-neutral probability in the non-linear probability weighting function $\pi(\cdot)$ where $\pi(p_i) = e^{-(-\ln(p_i))^{\alpha}}$ (Prelec, 1998). The parameter σ controls the shape of an individual's value function: $\sigma > 1$ indicates risk-taking, $\sigma = 1$ indicates risk-neutrality, and $0 < \sigma < 1$ indicates risk aversion. The parameter γ defines the curvature beneath 0 ($x_i < 0$), where $\gamma = 1$ results in a symmetric value function, while higher γ values indicate greater loss aversion. The parameter α measures non-linear probability weighting in Prelec (1998) function $\pi(p)$. If $\alpha < 1$, $\pi(p)$ has an inverted S shape, reflecting overweighting of low probabilities and underweighting of high probabilities. When $\alpha = 1$ and $\gamma = 1$, the model simplifies to the Expected Utility Theory.

To measure the three parameters, this study employed three series of lottery experiment design adapted from Tanaka et al. (2010), with payoffs modified to 10,000 CNY to suit the car purchase context (detailed in Appendix 4). Each series presented respondents with choices between Lotteries A and B across rows: 14 in the first two series and seven in the final. In the first series, Lottery A's payoff was constant ("30% chance of winning 200,000 CNY and 70% chance of winning 50,000 CNY"), while Lottery B's potential payoff with a 10% probability increased from 340,000 CNY to 8,500,000 CNY across 14 rows, with a constant 90% chance of winning 25,000 CNY. Initially, Lottery A's expected payoff was higher, but it decreased as rows progressed, eventually becoming negative. Given this series of two lotteries, respondents were required to answer the following two questions to indicate the specific row (from rows 1 to 14) at which they would switch their preference from Lottery A to Lottery B.

[4] The SP method, a type of behavioral experiment, uses hypothetical scenarios to elicit realistic decision-making responses. Owing to the employment of high hypothetical rewards, mirroring significant financial choices, such as car buying, a stated preference technique is suitable for our lottery experiment design.

- *"Do you always choose lottery A in series 1 (from row 1 to row 14)?"*
  ◯ Yes ◯ No
- *"If '**No**', you choose lottery B from row _____ to row 14."*

In the second series, Lottery A's payoff values and probabilities remained constant throughout the 14 rows, while Lottery B's high-probability payoff (70%) increased progressively, with the remaining 30% probability payoff staying constant. The third series introduced potential losses with respective probabilities in each lottery. In each series, respondents indicated whether they always chose Lottery A, and if not, the point at which they switched to Lottery B. Following Tanaka et al. (2010), it was assumed that respondents would switch their preference no more than once per series. Based on their answers, we estimated three PT-based risk parameters for each respondent (see the estimation procedure in Appendix 5).

Table II. The measurements of risk-taking personality

Measurement items [a]	**Source**
Q1. I would like to explore strange places.	Kam (2012)
Q2. I like to do frightening things.	
Q3. I like new and exciting experiences, even if I must break the rules.	
Q4. I prefer friends who are exciting and unpredictable.	
Q5. In general, how easy, or difficult is it for you to accept taking risks? [b]	
Q6. I am cautious in trying new/different products. [reverse coded]	Bao et al. (2003)
Q7. I would rather stick with a brand I usually buy than try something I am not very sure of. [reverse coded]	
Q8. I never buy something I don't know about at the risk of making a mistake. [reverse coded]	

[a] We translated measurement items from English to Chinese and then conducted back-translations to ensure accuracy.

[b] This term (Q5) was measured with a 7-point Likert scale (from 1 = "very difficult" to 7 = "very easy"); the other seven terms were measured with a 7-point Likert scale (from 1 = "strongly disagree" to 7 = "strongly agree").

Second, we also applied self-reported measures of risk preference from Kam (2012) and Bao et al. (2003), as outlined in Table II. Respondents rated their level of agreement with each statement on a 7-point Likert scale. Exploratory factor analysis was used to extract a risk-taking personality parameter τ, where larger τ value implies a stronger inclination toward risk-taking behaviors.

3.2. Design of Stated Preference Experiment

Our SP experiment consisted of three alternatives: namely, PCVs, PAVs, and SAVs. These alternatives were characterized by different values associated with nine alternative-related attributes. We chose these attributes after thoroughly reviewing the existing literature (e.g., Haboucha et al., 2017; Tian et al., 2021), which generally classifies attributes into three categories related to cost, service, and policy aspects.

Table III. The alternatives and attributes with corresponding levels of SP experiment

	Alternatives		
Attribute	PCV	PAV	SAV
Cost-related attributes			
Purchase price	Specified by the respondent [a]	(1). 100% of PCV price (2). 130 % of PCV price (3). 160% of PCV price	0 CNY
Running cost [b]	Average annual running cost based on vehicle class [c]	(1). 80% of PCV running cost (2). 100% of PCV running cost (3). 120% of PCV running cost	(1). 2.0 CNY per km (2). 2.5 CNY per km (3). 3.0 CNY per km
Access time	4 min	2 min	(1). 5 min (2). 10 min (3). 15 min
Egress time	(1). 1 min (2). 6 min	0 min	0 min
Service-related attributes			
Vehicle availability	100%	100%	(1). 40% (2). 70% (3). 100%
Privacy data security	Standard level	(1). Lower than standard level (2). Same as standard level (3). Higher than standard level	(1). Lower than standard level (2). Same as standard level (3). Higher than standard level
Multitasking during trips	No	(1). Yes (2). No	(1). Yes (2). No
Policy-related attributes			
Driver/user is liable for crashes	Yes	(1). Yes (2). No	(1). Yes (2). No
Exclusive lanes for AVs	No	(1). Yes (2). No	(1). Yes (2). No

[a] 80,000 CNY for an economy class car, 150,000 CNY for a mid-class car, 250,000 CNY for an up-mid class car, and 400,000 CNY for a luxury car.

[b] For PCV & PAV, running cost measures annual running cost, while for SAV, it measures running cost charged by kilometer.

[c] Following Huang, Qian, Soopramanien, & Tyfield (2021), the annual running cost of a PCV was based on market averages: 25,000 CNY for an economy class car, 40,000 CNY for a mid-class car, 48,000 CNY for an up-mid class car, and 50,000 CNY for a luxury car.

As outlined in Table III, our SP experiment considers four cost-related attributes: purchase price, running cost, access time, and egress time, with the latter two related to time cost. The purchase price, a monetary attribute commonly included in SP studies on vehicle preferences (Tian et al., 2021), represents the total cost of acquiring a private vehicle (i.e., PCV or PAV). Following existing SP studies (e.g., Hackbarth & Madlener, 2016; Qian, Grisolía, & Soopramanien, 2019), we employed a pivoting design technique to enhance the realism of choice scenarios and discern price preferences (Hensher, Rose, & Greene, 2015). Specifically, before the SP experiment, respondents were asked to choose their intended vehicle purchase price range, including less than 100,000 CNY for an economy class car, 100,000~200,000 CNY for a mid-class car,

200,000~300,000 CNY for an upper-mid class car and over 300,000 CNY for a luxury car [5]. Depending on their choice, the purchase price of PCVs was specified at 80,000 CNY (for an economy class car), 150,000 CNY (for a mid-class car), 250,000 CNY (for an upper-mid car), or 400,000 CNY (for a luxury car) for each respondent, aligning with Huang et al. (2021). In addition, since PAVs are equipped with advanced technologies and considered a disruptive innovation, they are likely more expensive than same-sized PCVs (Bansal, Kockelman, & Singh, 2016; Kyriakidis, Happee, & de Winter, 2015). Therefore, the purchase price of PAVs was set at three different levels: either the same as, or 30% or 60% higher than [6], that of the same-class PCVs. There is no purchase cost for SAVs.

Running costs, a crucial monetary component highlighted in previous research (Haboucha et al., 2017), pertains to the annual costs of operating and maintaining PCVs and PAVs; for SAVs, it represents the riding expense per kilometer (Asmussen et al., 2020). According to Huang et al. (2021), the annual PCV running costs were based on market averages: 25,000 CNY for an economy car, 40,000 CNY for a mid-class car, 48,000 CNY for an upper-mid class car, and 50,000 CNY for a luxury car [7]. Given the scarcity of data regarding the annual running costs of AVs, we estimate the annual running costs of PAVs by referencing those of similar-sized PCVs and establishing three cost levels: 80%, 100%, and 120% of PCV annual running costs. This range is designed to reflect potential variability in maintenance, energy, and operational expenses unique to AV technology (Fagnant & Kockelman, 2015; Greenblatt & Saxena, 2015; Litman, 2022). SAVs have no purchase costs for individual consumers, thus we assumed three levels for the running cost for SAVs; namely, 2, 2.5, and 3 CNY per kilometer, based on the average taxi fee in China [8] (Beijing Municipal Commission of Transport, 2023; Chongqing Municipal Transportation Commission, 2024; Guangzhou Daily, 2024; Shanghai Municipal Transportation Commission, 2022; Tian et al., 2021).

Both access and egress times represent the time cost associated with vehicle use (Papu Carrone, Hoening, Jensen, Mabit, & Rich, 2020). Access time measures the duration between scheduling a ride with an SAV and the moment the passenger boards the vehicle, whereas egress time calculates

[5] According to the CPCA (2024a), the Chinese car market is segmented by price into categories of under 100,000 CNY, 100,000–200,000 CNY, 200,000–300,000 CNY, and above 300,000 CNY. In 2022, these segments accounted for 26.2%, 47.3%, 16.4%, and 11.1% of the market, respectively. This segmentation supports the justification for our chosen price levels in the purchase price attribute for PCV.

[6] The selection of price levels for PAVs as 30% and 60% above that of a regular car is grounded in empirical data. Specifically, Bansal et al. (2016) found an average willingness to pay an additional US$7,253 for Level 4 automation. McKinsey & Company (2023) also reported that 85% of consumers interested in Level 4 or higher AVs were willing to pay US$5,500 extra, and 40% would pay US$13,000 more. Given the average car price in China was CNY 142,000 (USD 20,300) in 2019, these premiums represent 27.1% to 64.0% above a regular car price, justifying the chosen PAV pricing.

[7] Based on CPCA (2024a), there have been no significant changes in the Chinese passenger car market among the period between this survey and Huang et al. (2021), particularly in terms of price segmentation and distribution. Therefore, Huang et al. (2021) can be referenced to establish the running cost levels for the corresponding segments of PCVs in this study.

[8] According to recent data on average taxi fares in major Chinese cities such as Beijing, Shanghai, Guangzhou, and Chongqing (e.g., Beijing Municipal Commission of Transport, 2023; Shanghai Municipal Transportation Commission, 2022), taxi prices have remained relatively stable over the past three years, with only minor fluctuations. The average fare ranges between 2.0 CNY/km in Chongqing and 2.7 CNY/km in Shanghai. This data supports our selection of attribute levels for the operating costs of SAVs.

the time needed to walk from where the vehicle halts or parks to the destination (Qian et al., 2022). Access time for both PCVs and PAVs was assumed to be constant considering that private cars normally have a dedicated parking space, while SAVs can vary across three levels (i.e., 5, 10 and 15 minutes). This approach aligns with the experimental designs used by Wang, Safdar, et al. (2021), as well as the real traffic conditions in Chinese cities such as Beijing and Shanghai, where the average waiting time for taxi ranges from 5.6 to 13.4 minutes, and about 80% of waiting times fall between 5 and 15 minutes (Liu, 2021; Roland Berger, 2015). Finally, the egress time for PAVs and SAVs were assumed to be zero, as AVs should have the capability to drop off passengers at their desired destinations. In contrast, PCV users need to park vehicles and then walk to their destination, so we assumed an egress time of either 1 or 6 minutes, considering the different distances between parking lots and the destination.

For service-related attributes, we considered vehicle availability, privacy data security, and enabling multitasks during trips. Vehicle availability measured how promptly a vehicle could be hailed when needed. We assumed 100% availability for PCVs and PAVs since they are owned by users, while for SAVs, we considered 40%, 70%, and 100% availability, aligning with the experiments designed by Gu, Yang, Feng, and Timmermans (2019) and Tian et al. (2021). Privacy data security assessed how well vehicles protect passengers' personal data (e.g., identity, contact information, and destination), a significant concern for AV acceptance (e.g., Chen, Kuo, & Lee, 2020). We used privacy security of PCVs as a reference, while AVs could potentially have higher, lower, or the same security level as PCVs. The ability to multitask, considered a binary attribute (Yes or No) for both types of AVs (Tian et al., 2021), captures whether the vehicle allows passengers to engage in activities such as working, playing games, or sleeping during travel.

Finally, we considered two policy-related attributes [9] in our SP experiment: the liability of AV users in vehicle crashes and the availability of exclusive lanes for AVs (Shabanpour, Golshani, Shamshiripour, & Mohammadian, 2018). Since autonomous driving raises the question of whether users can be exempted from liability in traffic accidents (Taeihagh & Lim, 2019), we included the attribute of users' liability for vehicle crashes at two levels (Yes or No) for both AVs, while the level of the attribute value for PCVs was fixed as "Yes." In addition, as conventional cars and AVs are expected to coexist on roads, we considered whether exclusive lanes should be provided for AVs, which led to another binary attribute for both types of AVs.

Given the selected attributes and their levels, a full-factorial experiment design would result in $3^7 \times 2^6 = 139{,}968$ configurations, making data collection infeasible. Therefore, we used a D-optimal design to reduce the number of scenarios to a manageable level (Johnson et al., 2013; Qian et al., 2022; Walker, Wang, Thorhauge, & Ben-Akiva, 2018). A D-optimal design minimizes the D-error of the asymptotic variance-covariance (AVC) matrix (Rose & Bliemer, 2009), with zero prior for all parameters (Scarpa & Rose, 2008).

