

Article

Factors Influencing Purchase of Advanced Intelligent Driving Vehicles in China: A Perspective of Value-Based Adoption Model

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Abstract: Although Chinese consumers show an increasing acceptance of intelligent driving, their purchase intentions have declined. Advanced intelligent driving technologies play a crucial role in helping users transition from traditional driving to fully autonomous driving. However, low purchase intention may delay the market adoption of advanced intelligent driving technologies, further influencing the research and innovation of autonomous driving technology. This study, from the perspective of consumer perception, collected survey data and constructed a structural equation model to explore the mechanisms by which key variables—such as perceived usefulness, perceived enjoyment, perceived fee, perceived risk, and brand credibility—affect consumers' purchase intentions. The results indicate that perceived usefulness and perceived enjoyment significantly enhance consumers' perceived value. In contrast, perceived fee negatively impacts perceived value. Unlike previous studies, perceived risk does not have a significant impact on perceived value in the current stage of advanced autonomous driving. Perceived value has a significant positive impact on purchase intention, confirming its central role in consumer behavior models. Moreover, brand credibility significantly affects purchase intention but does not have a notable influence on perceived value.



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Keywords: advanced intelligent driving technologies; consumer perception; perceived value; brand credibility; purchase intention

1. Introduction

With the rapid advancement of Artificial Intelligence (AI) and automation technologies, the intelligent automotive industry is undergoing a profound structural transformation, gradually shifting from traditional driving paradigms toward a highly intelligent framework. The integration of multimodal sensor fusion technologies (e.g., LiDAR, cameras, and radar) with deep learning algorithms has significantly enhanced vehicles' perception and decision-making capabilities in complex environments [1]. These technologies, supported by robust hardware and software architectures, enable vehicles to achieve intelligent decision-making and autonomous control across various driving scenarios, representing a key advancement in advanced intelligent driving technologies. Furthermore, path planning and control algorithms based on Model Predictive Control (MPC) and reinforcement learning have further improved the stability and safety of autonomous vehicles [2]. Simultaneously, the widespread adoption of Vehicle-to-Everything (V2X) technology has strengthened the cooperative capabilities of autonomous driving systems by facilitating

real-time communication between vehicles, infrastructure, other vehicles, and pedestrians [3]. Against this backdrop, autonomous vehicles are entering a critical transition phase from testing and validation to commercialization. As an inevitable outcome of this transition, Advanced Intelligent Driving Vehicles (AIDVs) are driving the intelligent automotive industry toward a new stage of development.

Compared to traditional Level 2 (L2) driver assistance systems, AIDVs are capable of handling more complex driving scenarios and tasks. For instance, conditional autonomous driving on highways can enable functions such as automatic overtaking, lane changing, and maintaining a safe following distance. Additionally, some advanced intelligent driving systems feature capabilities such as intelligent navigation assistance, smart parking, and automatic parking space detection, further enhancing driving convenience and safety. Tesla's Full Self-Driving (FSD) serves as a notable example. This advanced driver assistance system, developed by Tesla, aims to achieve higher levels of autonomous driving functionality. Through its robust hardware and software architecture, FSD enables intelligent decision-making and autonomous control across various driving scenarios, positioning itself as a key representative in the field of intelligent driving.

The influence of intelligent driving experiences on consumers' vehicle purchase decisions has significantly increased, as highlighted by J.D. Power [4]. According to the 2024 Autonomous Driving Industry Research Report [5], 54% of automobile consumers now consider the level of intelligence as a critical factor in their purchase decisions. In the Chinese market, advanced intelligent driving technologies are equipped in nearly 100% of new energy vehicles priced above USD 40,000. A notable example of the practical application of advanced intelligent driving technologies is Huawei's HUAWEI ADS (Advanced Driving System) 3.0. This system integrates a range of cutting-edge intelligent driving features, such as navigation cruise assist (NCA), remote parking assist (RPA), and automated valet parking (AVP). These functionalities significantly enhance vehicle automation and safety performance, delivering a more convenient, intelligent driving experience for users. According to Huawei's official data, in 2023 alone, the AITO M7 series intelligent driving vehicles under Huawei's smart driving division successfully avoided more than 260,000 potential collision incidents. This achievement not only validates the potential of advanced intelligent driving technologies in improving traffic safety but also establishes a solid foundation for their widespread adoption in the market.

Advancements in autonomous driving technology have increased Chinese consumers' acceptance of AIDVs. According to the 2024 McKinsey China Automotive Consumer Insights Report [6], while the acceptance of intelligent driving among Chinese consumers is on the rise, their purchase intention for AIDVs has declined from 42% in 2022 to 28% in 2024. This decline has had a profound impact on the commercialization process of AIDVs. Existing studies on the adoption of innovative autonomous vehicle technologies predominantly focus on fully autonomous vehicles (FAVs), with limited research addressing AIDVs. As highlighted by Zhu et al. [7], AIDVs are an essential transitional phase for users moving from traditional driving to fully autonomous driving. However, the low purchase intention among consumers may delay the market adoption of advanced intelligent driving systems, further influencing the research and innovation of autonomous driving technologies. Thus, a comprehensive and in-depth exploration of the factors influencing consumers' purchase intentions for AIDVs, from the perspective of consumers, has become particularly critical.