We considered 36 choice scenarios for our SP experiment, based on the following three reasons. First, the D-efficiency showed little improvement beyond 36 scenarios, indicating high precision (Rose & Bliemer, 2009). Second, with both two-level and three-level attributes, 36 scenarios, a multiple of both two and three, ensured a balanced design (Rose & Bliemer, 2009).

[9] While policy factors such as subsidies and tax incentives could influence AV adoption (Chen, Wang, & Meng, 2020), they are closely related to the monetary factors already included in our SP experiment (e.g., purchase price, running costs and could result in multicollinearity. Additionally, adding more variables could increase complexity and potentially confuse respondents (Hensher et al., 2015). Therefore, we focused on the two primary policy attributes mentioned above to ensure a clear and effective design.

Third, the 13 attributes with varying levels of values across three alternatives in our SP experiment design yielded the minimal number of runs as 13 + 1 = 14 for a saturated model (Huang et al., 2021), which was smaller than the number of chosen scenarios.

To avoid overwhelming respondents with 36 scenarios (Caussade, Ortúzar, Rizzi, & Hensher, 2005), we used random blocking to distribute six choice scenarios to each respondent. A sample choice scenario is illustrated in Fig. 2.

Alternative / Attribute	PCV	PAV	SAV
Purchase price	150,000 CNY	195,000 CNY	0 CNY
Running cost	40,000 CNY	40,000 CNY	2.5 CNY/km
Access time	4 min	2 min	15 min
Egress time	1 min	0 min	0 min
Vehicle availability	100%	100%	40%
Privacy security	Reference level	Reference level	Higher level
Multitasking during trips	NO	YES	NO
Liability for crashes	YES	NO	YES
Exclusive lanes	NO	YES	YES
YOUR CHOICE:	☐	☐	☐

Fig. 2. A sample scenario in the SP experiment.

3.3. Data Collection and Sample Characteristics

Data were collected from five key Chinese cities—Beijing, Shanghai, Guangzhou, Chongqing, and Changsha—chosen for their geographic diversity and significant roles in promoting AV deployment. China, the world's largest car market since 2010 (Qian & Soopramanien, 2014), has aggressively advanced AV technology with substantial investments and extensive road testing in these major cities (Gasgoo Insititute, 2022; KMPG International, 2020). These cities, strategically located across China (see Fig. 3.), lead AV road testing initiatives (Beijing Innovation Center for Mobility Intelligent, 2021; China Industry Innovation Alliance for the Intelligent and Connected Vehicles, 2022). By the end of 2020, Shanghai had issued 152 AV testing licenses, followed by Beijing (87), Changsha (55), Guangzhou (43), and Chongqing (22) (EqualOcean Intelligence, 2022). Thus, these cities are ideal for studying AV adoption in China.

Fig. 3. Geographic location of research cities.
Source: http://bzdt.ch.mnr.gov.cn/

Data for this study were gathered via the sample service of Wenjuanxing,[10] a prominent online survey platform in China (Cao, Xie, & Qu, 2023; Jiang et al., 2021; Lin et al., 2022; Zhou et al., 2020). Aiming for around 1,000 respondents, we used quota sampling based on the adult population from China's seventh population census in 2020 (National Bureau of Statistics of China, 2021) (see Appendix 6). Prior to formal data collection, pilot surveys were conducted in late July 2022 to validate the survey platform and rectify language issues. Data collection took place in August and September 2022, attracting 1,742 respondents. After excluding invalid responses based on four criteria (see Appendix 7), 910 valid responses remained, yielding a 52.24% efficacy rate.

Table IV presents the demographic profile of our respondents, characterized by a nearly equal gender split (51.21% female, 48.79% male) and diverse age groups, including 34.29% aged from 18–30, 56.59% within the 31–50 age bracket, and approximately 10% over 50. Predominantly educated, 78.24% possessed a bachelor's degree or higher. Around 90% of respondents owned one or more private cars in their household. Household incomes in 2021 were predominantly (over 77% of respondents) between 100,000 and 400,000 CNY (approximately US$15,625–$62,500), with 10.33% earning below 100,000 CNY. Our sample shares the characteristics of similar studies in literature (e.g., Huang & Qian, 2021; Qian, Yin, Huang, & Liang, 2023), which commonly consist of young, well-educated and high-income consumers as these may display greater interest in adopting AVs and other technologies (e.g., Hardman, Berliner, & Tal, 2019; Hulse, Xie, & Galea, 2018; Kyriakidis et al., 2015; Rosell & Allen, 2020).

Finally, our sample included respondents from five cities: 225 from Shanghai, 196 from Chongqing, 186 from Beijing, and 152 and 151 from Changsha and Guangzhou, respectively.

[10] Our questionnaire was distributed via the Wenjuanxing (WJX) online survey platform (https://www.wjx.cn), one of the most widely used survey platforms in China, ensuring broad and diverse demographic coverage like international platforms such as SurveyMonkey and Qualtrics. For more details on why and how we selected the WJX platform for data collection, please refer to Appendix 3. The full questionnaire is available in Appendix 8.

Table IV. Sample description (n = 910)

Demographics	Frequency	Proportion (%)
Gender		
Male	444	48.79%
Female	466	51.21%
Age		
18~30	312	34.29%
31~40	246	27.03%
41~50	269	29.56%
51 or above	83	9.12%
Education level		
High school or below	70	7.69%
College	128	14.07%
Bachelor's degree	626	68.79%
Master or higher	86	9.45%
Household car ownership		
No owned car	97	10.66%
1 car	641	70.44%
2 cars	167	18.35%
3 cars and more	5	0.55%
Household income in 2021 (in CNY)		
100,000 or lower	94	10.33%
100,001 to 200,000	254	27.91%
200,001 to 300,000	290	31.87%
300,001 to 400,000	158	17.36%
400,001 to 500,000	72	7.91%
Higher than 500,000	42	4.62%
Cities		
Beijing	186	20.44%
Shanghai	225	24.73%
Guangzhou	151	16.59%
Chongqing	196	21.54%
Changsha	152	16.70%

3.4. Discrete Choice Model Specification

Using the collected SP data, we applied DCMs to analyze consumers' choice behaviors with the potential influence of their risk preferences in the AV acceptance context. DCMs employ random utility theory as the theoretical foundation to describe decision makers' choices among a set of alternatives (Hensher et al., 2015; Train, 2009). These models typically incorporate an observable utility component (V_{jnt}) and an indeterministic part (δ_{jnt}) to represent the utility of alternative j for consumer n in scenario t:

$$U_{jnt} = V_{jnt} + \delta_{jnt}. \quad (1)$$

The multinomial logit (MNL) model, the basic specification of DCMs, assumes that the error terms δ_{jnt} are independently and identically distributed following the Gumbel distribution. Thus, the choice probability of each alternative in the MNL model equals the ratio of the exponential value of its deterministic part and the sum of all L alternatives:

$$P_{jnt} = \frac{exp(V_{jnt})}{\sum_{l \in L} exp(V_{lnt})}. \quad (2)$$

However, the MNL model is limited in its ability to capture substitutions among alternatives due to its restrictive assumption of independence of irrelevant alternatives (IIA) (Hensher et al., 2015). As a specification of the mixed logit model, the error component logit (ECL) model[11] relaxes the IIA property by assuming the existence of alternative-specific error components (E_{jn}) in every utility function (Train, 2009). The utility function of an ECL model may be expressed as:

$$U_{jnt} = V_{jnt} + E_{jn} + \delta_{jnt}, \quad (3)$$

where E_{jn} measures the error component specific to each alternative, which follows a zero-mean normal distribution with the standard deviation to be estimated. The unconditional choice probability of the ECL model is:

$$P_{jnt} = \int_{E_{jn}} \frac{exp(V_{jnt})}{\sum_{l} exp(V_{lnt})} f(E_{jn}) dE_{jn}. \quad (4)$$

Considering reference dependence, we specify the linear utility function (3) for an individual (j) choosing alternative (n) in scenario (t) as follows (McFadden, 1974):

$$U_{jnt} = \Sigma_k Gain_{jnt} + \Sigma_m Loss_{jnt} + V^*_{jnt} + E_{jn} + \delta_{jnt}. \quad (5)$$

Specifically, the utility of every alternative consists of an observable part, which includes reference-dependent k gain terms ($\Sigma_k Gain_{jnt}$) and m loss terms ($\Sigma_m Loss_{jnt}$) for cost-related attributes as well as the utility of reference-independent factors (V^*_{jnt}), and a random part including an alternative-specific error component (E_{jn}) and an error term (δ_{jnt}).

4. RESULTS AND DISCRETE CHOICE ANALYSIS

4.1. Results of Estimating the Risk Parameters

Table V details the distributions of the three PT risk parameters among respondents. The average non-linear probability weighting parameter (α) stands at 0.655, below 1, indicating a tendency among respondents to overestimate low-probability events. The risk aversion parameter (σ) averages 0.397, suggesting prevalent risk aversion as it is also below 1. More significantly, the loss aversion parameter (γ) averages at 5.177, substantially exceeding 1, denoting a pronounced preference for avoiding losses. These findings align with PT's assertions that individuals typically overemphasize rare events, demonstrate risk aversion, and exhibit greater sensitivity to losses than to equivalent gains (Kahneman & Tversky, 1979). Nevertheless, each parameter is remarkably heterogeneous (see Fig. 4). The parameter α, despite its somewhat symmetric shape, possesses a broad distribution with two-sided long tails. In addition, σ is sharply right skewed. Regarding the distribution of γ, it has a saddle shape with two clusters: one is smaller than 6 and the other is larger than 6. Due to these significant heterogeneities, it is of the essence to not only include these

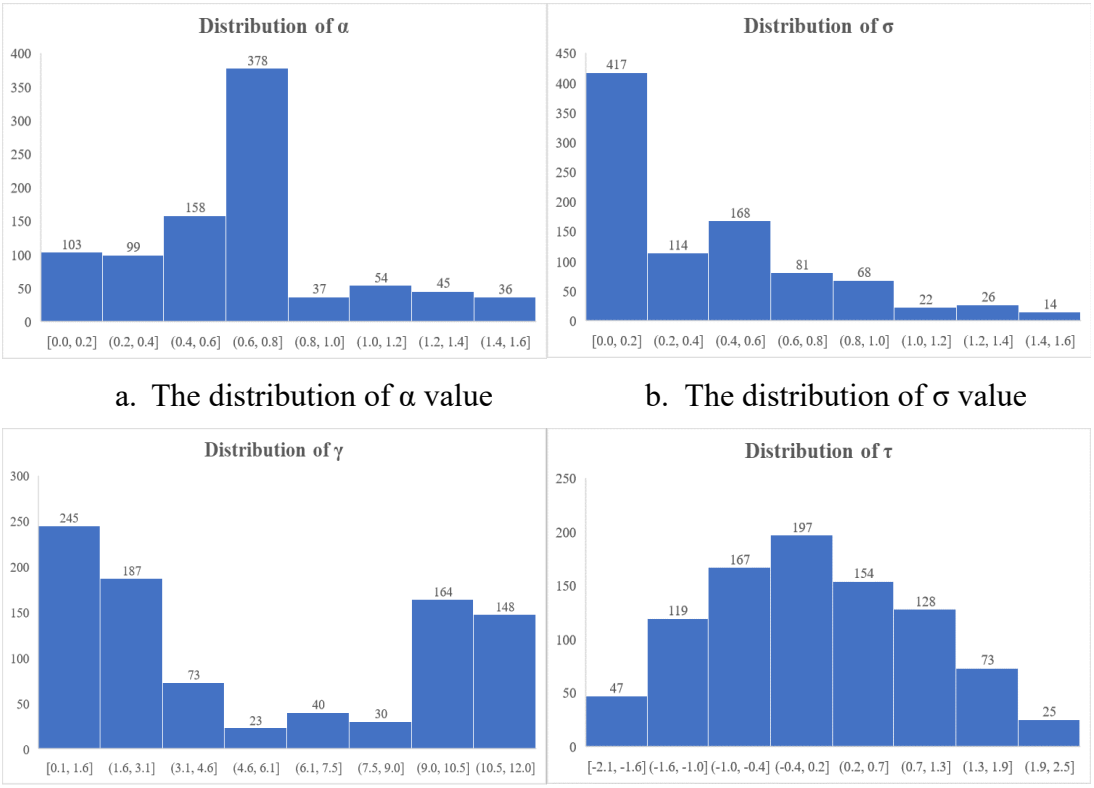
[11] We chose the ECL model, a type of mixed logit model, over alternatives such as the nested logit model and probit model since (1) nested logit models are invalid, indicated by their inclusive value parameters not significantly differing from 0 or 1 or not falling between 0 and 1, and (2) mixed logit models are more flexible, accommodating non-normal random utility terms that multinomial probit models cannot handle (McFadden & Train, 2000). More details are available on request.

personalized risk preference parameters but also account for the preference heterogeneity in the discrete choice analysis.

Table V. Descriptive statistics and correlation matrix of four risk parameters

	α	σ	γ	τ
Mean	**0.655**	**0.397**	**5.177**	**0.000**
Standard deviation	0.342	0.373	3.959	1.000
Minimum	0.030	0.030	0.110	-2.140
25th percentile	0.460	0.040	1.580	-0.720
50th percentile	0.650	0.310	3.510	-0.050
75th percentile	0.750	0.630	9.610	0.740
Maximum	1.540	1.540	12.010	2.480
Correlation matrix				
	α	σ	γ	τ
α	1.000			
σ	0.119 *	1.000		
γ	0.011	-0.271 *	1.000	
τ	0.010	-0.015	-0.039	1.000

Note: * $p < 0.05$.



a. The distribution of α value

b. The distribution of σ value

c. The distribution of γ value

d. The distribution of τ value

Fig. 4. The distributions of the four risk parameters.

We performed an exploratory factor analysis to derive the psychometric risk-taking personality parameter τ. The analysis yielded reliable results, confirmed by a Cronbach's α of 0.904 (much larger than 0.7) and factor loadings of 0.83, 0.82, 0.81, 0.78, 0.77, 0.76, 0.72, and 0.63, all exceeding 0.50, indicating robust measurement consistency and validity (Hair, Black, Babin, & Anderson, 2014). We then calculated the normalized factor score τ, which is presumed to follow a normal distribution with a mean of 0 and a standard deviation of 1, and included it as an individual characteristic in the discrete choice analysis.

4.2. Discrete Choice Analysis Results

4.2.1. Model performance comparison

We utilized NLOGIT version 6 (Greene, 2016) for our discrete choice analysis, starting with the basic MNL model (Model 1), which accounts for neither reference dependence on cost attributes nor alternative-specific preference heterogeneity. We then adopted another MNL model (Model 2) by accounting for reference dependence on cost-related attributes, including purchase price, running cost, access time, and egress time. As shown in Table VI, Model 2 outperforms Model 1, since the log-likelihood ratio test against Model 1 is significant ($\chi^2 = 150.778$, $df = 3$, $p < 0.001$). Furthermore, we developed an ECL model (Model 3) from Model 2 to account for preference heterogeneity, with a substantial improvement in performance ($\chi^2 = 1501.784$, $df = 3$, $p < 0.001$). Also, in Model 3, each error component possesses a statistically significant standard deviation, suggesting unobserved preference heterogeneity across the three alternatives (Hensher et al., 2015). In the following, therefore, we mainly discuss the results based on Model 3.

Table VI. The results of the three discrete choice models

Variable		Reference dependence (RD)	
	Model 1: MNL model (baseline)	**Model 2:** MNL model with RD	**Model 3:** ECL model with RD
Alternative Specific Constants (ASCs)			
PAVs	0.357 *	0.715 ***	1.286 **
SAVs	0.139	0.320	0.182
Monetary attributes			
Purchase price (in 1,000 CNY)	-0.002 ***		
Annual running cost for PCVs & PAVs (in 1,000 CNY)	-0.001		
Running cost per km for SAVs (in CNY)	-0.258 ***		
Service & policy attributes			
Access time (in minute)	-0.028 ***		
Egress time (in minute)	-0.019		
Vehicle availability (%)	0.006 ***	0.006 ***	0.011 ***
Privacy data security	0.206 ***	0.202 ***	0.301 ***
Enabling multitasks during trip	0.190 ***	0.191 ***	0.293 ***
Driver is liable for crashes	-0.187 ***	-0.170 ***	-0.283 ***
Exclusive lanes	0.092	0.088	0.091
Difference on attribute values with PCV as the reference			
Extra purchase price (loss in 1,000 CNY) × **PAVs**		-0.006 ***	-0.010 ***
Saved annual running cost (gain in 1,000 CNY) × **PAVs**		0.003	0.001
Extra annual running cost (loss in 1,000 CNY) × **PAVs**		-0.024 **	-0.035 ***
Saved egress time (gain in minute) × **PAVs** & **SAVs**		0.026 *	0.034 *
Saved purchase price (gain in 1,000 CNY) × **SAVs**		-0.003 ***	-0.005 **

Variable		Reference dependence (RD)	
	Model 1: MNL model (baseline)	**Model 2:** MNL model with RD	**Model 3:** ECL model with RD
Saved annual running cost (gain in CNY) × **SAVs**		0.020 *	0.034
Extra running cost per km (loss in CNY) × **SAVs**		-0.220 **	-0.333 **
Extra access time (loss in minute) × **SAVs**		-0.029 ***	-0.032 **
Risk measurement interacts with ASCs (PCV as the reference)			
Risk-taking personality (τ) × **PAVs**	0.313 ***	0.331 ***	0.490 ***
Risk-taking personality (τ) × **SAVs**	0.333 ***	0.368 ***	0.577 ***
α (non-linear probability weighting parameter) × **PAVs**	-0.146	-0.151	-0.225
α (non-linear probability weighting parameter) × **SAVs**	-0.200	-0.200	-0.307
σ (risk aversion parameter) × **PAVs**	0.206 *	0.219 *	0.336
σ (risk aversion parameter) × **SAVs**	0.331 **	0.343 **	0.553 *
γ (loss aversion parameter) × **PAVs**	-0.021 *	-0.023 **	-0.029
γ (loss aversion parameter) × **SAVs**	-0.022 *	-0.023 *	-0.034
Individual characteristics interact with ASCs (PCV as the reference)			
Age [a] × **PAVs**	0.090	0.078	0.024
Age [a] × **SAVs**	-0.150	-0.183 *	-0.289
Female [b] × **PAVs**	0.208 **	0.214 **	0.281
Female [b] × **SAVs**	0.168 *	0.155 *	0.218
Education (bachelor's degree & above) [c] × **PAVs**	0.282 ***	0.312 ***	0.536 **
Education (bachelor's degree & above) [c] × **SAVs**	0.334 ***	0.409 ***	0.748 **
Household income (no more than 200 *k* CNY) [d] × **PAVs**	-0.047	-0.183	-0.343
Household income (201 *k* ~ 300 *k* CNY) [d] × **PAVs**	-0.194	-0.285 *	-0.502 *
Household income (no more than 200 *k* CNY) [d] × **SAVs**	0.233	-0.122	-0.256
Household income (201 *k* ~ 300 *k* CNY) [d] × **SAVs**	-0.021	-0.275 *	-0.498
Number of vehicles × **PAVs**	-0.129	-0.089	-0.180
Number of vehicles × **SAVs**	-0.714 ***	-0.653 ***	-1.047 **
Prior knowledge of AVs × **PAVs**	0.239 ***	0.249 ***	0.359 ***
Prior knowledge of AVs × **SAVs**	-0.151 ***	0.158 ***	0.249 *
Standard deviation of error component (E_{in})			
Sigma PCVs			1.555 ***
Sigma PAVs			0.929 ***
Sigma SAVs			1.795 ***
Number of observations	5460	5460	5460
Number of variables	34	37	40
Log-likelihood (LL) of constant only model	-5859.456	-5859.456	-5859.456
Log-likelihood (LL) of converged model	-5612.765	-5537.376	-4786.484
McFadden's pseudo-R^2 [e]	0.042	0.055	0.183
LR test against constant only model [f]	493.382 *** (*df* = 32)	644.160 *** (*df* = 35)	2145.944 *** (*df* = 38)
LR test against the Model 1 [f]		150.778 *** (*df* = 3)	1652.562 *** (*df* = 6)
LR test against the Model 2 [f]			1501.784 *** (*df* = 3)

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. [a.] Aged over 30 years as the reference. [b.] Male as the reference. [c.] People without a bachelor's degree as reference. [d.] High-level (i.e., earning more than 400 *k* CNY in 2021) household income group as the reference.

[e.] McFadden's pseudo-R^2 = (1 – LL of converged model)/LL of constant only model (Hensher et al., 2015).

[f.] LR test is calculated as − 2 * (LL of constant only model – LL of converged model) ~ χ^2 with the degree of freedom equaling the difference in the number of parameters estimated between the two models (Hensher et al., 2015).

4.2.2. Estimated results

Taking PCV as a reference, the alternative-specific constants (ASCs) for PAVs and SAVs are both positive, and the ASC for PAVs is significant at 1% (β = 1.286), suggesting that users are generally not against accepting AVs and even prefer to ride PAVs if there are no distinguishing differences in all attributes among the three vehicle types.

In examining reference-dependent effects, all coefficients of reference-dependent terms in Model 3 exhibit expected signs, with only one exception. Specifically, the coefficients of both extra purchase price (β = –0.010) and annual running cost (β = –0.035) for PAVs are significant at 0.1%, and those of additional distance-based running cost (β = –0.333) and extra access time (β = –0.032) for SAVs are significant at the 1% level. These significantly negative coefficients on the loss terms suggest that individuals' preferences for AVs are significantly deterred by the potential cost increases compared to PCVs. In terms of gains, only the expected egress time saving for AVs shows positive significance (β = 0.034) at the 5% level, suggesting consumers' appreciation for the self-parking feature of AVs. Overall, these results indicate a heightened consumer sensitivity to the potential downsides of AV acceptance over perceived benefits, aligning with PT's assertion of loss aversion predominance (Hardie et al., 1993; Kahneman & Tversky, 1979; Liu, 2013). The exception lies in the significantly negative coefficient of the saved purchase price for SAVs (β = –0.005, $p < 0.01$). This could be attributed to our SP experiment's pivoting design, where the PCV purchase price is based on each respondent's intended budget for their next vehicle. Essentially, individuals planning to purchase more expensive private vehicles are less likely to choose SAVs. This aligns with evidence that people who invest in high-end private vehicles prioritize autonomy, comfort, and status over cost savings, making them more resistant to shared mobility options, despite the potential financial benefits (McKinsey & Company, 2017, 2021).

Beyond reference-dependent factors, our analysis finds significant coefficients for service and policy attributes, all with the expected signs, suggesting their crucial role in AV acceptance. Vehicle availability emerged as a significant positive influence (β = 0.011, $p < 0.001$) on SAV preference, highlighting the importance of service accessibility. Moreover, consumer preferences for AVs are significantly influenced by data privacy security and the ability of multitasking during trips, as evidenced by the positive coefficients for privacy data security (β = 0.301, $p < 0.001$) and in-trip multitasking (β = 0.293, $p < 0.001$). These findings are broadly consistent with recent research emphasizing the importance of service quality in SAV adoption (Krueger, Rashidi, & Rose, 2016; Tian et al., 2021). Conversely, user liability in crashes negatively affects AV selection, as indicated by a significantly adverse coefficient (β = –0.283, $p < 0.001$), aligning with findings that legal risks deter AV use (Shabanpour et al., 2018). The exclusive lane attribute showed no significant effect.

Regarding the effects of risk preference characteristics [12], our findings suggest that individuals inclined toward AVs typically exhibit risk-taking personalities, likely attributed to the early stage of AV introduction necessitating adventurous early adopters. The three PT risk parameters, α, γ, and σ, show consistent signs for both PAVs and SAVs: negative for α and γ and positive for σ. This pattern suggests AV adopters tend to overweigh small-probability events, exhibit lower risk aversion, and have less loss aversion compared to PCV users. This is consistent with studies on

[12] As shown in Appendix 9, the three models that include risk preference parameters perform significantly better than those without, as indicated by the LR test statistics (i.e., Model 1: 119.436; Model 2: 135.477; Model 3: 54.290), all of which far exceed the threshold value of χ^2 (8) = 15.51. This result highlights the importance of accounting for risk preferences in the models.

early technology adopters, who often discount low-probability risks and focus on potential benefits (Daziano, Sarrias, & Leard, 2017; König & Neumayr, 2017). However, in Model 3, only the coefficient for the σ parameter interacted with SAVs retains significance ($\beta = 0.553$, $p < 0.05$), contrasting with findings from Model 1 and Model 2. This discrepancy underscores the considerable heterogeneity in individuals' risk preferences for AVs (Wang & Zhao, 2019), effectively captured through the significant standard deviation of error components in Model 3.

For the individual characteristics interacted with the ASCs of SAVs or PAVs, we also find the expected signs of coefficients. We observed that individuals favoring AVs over PCVs tend to be well-educated (holding at least a bachelor's degree) and possess better prior knowledge of AVs. This is consistent with research showing that higher education levels are linked to greater openness to adopting new technologies (Daziano et al., 2017). Similarly, prior knowledge of AVs positively correlates with adoption, as familiarity is a key driver of acceptance in technology adoption studies (König & Neumayr, 2017). Additionally, households owning more vehicles are less likely to choose SAVs ($\beta = -1.047$, $p < 0.01$). Furthermore, mid-level income households, compared to higher-income households, exhibit a significantly negative preference for purchasing AVs ($\beta = -0.502$, $p < 0.05$), likely due to the potential unaffordability of these vehicles (Bansal et al., 2016). In contrast, the coefficients of age and gender were not significant for either PAVs or SAVs.

4.3. Willingness to Pay

Using the ECL model (Model 3) results, we calculate consumers' willingness to pay (WTP) for non-monetary attributes by taking the negative ratio of the coefficient of each non-monetary attribute to that of the monetary attribute (Hensher et al., 2011; Merkert, Bliemer, & Fayyaz, 2022), which is the purchase price for PAVs and distance-based running cost for SAVs. We also use the Delta method to calculate the 95% confidence intervals (CIs) for the WTP estimates (Hole, 2007). Our discussion focuses on the WTPs of key attributes that show significant effects in the model (Huang & Qian, 2018).

As shown in Table VII, our analysis suggests that consumers are willing to pay 3,500 CNY more on average (95% CI: [1,483 CNY, 5,517 CNY]) to buy a PAV for every 1,000 CNY it can save in annual running cost compared to a PCV. Additionally, consumers value the shorter egress time, with the average WTP of 3,400 CNY (95% CI: [230 CNY, 6,570 CNY]) for a PAV with one-minute shorter egress time than a PCV. For the features of enhanced privacy security, a multitasking-friendly in-vehicle environment, and the driver's exemption from crash liability, consumers are willing to pay 30,100 CNY, 29,300 CNY, and 28,300 CNY on average for a PAV, respectively. Regarding the WTP for SAVs, consumers are prepared to pay 0.096 CNY extra in the running cost per kilometer on average (95% CI: [0.014 CNY, 0.178 CNY]) for one-minute shorter access time to SAVs and approximately 0.033 CNY extra in running cost per kilometer for a 1% increase in SAV availability. For benefits such as enhanced privacy security, an environment conducive to multitasking, and driver's exemption from liability in crashes, consumers are willing to pay additional running cost of 0.904 CNY/km, 0.880 CNY/km, and 0.850 CNY/km, respectively, to use SAVs.

Table VII. Willingness to pay for significant key attributes

Attribute	**Coefficient**	**WTP for PAV's Attributes** (In 1,000 CNY)		**WTP for SAV's Attributes** (In CNY)	
		Point Estimate	95% CI	Point Estimate	95% CI
Extra purchase price (loss in 1,000 CNY) × **PAVs**	-0.010 ***				
Extra annual running cost (loss in 1,000 CNY) × **PAVs**	-0.035 ***	-3.500	[-5.517, -1.483]		
Saved egress time (gain in minute) × **PAVs**	0.034 *	3.400	[0.230, 6.570]		
Extra running cost per km (loss in CNY) × **SAVs**	-0.333 **				
Extra access time (loss in minute) × **SAVs**	-0.032 **			-0.096	[-0.178, -0.014]
Privacy data security	0.301 ***	30.100	[23.395, 36.805]	0.904	[0.320, 1.488]
Enables multitasking during trip	0.293 ***	29.300	[18.062, 40.538]	0.880	[0.217, 1.543]
Driver is liable for crashes	-0.283 ***	-28.300	[-38.266, -18.334]	-0.850	[-1.462, -0.238]
Vehicle availability (%)	0.011 ***			0.033	[0.023, 0.043]

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, *all in two tails.*

5. DISCUSSION AND CONCLUSION

The emergence of AVs, driven by AI technologies, signifies a major shift in mobility (Qian et al., 2023), sparking increased research into AV acceptance and consumer choices. Our study used a SP experiment to investigate how consumer risk preferences influence the choice between PAVs, SAVs, and PCVs, incorporating four risk parameters. We specified an ECL model with reference dependence to examine consumer preferences for AVs. Our results indicate that risk-takers favor AVs, although specific risk traits such as overestimating small-probability events or loss aversion had minimal impact. Moreover, our reference-dependence analysis shows that consumers emphasize potential losses (e.g., higher purchase price) over gains (e.g., reduced wait times) when considering AVs versus PCVs. Our study offers crucial insights for policymakers and business practitioners.

5.1. Contributions

Our study enriches the literature on AI-powered product adoption in two main areas. First, it enriches the understanding of AI-related risk analysis through examining the role of risk preferences in consumers' AV adoption. Although some studies have explored the effect of risk preference on AV acceptance (e.g. Huang & Qian, 2021; Wang & Zhao, 2019), they often lack a comprehensive inclusion of all risk preference facets. For example, Wang and Zhao (2019) did not address loss aversion, a critical component for a thorough analysis of risk preferences. We elicited consumers' risk preferences across multiple dimensions, emphasizing the significant roles of risk-taking personality and risk aversion in AV acceptance. Our findings reveal that early AV adopters in China tend to be more risk-seeking compared to those preferring PCVs. Furthermore, while the loss aversion parameter was significant in the MNL models, it became insignificant in the ECL model accounting for alternative-specific preference heterogeneity with superior performance. This suggests that the effect of loss aversion on AV preferences would be overestimated if the heterogeneity in consumer preferences is not sufficiently captured, highlighting the importance of accounting for preference heterogeneity when examining risk preferences toward AVs.

Second, this study is among the first to empirically incorporate reference dependence in the context of AI-powered product adoption; specifically, AVs. We calculated the gains and losses in key attributes of AVs, using PCVs as a reference, to assess the impact of reference dependence on consumer decision-making. The enhanced performance of the two reference-dependent DCMs over the baseline MNL model highlights the importance of this approach. Our findings indicate significant coefficients for losses and less significant or lower coefficients for gains, suggesting that potential losses associated with using AVs have a greater influence on consumer preferences than gains. This enriches our understanding of AV acceptance by highlighting the impact of specific AV-related risks (e.g., potential cost losses), and extending beyond prior research focused solely on absolute attribute values.

5.2. Practical Implications

This study also provides valuable policy and managerial insights. First, our findings suggest that risk-takers are more prone to early AV adoption. Given that AV technology is still in its nascent stage, with many uncertainties, potential adopters might require a higher risk tolerance. To promote

AV acceptance, industry stakeholders need to enhance individuals' risk tolerance by highlighting AV benefits to build trust and willingness to assume associated risks, as positive emphasis has been proven to mitigate apprehensions (Liu, Ma, & Zuo, 2019). Therefore, spotlighting AV advantages and increasing public engagement with the technology are strategic moves for marketers.

Second, our analysis underscores an asymmetric sensitivity among individuals, who react more to additional monetary costs of owning and using AVs than potential savings, which might hinder widespread acceptance. Automakers and service providers should emphasize cost-effectiveness and adopt strategic pricing, particularly during the initial market introduction. Furthermore, government intervention through subsidies, tax breaks, and rebates for AV purchases and usage can help mitigate the deterring effects of these higher costs. Integrating renewable energy technologies, such as electric or hybrid vehicles, with autonomous driving capabilities can enhance energy efficiency and reduce operating costs (Krupa et al., 2014; Rezvani, Jansson, & Bodin, 2015), aligning with sustainability goals and addressing consumer cost concerns.

Third, our research identifies user liability in the event of crashes as a significant barrier to AV adoption. As control shifts from drivers to AV systems, it is imperative for policy makers to establish clear legal frameworks that delineate liability responsibilities. Allocating liability to manufacturers and technology providers rather than individual users can significantly alleviate consumer concerns, as our findings indicate that consumers are willing to pay a premium for AVs that offer liability exemptions. Specifically, consumers are willing to pay an average of 28,300 CNY for exemption from crash liability in PAVs and are prepared to incur additional running fees of 0.850 CNY per kilometer to obtain the same benefit in SAVs. Providing legal certainty in this area will enhance trust and encourage the widespread adoption of AV technologies.

Fourth, our research underscores the significant impact of enhanced privacy security on consumer preferences for AVs, highlighting the protection of personal data as a critical factor influencing consumer decision-making. Governments must introduce and enforce robust privacy and data security regulations specifically tailored to AV technologies. Ensuring that personal data, such as travel patterns and identity information, is adequately protected through stringent data encryption, anonymization techniques, and regular security audits will build consumer trust. Additionally, public awareness campaigns should be launched to educate consumers on how their data is secured and utilized, thereby fostering a positive perception of AVs and effectively addressing privacy concerns. By implementing these measures, governments can enhance consumer confidence in AV technologies, facilitating their broader acceptance and adoption.

Fifth, our findings reveal the importance of reduced access time and higher vehicle availability in shaping consumer preferences for SAV services. Specifically, consumers are willing to incur an additional running cost of 0.096 CNY per kilometer for each minute reduction in access time and roughly 0.033 CNY more per kilometer for a 1% increase in SAV availability. This underscores the need for prompt and available SAV services on booking. Consequently, governments should incentivize fleet expansion through subsidies and financial incentives, particularly in densely populated urban areas. Investing in infrastructure that supports SAV operations, such as dedicated pick-up and drop-off zones, charging stations for electric SAVs, and integrated mobility platforms, will enhance SAV availability and reliability. Streamlining the licensing and permitting processes for SAV operators can facilitate quicker service deployment and fleet growth.

5.3. Future Research Directions

This study acknowledges several limitations that serve to guide future research avenues. First,

while the SP approach offers valuable insights into consumer preferences for AVs, its reliance on hypothetical scenarios may not fully capture actual consumer decision-making behavior. Future research should consider integrating RP data, once sufficient real-world usage information becomes available, to complement the SP data and provide more accurate and realistic insights into AV adoption trends. Second, regarding the experiment design, our research did not account for budget-based decision processes, an essential aspect of consumer behavior. We plan to explore how budget constraints affect vehicle choices across different AV classes in future work. Third, our study focused on two policy-related attributes—the liability for users in crashes and the availability of AV exclusive lanes. Future research can incorporate additional policy factors, such as subsidies, tax incentives, and infrastructure support, to offer a more comprehensive understanding of how public policy influences AV adoption. Finally, our cross-sectional method does not capture changing attitudes, suggesting a need for longitudinal research to trace the evolution of consumer opinion regarding AVs.

ACKNOWLEDGEMENTS

We express our sincere gratitude to the Editor, the Area Editor, and the anonymous reviewers for their constructive feedback and valuable suggestions, which have greatly improved the quality of this manuscript. This research is supported by the National Natural Science Foundation of China (Grant Number: 72473112, 71973107, 72431007 and 72021002), and Xi'an Jiaotong-Liverpool University Research Development Fund (RDF-20-02-65). The first author, Dr. Ya Liang, was studying at Xi'an Jiaotong-Liverpool University when conducting this research.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

APPENDIX 1: A SUMMARY OF TECHNOLOGIES BEHIND AVS

Table A1. A summary of technologies behind AVs

Category	Technology/Model	Function	Role in AVs
Sensor Technologies	LiDAR (Light Detection and Ranging)	Use light in the form of a pulsed laser to measure distances.	Provide precise distance measurements and create high-resolution 3D maps of the environment, crucial for obstacle detection and navigation.
	Radar (Radio Detection and Ranging)	Use radio waves to determine the speed, angle, and distance of objects.	Work well in adverse weather conditions, aiding in vehicle detection and speed measurement, and complement LiDAR and cameras.
	Cameras	Capture visual information in a similar way to the human eye.	Essential for detecting and recognizing traffic signs, signals, road lanes, pedestrians, and other vehicles. Provide visual context to the vehicle's surroundings.
	GPS (Global Positioning System)	Provide precise location information to help the vehicle navigate and position itself.	Essential for ensuring AVs can navigate accurately, stay on course, and make informed driving decisions based on their precise location.
AI Algorithms	Perception Algorithms	Process input from various sensors to build a model of the environment.	Enable the vehicle to understand and interpret its surroundings, by identifying objects and their position and movement.
	Decision-Making Algorithms	Analyze the environmental model to make strategic decisions such as when to change lanes or adjust speed.	Key for planning the vehicle's path and interactions with its environment in real-time, ensuring safe navigation through complex scenarios.
	Control Algorithms	Execute the driving decisions by controlling the vehicle's steering, braking, and throttle.	Directly control the vehicle's operations based on the decisions made by AI, adjusting to the dynamic driving environment.

APPENDIX 2: THE STATE OF AV USAGE IN DIFFERENT REGIONS WORLDWIDE

Table A2. The state of AV usage in different regions worldwide

Scenarios	Key Players	Key Milestones/Highlights	Challenges Faced	Sources
Robotaxis	***U.S.:*** Cruise, Waymo, Tesla, Motional, Aurora, Zoox, etc. ***China:*** Apollo, AutoX, DeepRoute, Momenta, Pony.ai, WeRide, etc. ***Europe:*** Mobileye, etc.	• Waymo launched the first commercial autonomous ride-hailing service in the U.S. in 2019. • Cruise received approval to operate commercially in California in 2023. • In China, there have been 3.5 million rides and 55 million miles driven, with Apollo alone accounting for 28 million miles across multiple cities. • In Europe, testing has been limited but growing since 2022, with partnerships forming with multiple companies.	• Regulatory hurdles, public acceptance. • Safety concerns, especially in complex urban environments. • High costs of technology and infrastructure development.	Betz (2024); Juliussen (2022, 2023)
Robotrucks	***U.S.:*** Waymo, Aurora, Plus, TuSimple, Kodiak, Gatik, etc. ***China:*** Inseptio, Plus, TuSimple, Pony.ai, WeRide, etc. ***Europe:*** Einride, Daimler (Torc Robotics), Plus, etc.	• In the U.S., six key companies (e.g., Waymo, Plus, etc.) are leading significant trials and forming partnerships with OEMs and logistics firms. • In China, leading developers, such as Plus and Pony.ai, are achieving significant mileage with L3 operations. • In Europe, particularly Sweden, Einride offered the first electric autonomous truck for commercial operations in 2019.	• Technological integration in varying traffic and weather conditions. • Market entry barriers and technological development.	Einride (2019); Juliussen (2023)
Roboshuttles	***U.S.:*** May Mobility, Beep, Via, etc. ***China:*** Apollo (Apalong), Dongfeng, WeRide, etc. ***Europe:*** EasyMile, Navya, ZF, Holon, etc.	• May Mobility has conducted 320,000 rides in 8 U.S. cities, focusing on areas lacking mass-transit services. • Apollo's Apalong has completed 38 trials across 22 cities, covering 140,000 km. • WeRide is set to launch a mini robobus and robovan in China. • Europe leads to fixed-route AV shuttles, developed by EasyMile and Navya.	• Integration with existing public transport systems. • Adoption rate, public trust, technological integration.	Juliussen (2023)
Goods delivery AVs	***U.S.:*** Nuro, Starship, etc. ***China:*** Neolix, Apollo, etc. ***Europe:*** Starship Technologies, etc.	• Nuro is conducting trials with Walmart, Kroger, and Uber Eats. • Starship is active in 25 universities with 5.5 million deliveries in the U.S. • Neolix, certified for ISO 22737, operates in 40 cities across 13 countries. • In Europe, Starship leads sidewalk AVs for goods delivery, with 10 million km traveled, 2,000 sidewalk AVs, and 5.5 million deliveries.	• Balancing innovation with traditional logistics needs. • Scalability, regulatory approval, technological complexities.	Juliussen (2022, 2023)

APPENDIX 3: REASONS FOR CHOOSING STATED PREFERENCE OVER REVEALED PREFERENCE

We choose the Stated Preference (SP) approach over the Revealed Preference (RP) approach due to the emerging nature of AV technology and several key factors. Below, we outline several reasons for this decision:

1) Fully AVs are not yet widely available in the market, which makes it impossible to obtain actual usage data for employing the RP approach. As Louviere et al. (2000) emphasize, the SP approach is essential for modeling demand for new products with attributes that lack historical market data, as is the case for AVs. In contrast, RP method, which reflects actual market behavior, is better suited for analyzing existing technologies and products but is less applicable for forecasting adoption of emerging innovations.
2) The SP approach allows researchers to design experiments that include hypothetical variables and options, which can yield richer insights into consumer preferences for new technologies and attributes. This method is particularly effective for assessing willingness to pay and preferences for novel configurations, features, and services in emerging transportation systems (Louviere et al., 2000; Train, 2009). By creating forward-looking scenarios, the SP approach offers a significant advantage in studying innovations like AVs, where market data is currently absent (Gupta, Verma, & Victorino, 2006).
3) In emerging technologies, even if the real data are available to researchers for RP analysis, they often suffer from limited variability and high collinearity among attributes, primarily driven by existing market technologies and competitive forces (Hensher, Louviere, & Swait, 1998). SP approach circumvents these issues by allowing researchers to design experiments where attributes can be systematically varied, thus providing clearer insights into their individual effects on consumers' choice decisions (Hensher et al., 1998; Mark & Swait, 2004).
4) Even if we can ask respondents about the individual functional features of AVs, respondents are likely to choose the best level on each feature, such as the lowest price, shortest access time, highest level of vehicle availability and highest level of privacy data security in our case. By doing so, we cannot infer consumers' preferences in the choice situations. In comparison, using the SP approach can enable researchers to elicit consumer preferences based on the tradeoff among different options that are described with a set of features, so that we can infer consumers' preferences through the tradeoff or choice.
5) While the RP approach is common in vehicle-selection models for existing technologies, many studies on emerging technologies have successfully utilized the SP approach to capture user preferences (see Haboucha et al., 2017; Lavieri & Bhat, 2019; Tian et al., 2021). Our methodology aligns with these studies, ensuring that our findings are comparable with the broader literature.

APPENDIX 4: THE THREE SERIES OF LOTTERIES IN THE LOTTERY EXPERIMENT

Table A3. The three series of lotteries in the lottery experiment

	Lottery A (CNY)	Lottery B (CNY)	E(A-B) [a]
Series 1			
1	30% winning 200,000 and 70% winning 50,000	10% winning 340,000 and 90% winning 25,000	38,500
2	30% winning 200,000 and 70% winning 50,000	10% winning 375,000 and 90% winning 25,000	35,000
3	30% winning 200,000 and 70% winning 50,000	10% winning 415,000 and 90% winning 25,000	30,000
4	30% winning 200,000 and 70% winning 50,000	10% winning 465,000 and 90% winning 25,000	26,000
5	30% winning 200,000 and 70% winning 50,000	10% winning 530,000 and 90% winning 25,000	19,500
6	30% winning 200,000 and 70% winning 50,000	10% winning 625,000 and 90% winning 25,000	10,000
7	30% winning 200,000 and 70% winning 50,000	10% winning 750,000 and 90% winning 25,000	-2,500
8	30% winning 200,000 and 70% winning 50,000	10% winning 925,000 and 90% winning 25,000	-20,000
9	30% winning 200,000 and 70% winning 50,000	10% winning 1,100,000 and 90% winning 25,000	-37,500
10	30% winning 200,000 and 70% winning 50,000	10% winning 1,500,000 and 90% winning 25,000	-77,500
11	30% winning 200,000 and 70% winning 50,000	10% winning 2,000,000 and 90% winning 25,000	-127,500
12	30% winning 200,000 and 70% winning 50,000	10% winning 3,000,000 and 90% winning 25,000	-227,500
13	30% winning 200,000 and 70% winning 50,000	10% winning 5,000,000 and 90% winning 25,000	-427,500
14	30% winning 200,000 and 70% winning 50,000	10% winning 8,500,000 and 90% winning 25,000	-777,500

	Lottery A (CNY)	Lottery B (CNY)	E(A-B) [a]
Series 2			
1	90% winning 200,000 and 10% winning 150,000	70% winning 270,000 and 30% winning 25,000	-1,500
2	90% winning 200,000 and 10% winning 150,000	70% winning 280,000 and 30% winning 25,000	-8,500
3	90% winning 200,000 and 10% winning 150,000	70% winning 290,000 and 30% winning 25,000	-15,500
4	90% winning 200,000 and 10% winning 150,000	70% winning 300,000 and 30% winning 25,000	-22,500
5	90% winning 200,000 and 10% winning 150,000	70% winning 310,000 and 30% winning 25,000	-29,500
6	90% winning 200,000 and 10% winning 150,000	70% winning 325,000 and 30% winning 25,000	-40,000
7	90% winning 200,000 and 10% winning 150,000	70% winning 340,000 and 30% winning 25,000	-50,500
8	90% winning 200,000 and 10% winning 150,000	70% winning 360,000 and 30% winning 25,000	-64,500
9	90% winning 200,000 and 10% winning 150,000	70% winning 385,000 and 30% winning 25,000	-82,000
10	90% winning 200,000 and 10% winning 150,000	70% winning 415,000 and 30% winning 25,000	-103,000
11	90% winning 200,000 and 10% winning 150,000	70% winning 450,000 and 30% winning 25,000	-127,500
12	90% winning 200,000 and 10% winning 150,000	70% winning 500,000 and 30% winning 25,000	-162,500
13	90% winning 200,000 and 10% winning 150,000	70% winning 550,000 and 30% winning 25,000	-197,500
14	90% winning 200,000 and 10% winning 150,000	70% winning 650,000 and 30% winning 25,000	-267,500

	Lottery A (CNY)	Lottery B (CNY)	E(A-B) [a]
Series 3			
1	50% winning 125,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000	30,000
2	50% winning 20,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000	-22,500
3	50% winning 5,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000	-30,000
4	50% winning 5,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 80,000	-42,500
5	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 80,000	-52,500
6	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 70,000	-57,500
7	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 55,000	-65,000

[a.] This column was not shown to respondents.

APPENDIX 5: ESTIMATION PROCESS FOR THREE PT RISK PARAMETERS

To estimate the non-linear probability weighting parameter (α) and the risk aversion parameter (σ) for every respondent, we leverage their switching points in series 1 and series 2. Following this, the switching point from series 3 is employed to determine the loss aversion measure (γ).

When a respondent changes the preference for Lottery A to Lottery B at row R, it is deduced that he/she favors Lottery A over Lottery B at row R − 1, and vice versa at row R. This switch yields a pair of inequalities, written as follows:

$$Utility\left(x_{A,R-1}, p_{A,R-1}, y_{A,R-1}, q_{A,R-1}\right) > Utility\left(x_{B,R-1}, p_{B,R-1}, y_{B,R-1}, q_{B,R-1}\right)$$

and

$$Utility\left(x_{A,R}, p_{A,R}, y_{A,R}, q_{A,R}\right) < Utility\left(x_{B,R}, p_{B,R}, y_{B,R}, q_{B,R}\right)$$

Utilizing the switching points from both series 1 and series 2 enables us to determine the boundaries of α and σ that adhere to the given inequalities. For instance, if a respondent demonstrates switching behavior from Lottery A to Lottery B at row 7 in both series, the parameters that meet these inequalities are calculated as $0.66 < \alpha < 0.74$ and $0.64 < \sigma < 0.74$. Following the methodology proposed by Tanaka et al. (2010), we estimate α and σ by selecting the midpoint of their respective intervals. Hence, we infer values of 0.70 for α and 0.69 for σ.

Based on each respondent's switching point in series 3, we generate two inequalities to pinpoint the range for γ. Using the midpoint of this identified range provides our estimate for γ. Should a respondent choose no change or change at row 1 in series 3, we can obtain only one inequality, and hence we adopt the lower/upper boundary value as the estimation of γ. Tanaka et al. (2010) offer a comprehensive breakdown of this estimation process in their appendix.

APPENDIX 6: DETAILS OF THE DATA COLLECTION

Our questionnaire was distributed via the Wenjuanxing (WJX) online survey platform (*https://www.wjx.cn*; formerly known as *Sojump*), one of the most widely used survey platforms in China. This platform ensures broad and diverse demographic coverage like international platforms such as SurveyMonkey and Qualtrics. WJX has successfully administered millions of surveys, collecting billions of responses, demonstrating its capacity for large-scale data collection and reliable survey tools (Cao et al., 2023). Specifically, we utilized WJX's sample service,[13] which includes over 6.2 million registered participants. To date, this service has conducted over 88,000 projects with more than 56 million responses, showcasing its wide reach and high reliability. WJX also offers quality control services to meet target demographic requirements and maintain response quality. This sample service is recognized and utilized by prestigious institutions and organizations, including Peking University, Tsinghua University, The Chinese University of Hong Kong, the London School of Economics, and Huawei. This ensures our sample is both reliable and representative of the population. Additionally, studies have shown that online data collection methods, when properly administered, can yield data of comparable quality to traditional methods (Dillman, Smyth, & Christian, 2014).

After finalizing the questionnaire design and experiment setup on the platform, we specified requirements for data collection, such as sample size, cities, and/or age groups. The platform then invited registered participants who met these criteria to complete the survey. To ensure sample representativeness across cities, we first recruited 100 respondents in each city, then 50 respondents more in each city, and finally 70 more responses in Shanghai (10 female and 60 male), 50 more in Chongqing, and 35 more in Beijing. In actuality, the platform collected 910 samples for us. The cost of data collection was about 13.5 CNY (approximately US$1.85) per valid questionnaire, including the lottery experiment and choice experiment.

[13] WJX sample service: *https://www.wjx.cn/sample/service.aspx*

APPENDIX 7: DETAILS OF THE DATA COLLECTION

To ensure the quality of the collected data, we applied four exclusion criteria on the collected data, whereby responses failing to meet any of these criteria were excluded from subsequent analysis. The exclusion criteria were as follows:

(1). On the cities surveyed, the responses should be from the five designated cities only. Thus, any response from other cities, based on the IP address, was excluded.

(2). On the family size, the number of licensed drivers should not exceed the family size of the same household. Thus, the response was excluded if the number of licensed drivers exceeded the family size of the same household.

(3). On the response attention, risk attitude is measured with the eight 7-point Likert scale items, including three reverse-coded items (see full questionnaire). Thus, the response was excluded if the answers to the reverse-coded items presented a similar trend to those for the other five items.

(4). On the response time, the questionnaire was required to be completed in no less than 5 minutes, taking into consideration the number of questions and the length of time that respondents needed to comprehend the concept and levels of vehicle automation presented at the beginning of the questionnaire.

APPENDIX 8: FULL QUESTIONNAIRE

1. Currently, how many cars does your household own? (You are welcome to participate in this survey even if your household has no cars) [single choice] *

○ 0 (Skip to question 3)

○ 1

○ 2

○ more than 2

2. How many years of experience have you had since you first owned a car? (You are welcome to participate in this survey even if you have no experience in using cars) [single choice] *

○ less than 1 year (including no experience)

○ 1-3 years

○ 3-6 years

○ 6-10 years

○ more than 10 years

3. How many years have you held a Chinese driver's license? (Limited to A license, B license and C1 and C2 license) (You are welcome to participate in this survey even if you have no Chinese driver's license now) [single choice] *

○ no license (Skip to question 5)

○ less than 1 year

○ 1-3 years

○ 3-6 years

○ more than 6 years

4. How often do you drive? (Travel includes commuting, shopping, playing, etc.) (You are welcome to participate in this survey even if you have no driving experience) [single choice] *

○ never drive

○ not more than once a week

○ 2 to 3 times a week

○ 4 to 5 times a week

○ more than 5 times a week

5. How many people in your household currently have Chinese driver's licenses (Limited to A license, B license and C1 and C2 license) [single choice] *

○ 0 persons

○ 1 person

○ 2 persons

○ 3 persons

○ 4 or more persons

Part I

Now, we will give you some statements about your ***knowledge*** of AVs, respectively, and ask you to choose below how much you agree with each statement.

1. To what extent do you agree with the following statements? (1= totally disagree; …; 7= totally agree) [matrix scale question] *
   - I am largely ignorant of AVs.
   - I have not read or seen much information about AVs.
   - I am quite familiar with the idea of AVs (reverse scored).

1.1. Introduction of The Research Background

Autonomous vehicles (AVs), also known as driverless vehicles, computer-driven vehicles, or wheeled mobile robots, are intelligent vehicles that realize driverless driving through computer systems. At present, many cities in China, such as Beijing, Guangzhou and Changsha, have carried out road tests for AV.

At present, vehicle automation is divided into six levels in China. Among them, level 0-2 is driving assistance. The system assists human beings to perform certain dynamic driving tasks, however, the driving subject is still the human driver; Level 3-5 refers to autonomous driving. The system performs dynamic driving tasks instead of humans under the designed operating conditions. When the function is activated, the driving subject is the system. The definitions of each level are as follows:

Automation level	Description
level 0: Emergency Assistance	*The system cannot continuously perform vehicle lateral or longitudinal motion control in dynamic driving tasks but can continuously perform some target and event detection and response in dynamic driving tasks.*
level 1: Partial Driving Assistance	*The system continuously performs vehicle lateral or longitudinal motion control in dynamic driving tasks under its designed operating conditions and can detect and respond to some targets and events corresponding to the vehicle lateral or longitudinal motion control.*
Level 2: Combined Driving Assistance	*The system continuously performs vehicle lateral and longitudinal motion control in dynamic driving tasks under its designed operating conditions and can detect and respond to some targets and events corresponding to the vehicle lateral and longitudinal motion control.*
Level 3: Conditional Autonomous Driving	*The system continuously performs all dynamic driving tasks under its designed operating conditions.*
level 4: Highly Autonomous Driving	*The system continuously performs all dynamic driving tasks under its designed operating conditions and automatically implements the minimum risk strategy.*
level 5: Fully Autonomous Driving	*The system continuously performs all dynamic driving tasks under any driving conditions and automatically implements the minimum risk strategy.*

This study only focuses on level 5 driving automation, i.e., full automation. Therefore, the AVs involved in the following are all fully AVs.

1.2. Alternatives and Attributes in Our Choice Experiment

Next, we will conduct a hypothetical choice experiment on whether you will choose to drive automatically. You will see six scenarios, each of which contains three different types of vehicles for you to choose from:

- **Private conventional vehicle (PCV)**
- **Private autonomous vehicle (PAV)**
- **Shared autonomous vehicle (SAV)**

Among them, PAV refers to the AV purchased, owned and used by individuals (or families). SAVs are AVs that are not monopolized by individuals or single families. They are open to the

public. People can pay for using SAVs through specific channels (such as online rental / taxi platforms) according to their needs.

Each scenario will contain 9 attributes which distinguish the three alternatives. Next, we will briefly introduce these attributes.

Attributes		**Brief introduction**
Monetary attributes	Purchase price	◆ *It measures the total cost of buying a car. For SAV, purchase price is 0 by default.*
	Running cost	◆ *For PCV and PAV, it refers to the fuel or charging costs, maintenance costs, insurance premiums, parking fees and other costs generated by the daily use of cars, which are calculated on an annual basis.* ◆ *For SAV, it mainly refers to the fees paid for the daily use of the corresponding services, calculated at the price per kilometer.*
Service attributes	Egress time	◆ *It mainly refers to the parking time required after arrival. For PAV and SAV, it is 0 by default.*
	Access time	◆ *It refers to the time between "deciding to use the vehicle" and "actually getting on the vehicle".*
	Vehicle availability	◆ *It measures the extent to which a SAV demander can immediately meet his/her vehicle needs. For private cars, it defaults to 100%.*
	Enabling multitasks during trip	◆ *It refers to whether the user can carry out work or leisure activities other than "driving" when riding on a vehicle. For PCVs, the default of the attribute is "no".*
	Data privacy security	◆ *It mainly measures to what extent the vehicle collects and protects users' data information (such as identity information, destination information, etc.). The privacy security level of conventional vehicles is regarded as the standard level.*
Policy attributes	Driver is liable for crashes	◆ *In the future, the users of AVs may be exempted from the responsibility in traffic accidents since AVs can drive without any human interference. For PCV, the attribute level is "no" by default.*
	Exclusive lanes are provided	◆ *In the future, the government may open exclusive lanes for AVs. For PCV, it is "no" by default.*

1. if your family is going to buy a car in the next few years, what price range are you going to choose? [single choice] *

○ 100000 and below

○ 100001 ~ 200000

○ 200001 ~ 300000

○ 300001 and above

Now, we are showing you SIX choice scenarios.

[*Note: Table S4 presents the 36 hypothetical choice scenarios included in our SP experiment design. Each respondent is randomly assigned six of these scenarios to complete choice tasks*.]

For each scenario, respondents are asked to answer the following two questions:

1. if you must choose one of three ways for your daily travel, which one in the scenario are you most likely to choose? [single choice] *

○ private conventional vehicle

○ private autonomous vehicle

○ shared autonomous vehicle

2. in the scenario, if you have the right to give up the choice, will you give up? [single choice] *

○ yes

○ no.

Table A4. Configurations of 36 choice scenarios in the SP experiment design

	Purchase price [a]	Running cost [b]		Vehicle availability	Access time	Egress time	Privacy security		Multitasks		Taking liability for crash		Exclusive lanes
Scenario	PAV	PAV	SAV	SAV	SAV	PCV	PAV	SAV	PAV	SAV	PAV	SAV	PAV/SAV
1	160%	120%	3	40%	10 min	1 min	higher level	reference level	No	No	Yes	No	Yes
2	160%	120%	2.5	70%	15 min	6 min	lower level	higher level	No	No	No	No	No
3	160%	120%	2.5	70%	15 min	1 min	lower level	higher level	Yes	No	No	Yes	Yes
4	160%	120%	2	100%	5 min	6 min	reference level	lower level	Yes	No	Yes	Yes	No
5	160%	100%	3	70%	15 min	6 min	lower level	lower level	No	Yes	Yes	Yes	Yes
6	160%	100%	2.5	100%	5 min	6 min	reference level	reference level	Yes	Yes	No	No	Yes
7	160%	100%	2.5	100%	5 min	1 min	reference level	reference level	No	No	Yes	No	Yes
8	160%	100%	2	40%	10 min	6 min	higher level	higher level	Yes	Yes	No	No	Yes
9	160%	100%	2	40%	10 min	1 min	higher level	higher level	No	Yes	No	Yes	No
10	160%	80%	3	100%	5 min	1 min	reference level	higher level	No	Yes	No	Yes	No
11	160%	80%	2.5	40%	10 min	6 min	higher level	lower level	Yes	No	Yes	Yes	No
12	160%	80%	2	70%	15 min	1 min	lower level	reference level	Yes	Yes	Yes	No	No
13	130%	120%	3	70%	5 min	6 min	higher level	higher level	Yes	No	Yes	Yes	No
14	130%	120%	2.5	100%	10 min	1 min	lower level	lower level	Yes	Yes	Yes	No	No
15	130%	120%	2	40%	15 min	6 min	reference level	reference level	No	Yes	Yes	Yes	Yes
16	130%	120%	2	40%	15 min	6 min	reference level	reference level	No	No	No	No	No
17	130%	100%	3	100%	10 min	1 min	lower level	reference level	Yes	No	No	Yes	Yes
18	130%	100%	2.5	40%	15 min	1 min	reference level	higher level	Yes	No	No	Yes	Yes
19	130%	100%	2	70%	5 min	1 min	higher level	lower level	No	Yes	No	Yes	No
20	130%	100%	2	70%	5 min	1 min	higher level	lower level	No	No	Yes	No	Yes

Scenario	Purchase price [a]	Running cost [b]		Vehicle availability	Access time	Egress time	Privacy security		Multitasks		Taking liability for crash		Exclusive lanes
	PAV	PAV	SAV	SAV	SAV	PCV	PAV	SAV	PAV	SAV	PAV	SAV	PAV/SAV
21	130%	80%	3	40%	15 min	1 min	reference level	lower level	Yes	Yes	Yes	No	No
22	130%	80%	2.5	70%	5 min	6 min	higher level	reference level	Yes	Yes	No	No	Yes
23	130%	80%	2	100%	10 min	6 min	lower level	higher level	No	Yes	Yes	Yes	Yes
24	130%	80%	2	100%	10 min	6 min	lower level	higher level	No	No	No	No	No
25	100%	120%	3	100%	15 min	6 min	higher level	lower level	Yes	Yes	No	No	Yes
26	100%	120%	3	100%	15 min	1 min	higher level	lower level	No	Yes	No	Yes	No
27	100%	120%	2.5	40%	5 min	1 min	lower level	reference level	No	Yes	No	Yes	No
28	100%	120%	2	70%	10 min	1 min	reference level	higher level	Yes	Yes	Yes	No	No
29	100%	100%	3	40%	5 min	6 min	lower level	higher level	No	No	No	No	No
30	100%	100%	3	40%	5 min	1 min	lower level	higher level	Yes	Yes	Yes	No	No
31	100%	100%	2.5	70%	10 min	6 min	reference level	lower level	No	Yes	Yes	Yes	Yes
32	100%	100%	2.5	70%	10 min	6 min	reference level	lower level	No	No	No	No	No
33	100%	100%	2	100%	15 min	6 min	higher level	reference level	Yes	No	Yes	Yes	No
34	100%	80%	3	70%	10 min	1 min	reference level	reference level	Yes	No	No	Yes	Yes
35	100%	80%	2.5	100%	15 min	1 min	higher level	higher level	No	No	Yes	No	Yes
36	100%	80%	2	40%	5 min	1 min	lower level	lower level	Yes	No	No	Yes	Yes

Note: PCV = private conventional vehicles, PAV = private autonomous vehicles, SAV = shared autonomous vehicles; CNY = Chinese Yuan.

[a.] The purchase price of a PAV is represented as a percentage of the purchase price for a similar-size PCV.

[b.] The running cost of a PAV is shown as a percentage of the annual running cost for a similar-size PCV, while the running cost of an SAV reflects the average charge per kilometer (CNY/km).

Next, we will give you some statements about your ***attitude*** to risk and ask you to choose below how much you agree with each statement.

1. To what extent do you agree with the following statements? (1= totally disagree; …; 7= totally agree) [matrix scale question] *
   - I would like to explore strange places.
   - I like to do frightening things.
   - I like new and exciting experiences, even if I have to break the rules.
   - I prefer friends who are exciting and unpredictable.
   - I always buy something I don't know about at the risk of making a mistake.
   - I am cautious in trying new/different products. (reverse scored)
   - I would rather stick with a brand I usually buy than try something I am not very sure of. (reverse scored)
   - I never buy something I don't know about at the risk of making a mistake. (reverse scored)
2. Please estimate how easily you accept the risk (1= very easy; …; 7= very difficult) [matrix scale question] *
   - In general, how easy or difficult is it for you to accept taking risks?

Part II

Suppose you are invited to participate in three series of combination choice games.

In this part, you will see three series of lottery games. *Series 1* and *2* respectively contain 14 pairs of lottery tickets (Lottery A & B), and *Series 3* only contain 7 pairs. In each series, you need to compare Lottery A and Lottery B pair by pair and answer the following questions at the end of each series.

Shown below is ***Series 1***, which contains 14 pairs of lotteries. It is worth noting that (1) in each pair of lotteries, the probability and value of the payoffs in Lottery A are fixed, that is, 30% probability of winning 200,000 CNY, 70% probability of winning 50,000 CNY; (2) in Lottery B, the payoff corresponding to 90% probability is fixed at 25,000 CNY, while the payoff corresponding to 10% probability increases gradually from 340,000 CNY to 8.5 million CNY. Please carefully compare Lottery A & B pair by pair and answer the following questions:

	Lottery A (CNY)	**Lottery B (CNY)**
Series 1		
1	30% winning 200,000 and 70% winning 50,000	10% winning 340,000 and 90% winning 25,000
2	30% winning 200,000 and 70% winning 50,000	10% winning 375,000 and 90% winning 25,000
3	30% winning 200,000 and 70% winning 50,000	10% winning 415,000 and 90% winning 25,000
4	30% winning 200,000 and 70% winning 50,000	10% winning 465,000 and 90% winning 25,000
5	30% winning 200,000 and 70% winning 50,000	10% winning 530,000 and 90% winning 25,000
6	30% winning 200,000 and 70% winning 50,000	10% winning 625,000 and 90% winning 25,000
7	30% winning 200,000 and 70% winning 50,000	10% winning 750,000 and 90% winning 25,000
8	30% winning 200,000 and 70% winning 50,000	10% winning 925,000 and 90% winning 25,000
9	30% winning 200,000 and 70% winning 50,000	10% winning 1,100,000 and 90% winning 25,000
10	30% winning 200,000 and 70% winning 50,000	10% winning 1,500,000 and 90% winning 25,000
11	30% winning 200,000 and 70% winning 50,000	10% winning 2,000,000 and 90% winning 25,000
12	30% winning 200,000 and 70% winning 50,000	10% winning 3,000,000 and 90% winning 25,000
13	30% winning 200,000 and 70% winning 50,000	10% winning 5,000,000 and 90% winning 25,000
14	30% winning 200,000 and 70% winning 50,000	10% winning 8,500,000 and 90% winning 25,000

1. In Series 1, will you ALWAYS choose Lottery A from row 1 to row 14? [Multiple choice] *
○ Yes (Skip to next page) ○ No
2. If "No", you will select Lottery B from row _____ to row 14. [Fill in the blank] *

Shown below is ***Series 2***, which contains 14 pairs of lotteries. It is worth noting that (1) in each pair of lotteries, the probability and value of the payoffs in Lottery A are fixed, that is, 90% probability of winning 200,000 CNY, 10% probability of winning 150,000 CNY; (2) in Lottery B, the payoff corresponding to 30% probability is fixed at 25,000 CNY, while the payoff corresponding to 70% probability increases gradually from 270,000 CNY to 650,000 CNY. Please carefully compare Lottery A & B pair by pair and answer the following questions:

	Lottery A (CNY)	**Lottery B (CNY)**
Series 2		
1	90% winning 200,000 and 10% winning 150,000	70% winning 270,000 and 30% winning 25,000
2	90% winning 200,000 and 10% winning 150,000	70% winning 280,000 and 30% winning 25,000
3	90% winning 200,000 and 10% winning 150,000	70% winning 290,000 and 30% winning 25,000
4	90% winning 200,000 and 10% winning 150,000	70% winning 300,000 and 30% winning 25,000
5	90% winning 200,000 and 10% winning 150,000	70% winning 310,000 and 30% winning 25,000
6	90% winning 200,000 and 10% winning 150,000	70% winning 325,000 and 30% winning 25,000
7	90% winning 200,000 and 10% winning 150,000	70% winning 340,000 and 30% winning 25,000
8	90% winning 200,000 and 10% winning 150,000	70% winning 360,000 and 30% winning 25,000
9	90% winning 200,000 and 10% winning 150,000	70% winning 385,000 and 30% winning 25,000
10	90% winning 200,000 and 10% winning 150,000	70% winning 415,000 and 30% winning 25,000
11	90% winning 200,000 and 10% winning 150,000	70% winning 450,000 and 30% winning 25,000
12	90% winning 200,000 and 10% winning 150,000	70% winning 500,000 and 30% winning 25,000
13	90% winning 200,000 and 10% winning 150,000	70% winning 550,000 and 30% winning 25,000
14	90% winning 200,000 and 10% winning 150,000	70% winning 650,000 and 30% winning 25,000

1. In Series 2, will you ALWAYS choose Lottery A from row 1 to row 14? [Multiple choice] *
○ Yes (Skip to next page) ○ No
2. If "No", you will select Lottery B from row _____ to row 14. [Fill in the blank] *

Shown below is ***Series 3***, which contains 7 pairs of lotteries. In this series, whether Lottery A or B provides you with a 50% chance to win and a 50% probability to lose some money. Please carefully compare Lottery A & B pair by pair and answer the following questions:

	Lottery A (CNY)	**Lottery B (CNY)**
Series 3		
1	50% winning 125,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000
2	50% winning 20,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000
3	50% winning 5,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 105,000
4	50% winning 5,000 and 50% losing 20,000	50% winning 150,000 and 50% losing 80,000
5	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 80,000
6	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 70,000
7	50% winning 5,000 and 50% losing 40,000	50% winning 150,000 and 50% losing 55,000

1. In Series 3, will you ALWAYS choose Lottery A from row 1 to row 7? [Multiple choice] *
○ Yes (Skip to next page) ○ No
2. If "No", you will select Lottery B from row _____ to row 7. [Fill in the blank] *

Next, we would like to know some basic information about you and your family.

1. How old are you? [Multiple choice] *

☐ 18 ~ 20
☐ 21 ~ 30
☐ 31 ~ 40
☐ 41 ~ 50
☐ 51 ~ 60
☐ 61 and above

2. What is your gender? [Multiple choice] *

☐ male
☐ female

3. Your highest education is _____ [Multiple choice] *

☐ junior high school and below
☐ high school
☐ junior college
☐ undergraduate
☐ postgraduate and above

4. There are _____ people in your family? [Multiple choice] *

☐ 1
☐ 2
☐ 3
☐ 4
☐ 5 and above

5. The household income of your family in 2021 is _____ CNY [Multiple choice] *

☐ less than 100,000
☐ From 100,000 to 200,000
☐ From 200,001 to 300,000
☐ From 300,001 to 400,000
☐ More than 400,000

APPENDIX 9: MODEL VALIDATION

To further validate our proposed Model 3 (i.e., the ECL model with reference dependence as well as risk preference parameters), we compared its goodness of fit against those of a range of alternative models (including Model 1 and Model 2 presented in the manuscript, as well as three other models without accounting for risk preference parameters) and confirmed the superior performance of our model. As summarized in Table A5, the comparison results are as follows:

1) According to the Akaike Information Criterion (AIC), the three models incorporating risk preference (i.e., Model 1 to Model 3 presented in the manuscript) possess smaller AIC values compared to their counterparts without risk preference parameters (see the comparison in the table below). Furthermore, our proposed ECL model has the smallest AIC value, indicating that this model has the best fitness.
2) Regarding McFadden's pseudo-R^2, our proposed ECL model with reference dependence as well as risk preference parameters has the highest value among the six models, again confirming its best goodness of fit.
3) Additionally, the LR test was used to verify the validity of the proposed model. As shown in the following table, the three models incorporating risk preference are significantly better than their counterparts without risk preference parameters, evidenced by the LR test statistics (i.e., Model 1: 119.436; Model 2: 135.477; Model 3: 54.290) being much larger than the threshold value of χ^2 (8) = 15.51.
4) Among all models with risk preference parameters, the proposed ECL model with reference dependence is also better than the other MNL models (i.e., Model 1 and Model 2), as evidenced by the LR tests.

In summary, our proposed ECL model with RD is the best among the alternative models.

Table A5. The performance comparison of the proposed and alternative models

		Reference dependence (RD)	
	Model 1: MNL model (baseline)	**Model 2:** MNL model with RD	**Model 3:** ECL model with RD
Models ***accounting for*** four risk preference parameters			
Number of variables	34	37	40
Log-likelihood (LL) of converged model	-5612.765	-5537.376	-4786.484
Akaike Information Criterion (AIC) [a]	11293.500	11148.800	9653.000
McFadden's pseudo-R^2 [b]	0.042	0.055	0.183
LR test against the corresponding model without risk preference parameters [c]	119.436 *** (*df* = 8)	135.477 *** (*df* = 8)	54.290 *** (*df* = 8)
LR test against the Model 1 [c]		150.778 *** (*df* = 3)	1652.562 *** (*df* = 6)
LR test against the Model 2 [c]			1501.784 *** (*df* = 3)
Models ***without accounting for*** risk preference parameters			
Number of variables	26	29	32
Log-likelihood (LL) of converged model	-5672.483	-5605.114	-4813.629
Akaike Information Criterion (AIC) [a]	11397.000	11268.200	9691.300
McFadden's pseudo-R^2 [b]	0.032	0.055	0.179

[a.] Akaike Information Criterion: Lower AIC value indicates a better fit, balancing model complexity and goodness of fit.

[b.] McFadden's pseudo-R^2 = (1 – LL of a specific model) / (LL of constant only model). In our study, the LL value of constant only model is −5859.456.

[c.] LR test is calculated as −2 * (LL of constant only model – LL of a specific model) ~ χ^2 with the degree of freedom equaling the difference in the number of parameters estimated between the two models (Hensher et al., 2015).

REFERENCES

Abe, R. (2021). Preferences of urban rail users for first- and last-mile autonomous vehicles: Price and service elasticities of demand in a multimodal environment. *Transportation Research Part C: Emerging Technologies*, *126*, 103105.

Arslan, R. C., Brummer, M., Dohmen, T., Drewelies, J., Hertwig, R., & Wagner, G. G. (2020). How people know their risk preference. *Scientific Reports*, *10*(1), 15365.

Asmussen, K. E., Mondal, A., & Bhat, C. R. (2020). A socio-technical model of autonomous vehicle adoption using ranked choice stated preference data. *Transportation Research Part C: Emerging Technologies*, *121*, 102835.

Awad, E., Dsouza, S., Kim, R., Schulz, J., Henrich, J., Shariff, A., Bonnefon, J. F., & Rahwan, I. (2018). The Moral Machine experiment. *Nature*, *563*(7729), 59-64.

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, *67*, 1-14.

Bao, Y., Zhou, K. Z., & Su, C. (2003). Face consciousness and risk aversion: Do they affect consumer decision-making? *Psychology & Marketing*, *20*(8), 733-755.

Beijing Innovation Center for Mobility Intelligent. (2021). *Beijing Autonomous Vehicle Road Testing Annual Report (2020)*. Retrieved from http://www.mzone.site/Uploads/Download/2021-02-09/6021eebaccba2.pdf

Beijing Municipal Commission of Transport. (2023). *The Regulations on Fare Standards for Cruise Taxis*. Retrieved from https://jtw.beijing.gov.cn/czqc/zxts/202303/t20230310_2933641.html

Betz, S. (2024). *28 Self-Driving Car Companies You Should Know*. Retrieved from https://builtin.com/articles/self-driving-car-companies

Bonnefon, J. F., Shariff, A., & Rahwan, I. (2016). The social dilemma of autonomous vehicles. *Science*, *352*(6293), 1573-1576.

Cao, L., Xie, D., & Qu, Y. (2023). A process perspective on experience co-creation: How pre-trip involvement prompts destination loyalty. *Tourism Management*, *96*, 104711.

Caussade, S., Ortúzar, J. d. D., Rizzi, L. I., & Hensher, D. A. (2005). Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B: Methodological*, *39*(7), 621-640.

Chen, S.-Y., Kuo, H.-Y., & Lee, C. (2020). Preparing Society for Automated Vehicles: Perceptions of the Importance and Urgency of Emerging Issues of Governance, Regulations, and Wider Impacts. *Sustainability*, *12*(19), 7844.

Chen, S., Wang, H., & Meng, Q. (2020). Optimal purchase subsidy design for human-driven electric vehicles and autonomous electric vehicles. *Transportation Research Part C: Emerging Technologies*, 116, 102641.

Chikaraishi, M., Khan, D., Yasuda, B., & Fujiwara, A. (2020). Risk perception and social acceptability of autonomous vehicles: A case study in Hiroshima, Japan. *Transport Policy*, *98*, 105-115.

China Industry Innovation Alliance for the Intelligent and Connected Vehicles. (2022). *Research on development status of road test and test mutual recognition of intelligent connected vehicles in China*. Retrieved from http://www.catarc.org.cn/upload/202207/20/202207201841030442.pdf

Choi, J. K., & Ji, Y. G. (2015). Investigating the Importance of Trust on Adopting an Autonomous Vehicle. *International Journal of Human-Computer Interaction*, *31*(10), 692-702.

Chongqing Municipal Transportation Commission. (2024). *Operating Fare of Taxis in Chongqing's Main Urban Districts*. Retrieved from https://jtj.cq.gov.cn/cx/ggcx/taxi.html

Cordera, R., González-González, E., Nogués, S., Arellana, J., & Moura, J. L. (2022). Modal Choice for the Driverless City: Scenario Simulation Based on a Stated Preference Survey. *Journal of Advanced Transportation*, *2022*, 1108272.

CPCA. (2024a). *In-Depth Analysis Report: China's New Energy Market in July 2024*. Retrieved from http://www.cpcaauto.com/newslist.php?types=csjd&id=3575

CPCA. (2024b). *Weekly Analysis: Automotive Market Overview (June 11–16, 2024)*. Retrieved from http://www.cpcaauto.com/newslist.php?types=csjd&id=3498

Daziano, R. A., Sarrias, M., & Leard, B. (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, 78, 150-164.

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail and mixed-mode surveys: the tailored design method* (4th Edition). Wiley.

Ding, Y., Li, R., Wang, X., & Schmid, J. (2021). Heterogeneity of autonomous vehicle adoption behavior due to peer effects and prior-AV knowledge. *Transportation*. *49*, 1837–1860.

Dixit, V., Xiong, Z., Jian, S., & Saxena, N. (2019). Risk of automated driving: Implications on safety acceptability and productivity. *Accident Analysis and Prevention*, *125*, 257-266.

Einride. (2019). *World premiere: First cab-less and autonomous, fully electric truck in commercial operations on public road*. Retrieved from https://einride.tech/insights/world-premiere-first-cab-less-and-autonomous-fully-electric-truck-in-commercial-operations-on-public-road

EqualOcean Intelligence. (2022). *2021-2022 China Autonomous Driving Commercial Series Research: Manned Scenarios and Demonstration Area*. E. Intelligence. Retrieved from https://pdf.dfcfw.com/pdf/H3_AP202203101551759056_1.pdf?1646931504000.pdf

Fagnant, D. J., & Kockelman, K. (2015). Preparing a nation for autonomous vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, *77*, 167-181.

Feder, G. (1980). Farm size, risk aversion and the adoption of new technology under uncertainty. *Oxford Economic Papers*, *32*(2), 263-283.

Gao, K., Sun, L., Yang, Y., Meng, F., & Qu, X. (2021). Cumulative prospect theory coupled with multi-attribute decision making for modeling travel behavior. *Transportation Research Part A: Policy and Practice*, *148*, 1-21.

Gasgoo Insititute. (2022). *Driverless vehicle industry research report (2022 version)*. Retrieved from https://auto.gasgoo.com/institute/report-0

Gkartzonikas, C., & Gkritza, K. (2019). What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 323-337.

Greenblatt, J. B., & Saxena, S. (2015). Autonomous taxis could greatly reduce greenhouse-gas emissions of US light-duty vehicles. *Nature Climate Change*, *5*(9), 860-863.

Greene, W. H. (2016). *NLOGIT 6 Reference Guide*. Econometric Software, Inc. Retrieved from https://pages.stern.nyu.edu/~wgreene/DiscreteChoice/Software/manual/NLOGIT%206%20Reference%20Guide.pdf

Gu, G., Yang, D., Feng, T., & Timmermans, H. (2019). Household vehicle holding decisions in response to life cycle events. *Transportation Research Procedia*, *37*, 171-178.

Guangzhou Daily. (2024). *Guangzhou on March 28 held a cruise taxi fare optimization adjustment hearing*. Retrieved from https://www.gz.gov.cn/zwfw/zxfw/jtfw/content/post_9566996.html

Gupta, S., Verma, R., & Victorino, L. (2006). Empirical Research Published in Production and Operations Management (1992–2005): Trends and Future Research Directions. *Production and Operations Management*, 15(3), 432-448.

Gurumurthy, K. M., & Kockelman, K. M. (2020). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting & Social Change*, *150*, 119792.

Haboucha, C. J., Ishaq, R., & Shiftan, Y. (2017). User preferences regarding autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *78*, 37-49.

Hackbarth, A., & Madlener, R. (2016). Willingness-to-pay for alternative fuel vehicle characteristics: A stated choice study for Germany. *Transportation Research Part A: Policy and Practice*, *85*, 89-111.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate Data Analysis: Pearson New International Edition* (7th ed.). Essex: Pearson Education Limited.

Hardie, B. G. S., Johnson, E. J., & Fader, P. S. (1993). Modeling Loss Aversion and Reference Dependence Effects on Brand Choice. *Marketing Science*, *12*(4), 378-394.

Hardman, S., Berliner, R., & Tal, G. (2019). Who will be the early adopters of automated vehicles? Insights from a survey of electric vehicle owners in the United States. *Transportation Research Part D: Transport and Environment*, *71*, 248-264.

Hensher, D., Greene, W. H., & Li, Z. (2011). Embedding risk attitude and decision weights in non-linear logit to accommodate time variability in the value of expected travel time savings. *Transportation Research Part B: Methodological*, *45*(7), 954-972.

Hensher, D., Ho, C., & Knowles, L. (2016). Efficient contracting and incentive agreements between regulators and bus operators: The influence of risk preferences of contracting agents on contract choice. *Transportation Research Part A: Policy and Practice*, *87*, 22-40.

Hensher, D., Louviere, J., & Swait, J. (1998). Combining sources of preference data. *Journal of Econometrics*, 89(1), 197-221.

Hensher, D., Rose, J. M., & Greene, W. H. (2015). *Applied choice analysis* (second ed.). Cambridge University Press.

Hole, A. R. (2007). A comparison of approaches to estimating confidence intervals for willingness to pay measures. *Health economics*, *16*(8), 827-840.

Huang, Y., & Qian, L. (2018). Consumer preferences for electric vehicles in lower tier cities of China: Evidences from south Jiangsu region. *Transportation Research Part D: Transport and Environment*, *63*, 482-497.

Huang, Y., & Qian, L. (2021). Understanding the potential adoption of autonomous vehicles in China: The perspective of behavioral reasoning theory. *Psychology & Marketing*, *38*(4), 669-690.

Huang, Y., Qian, L., Soopramanien, D., & Tyfield, D. (2021). Buy, lease, or share? Consumer preferences for innovative business models in the market for electric vehicles. *Technological Forecasting & Social Change*, *166*, 120639.

Hulse, L. M., Xie, H., & Galea, E. R. (2018). Perceptions of autonomous vehicles: Relationships with road users, risk, gender and age. *Safety Science*, *102*, 1-13.

Jiang, H., Jin, L., Qian, X., Xiong, X., La, X., Chen, W., … Li, M. (2021). Maternal Mental Health Status and Approaches for Accessing Antenatal Care Information During the COVID-19 Epidemic in China: Cross-Sectional Study. *Journal of Medical Internet Research*, *23*(1), e18722.

Johnson, F. R., Lancsar, E., Marshall, D., Kilambi, V., Mühlbacher, A., Regier, D. A., … Bridges,

J. F. P. (2013). Constructing experimental designs for discrete-choice experiments: Report of the ISPOR conjoint analysis experimental design good research practices task force. *Value in Health*, *16*(1), 3-13.

Juliussen, E. (2022). *Autonomous Vehicles: How Is Europe Doing?* Retrieved from https://www.eetimes.eu/autonomous-vehicles-how-is-europe-doing/

Juliussen, E. (2023). *What Is Needed for Autonomous Vehicle Success?* Retrieved from https://www.eetimes.eu/what-is-needed-for-autonomous-vehicle-success/

Kagaigai, A., & Grepperud, S. (2023). The role of risk preferences: voluntary health insurance in rural Tanzania. *Health Economics Review*, *13*(1), 20.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*, 263-291.

Kam, C. D. (2012). Risk Attitudes and Political Participation. *American Journal of Political Science*, *56*, 817-836.

Kapser, S., & Abdelrahman, M. (2020). Acceptance of autonomous delivery vehicles for last-mile delivery in Germany – Extending UTAUT2 with risk perceptions. *Transportation Research Part C: Emerging Technologies*, *111*, 210-225.

KMPG International. (2020). 2020 *Autonomous Vehicles Readiness Index.* Retrieved from https://assets.kpmg/content/dam/kpmg/xx/pdf/2020/07/2020-autonomous-vehicles-readiness-index.pdf

König, M., & Neumayr, L. (2017). Users' resistance towards radical innovations: The case of the self-driving car. *Transportation Research Part F: Traffic Psychology and Behaviour*, *44*, 42-52.

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared autonomous vehicles. *Transportation Research Part C: Emerging Technologies*, *69*, 343-355.

Krupa, J. S., Rizzo, D. M., Eppstein, M. J., Brad Lanute, D., Gaalema, D. E., Lakkaraju, K., & Warrender, C. E. (2014). Analysis of a consumer survey on plug-in hybrid electric vehicles. *Transportation Research Part A: Policy and Practice*, *64*, 14-31.

Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, *32*, 127-140.

Lavieri, P. S., & Bhat, C. R. (2019). Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A: Policy and Practice*, 124, 242-261.

LeBeau, P. (2018). *Waymo starts commercial ride-share service*. Retrieved from https://www.cnbc.com/2018/12/05/waymo-starts-commercial-ride-share-service.html

Lin, C., Tong, Y., Bai, Y., Zhao, Z., Quan, W., Liu, Z., … Dong, W. (2022). Prevalence and correlates of depression and anxiety among Chinese international students in US colleges during the COVID-19 pandemic: A cross-sectional study. *PLoS One*, *17*(4), e0267081.

Litman, T. (2022). *Autonomous Vehicle Implementation Predictions: Implications for Transport Planning*. V. T. P. Institute. Retrieved from https://vtpi.org/avip.pdf

Liu, E. M. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *The Review of Economics and Statistics*, *95*(4), 1386-1403.

Liu, N., Nikitas, A., & Parkinson, S. (2020). Exploring expert perceptions about the cyber security and privacy of Connected and Autonomous Vehicles: A thematic analysis approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, *75*, 66-86.

Liu, P., Guo, Q., Ren, F., Wang, L., & Xu, Z. (2019). Willingness to pay for self-driving vehicles:

Influences of demographic and psychological factors. *Transportation Research Part C: Emerging Technologies*, *100*, 306-317.
Liu, P., Ma, Y., & Zuo, Y. (2019). Self-driving vehicles: Are people willing to trade risks for environmental benefits? *Transportation Research Part A: Policy and Practice*, *125*, 139-149.
Liu, P., Yang, R., & Xu, Z. G. (2018). Public Acceptance of Fully Automated Driving: Effects of Social Trust and Risk/Benefit Perceptions. *Risk Analysis*, *39*(2), 326-341.
Liu, X. (2021). *This 'crazy' professor took 800+ taxi rides and discovered some secrets*. Retrieved from http://www.why.com.cn/wx/article/2021/02/18/16136548791188476413.html
Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: analysis and applications*. Cambridge university press.
Lowery, L. (2023). *Waymo & Cruise approved for San Francisco 24-hour operation of robotaxis*. Retrieved from https://www.repairerdrivennews.com/2023/08/16/waymo-cruise-approved-for-san-francisco-24-hour-operation-of-robotaxis/
Maeng, K., Jeon, S. R., Park, T., & Cho, Y. (2021). Network effects of connected and autonomous vehicles in South Korea: A consumer preference approach. *Research in Transportation Economics*, *90*, 100998.
Mark, T. L., & Swait, J. (2004). Using stated preference and revealed preference modeling to evaluate prescribing decisions. *Health Economics*, 13(6), 563-573.
Mata, R., Frey, R., Richter, D., Schupp, J., & Hertwig, R. (2018). Risk Preference: A View from Psychology. *Journal of Economic Perspectives*, *32*(2), 155-172.
McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics*, 105-142.
McKinsey & Company. (2017). *What US consumers think of shared mobility*. Retrieved from https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/what-us-consumers-think-of-shared-mobility
McKinsey & Company. (2021). *Shared mobility: Where it stands, where it's headed*. Retrieved from https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/shared-mobility-where-it-stands-where-its-headed
Merkert, R., Bliemer, M. C. J., & Fayyaz, M. (2022). Consumer preferences for innovative and traditional last-mile parcel delivery. *International Journal of Physical Distribution & Logistics Management*, *52*(3), 261-284.
Mo, B., Wang, Q. Y., Moody, J., Shen, Y., & Zhao, J. (2021). Impacts of subjective evaluations and inertia from existing travel modes on adoption of autonomous mobility-on-demand. *Transportation Research Part C: Emerging Technologies*, *130*, 103281.
Nair, G. S., Astroza, S., Bhat, C. R., Khoeini, S., & Pendyala, R. M. (2018). An application of a rank ordered probit modeling approach to understanding level of interest in autonomous vehicles. *Transportation*, *45*(6), 1623-1637.
National Bureau of Statistics of China. (2021). *China Statistical Yearbook 2021*. Retrieved from http://www.stats.gov.cn/tjsj/ndsj/2021/indexeh.htm
Padmaja, B., Moorthy, C. V. K. N. S. N., Venkateswarulu, N., & Bala, M. M. (2023). Exploration of issues, challenges and latest developments in autonomous cars. *Journal of Big Data*, *10*(1), 61.
Panagiotopoulos, I., & Dimitrakopoulos, G. (2018). An empirical investigation on consumers' intentions towards autonomous driving. *Transportation Research Part C: Emerging Technologies*, *95*, 773-784.
Papu Carrone, A., Hoening, V. M., Jensen, A. F., Mabit, S. E., & Rich, J. (2020). Understanding

car sharing preferences and mode substitution patterns: A stated preference experiment. *Transport Policy*, *98*, 139-147.
Prelec, D. (1998). The Probability Weighting Function. *Econometrica*, *66*(3), 497-527.
Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*(1), 131-151.
Qian, L., Grisolía, J. M., & Soopramanien, D. (2019). The impact of service and government-policy attributes on consumer preferences for electric vehicles in China. *Transportation Research Part A: Policy and Practice*, *122*, 70-84.
Qian, L., Pang, Z., & Soopramanien, D. (2022). Influences of car sharing and car license plate lottery policy on consumer preference and accessibility in urban mobility system: A stated choice experiment in Beijing. *Journal of Cleaner Production*, *362*, 132505.
Qian, L., & Soopramanien, D. (2014). Using diffusion models to forecast market size in emerging markets with applications to the Chinese car market. *Journal of Business Research*, *67*(6), 1226-1232.
Qian, L., Yin, J., Huang, Y., & Liang, Y. (2023). The role of values and ethics in influencing consumers' intention to use autonomous vehicle hailing services. *Technological Forecasting & Social Change*, *188*, 122267.
Rezvani, Z., Jansson, J., & Bodin, J. (2015). Advances in consumer electric vehicle adoption research: A review and research agenda. *Transportation Research Part D: Transport and Environment*, *34*, 122-136.
Roland Berger. (2015). *Mobile Internet and the Urban Transport Revolution*. Retrieved from https://www.rolandberger.com/publications/publication_pdf/roland_berger_mobile_internet_and_the_urban_transport_revolution_4.pdf
Rose, J. M., & Bliemer, M. C. J. (2009). Constructing Efficient Stated Choice Experimental Designs. *Transport Reviews*, *29*(5), 587-617.
Rosell, J., & Allen, J. (2020). Test-riding the driverless bus: Determinants of satisfaction and reuse intention in eight test-track locations. *Transportation Research Part A: Policy and Practice*, *140*, 166-189.
SAE. (2021). *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles*. Retrieved from https://www.sae.org/standards/content/j3216_202107/
Scarpa, R., & Rose, J. M. (2008). Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why. *Australian Journal of Agricultural and Resource Economics*, *52*(3), 253-282.
Shabanpour, R., Golshani, N., Shamshiripour, A., & Mohammadian, A. (2018). Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. *Transportation Research Part C: Emerging Technologies*, *93*, 463-478.
Shanghai Municipal Transportation Commission. (2022). *Adjustment of Cruise Taxi Fares in the City.* Retrieved from https://jtw.sh.gov.cn/zsk/20220119/df77a6e1817b4a269464fe575c572ebb.html
Stoiber, T., Schubert, I., Hoerler, R., & Burger, P. (2019). Will consumers prefer shared and pooled-use autonomous vehicles? A stated choice experiment with Swiss households. *Transportation Research Part D: Transport and Environment*, *71*, 265-282.
Sun, S., & Wong, Y. D. (2023). Drivers' attention economy and adoption to autonomous vehicle. *Transport Policy*, *138*, 108-118.
Taeihagh, A., & Lim, H. S. M. (2019). Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks. *Transport Reviews*, *39*(1), 103-128.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*, *100*(1), 557-571.

Tian, Z. H., Feng, T., Timmermans, H. J. P., & Yao, B. Z. (2021). Using autonomous vehicles or shared cars? Results of a stated choice experiment. *Transportation Research Part C: Emerging Technologies*, *128*, 103117.

Train, K. E. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge University Press.

Tu, Y., Jabbari, P., Khan, N. A., & MacKenzie, D. (2022). Effects of trip-level characteristics on autonomous vehicle ownership: A U.S. analysis. *Transportation Research Part D: Transport and Environment*, *108*, 103321.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, *5*(4), 297-323.

Walker, J. L., Wang, Y., Thorhauge, M., & Ben-Akiva, M. (2018). D-efficient or deficient? A robustness analysis of stated choice experimental designs. *Theory and Decision*, *84*(2), 215-238.

Wang, K., Salehin, M. F., & Nurul Habib, K. (2021). A discrete choice experiment on consumer's willingness-to-pay for vehicle automation in the Greater Toronto Area. *Transportation Research Part A: Policy and Practice*, *149*, 12-30.

Wang, S., & Zhao, J. (2019). Risk preference and adoption of autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *126*, 215-229.

Wang, Z., Safdar, M., Zhong, S., Liu, J., & Xiao, F. (2021). Public Preferences of Shared Autonomous Vehicles in Developing Countries: A Cross-National Study of Pakistan and China. *Journal of Advanced Transportation*, *2021*, 5141798.

Wu, H., Ge, Y., & Li, J. (2023). Uncertainty, time preference and households' adoption of rooftop photovoltaic technology. *Energy*, *276*, 127468.

Xu, Z., Zhang, K., Min, H., Wang, Z., Zhao, X., & Liu, P. (2018). What drives people to accept automated vehicles? Findings from a field experiment. *Transportation Research Part C: Emerging Technologies*, *95*, 320-334.

Yap, M. D., Correia, G., & van Arem, B. (2016). Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A: Policy and Practice*, *94*, 1-16.

Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C: Emerging Technologies*, *98*, 207-220.

Zhou, Y., Yang, Y., Shi, T., Song, Y., Zhou, Y., Zhang, Z., … Tang, Y. (2020). Prevalence and Demographic Correlates of Poor Sleep Quality Among Frontline Health Professionals in Liaoning Province, China During the COVID-19 Outbreak. *Frontiers in Psychiatry*, *11*, 520.