Existing research indicates that various factors influence consumers' purchase intentions for intelligent driving services. At the individual level, factors such as gender, age, and income have been shown to significantly affect purchase intentions. For example, younger individuals, higher-income consumers, and male buyers typically exhibit higher purchase intentions [8–10]. Female consumers, on the other hand, tend to experience

higher levels of anxiety regarding autonomous driving technologies, resulting in lower purchase intentions compared to their male counterparts [11]. Additionally, based on the theory of planned behavior (TPB), both attitude and perceived behavioral control have been identified as significant predictors of purchase intention [12–14]. External incentives, such as government subsidies and policy support, have also been found to significantly increase consumers' purchase intentions [15–17].

In the field of technology adoption, the Technology Acceptance Model (TAM) serves as a classic theoretical framework widely used to predict users' adoption behavior toward new technologies. TAM explains users' behavioral intentions through the variables of perceived usefulness and perceived ease of use. However, TAM exhibits certain limitations when applied to complex and advanced technologies, particularly in evaluating users' cost-benefit trade-offs [18]. To address these limitations in defining the adoption of advanced technologies, Kim et al. [18] proposed the Value-Based Adoption Model (VAM). Studies have demonstrated that the VAM model exhibits strong explanatory power in predicting users' intentions to adopt artificial intelligence (AI) devices [19]. Perceived value, the core variable of the VAM model, comprehensively reflects consumers' overall assessment of a product or service based on its utility, emotional satisfaction, social recognition, and potential risks. Perceived value not only has a significant impact on users' adoption decisions but also plays a critical role in predicting consumers' purchase intentions [20].

Moreover, brand credibility, as a crucial factor influencing product purchase intentions, can effectively reduce consumers' decision-making risks and enhance the perceived quality of a product or service [21,22]. Given that AIDVs involve higher value and risk factors, the role of brand credibility becomes even more pronounced. However, research on brand credibility within the emerging field of intelligent driving remains insufficient, and whether brand credibility significantly impacts consumers' purchase intentions warrants further investigation.

In light of the above context, this study will address the following key questions:

1. What factors influence consumers' perceived value in the context of AIDVs?
2. Does brand credibility play a facilitative role in enhancing perceived value and purchase intention?

This study focuses on the key driving factors of consumers' perceived value in the context of AIDVs and systematically explores the role of brand credibility in the relationship between perceived value and purchase intention to clarify its influence on technology adoption decisions. Grounded in the VAM, this study constructs a comprehensive theoretical framework aimed at providing empirical support for the marketization strategies of advanced intelligent driving technology, particularly in optimizing technology design and market promotion from the perspective of consumer perceived value. Furthermore, this research conducts an in-depth analysis of the application potential of brand credibility in marketing strategies, offering data-driven policy recommendations to enhance public willingness to adopt AIDVs. By employing a multi-level analytical approach, this study not only extends the theoretical application of the VAM model in the field of advanced intelligent driving but also provides critical theoretical and practical insights for technology enterprises, policymakers, and consumer education initiatives. The findings provide a scientific basis for facilitating the commercialization of AIDVs while fostering public trust and acceptance of emerging technologies.

2. Conceptual Framework

2.1. Value-Based Adoption Model

The Value-Based Adoption Model (VAM), proposed by Kim et al. [18], is a significant theoretical framework for predicting technology adoption intention. This model adopts a

consumer-centric perspective to examine the decision-making process of users adopting new technologies. At its core, VAM is founded on the motivation of consumers to maximize value within the constraints of limited resources, emphasizing the critical role of users' comprehensive evaluation of costs and benefits in technology adoption [23]. VAM overcomes the limitations of the traditional Technology Acceptance Model (TAM) and provides a valuable theoretical foundation and practical guidance for understanding user behavior in the context of emerging information and communication technology (ICT). Unlike TAM, which assumes a unidirectional influence of factors such as perceived usefulness and perceived ease of use, VAM introduces the concept of perceived value as a key variable. Perceived value is determined by two dimensions: perceived benefit (including perceived usefulness and perceived enjoyment) and perceived sacrifice (comprising technicality and perceived fee). As the core variable of the VAM model, perceived value represents users' overall assessment of a product or service [20].

According to prospect theory, proposed by Kahneman and Tversky [24], the core principle underlying consumer decision-making is the value maximization principle, whereby individuals make decisions by comprehensively evaluating potential gains and losses. Specifically, during the decision-making process, consumers not only assess the positive returns associated with a technology or product but also weigh its potential negative consequences. Thus, consumer decisions are based on a holistic evaluation of both benefits and sacrifices. By integrating a global assessment of costs and benefits, the VAM offers a more comprehensive explanation of users' intentions to adopt technology. Kim et al. [18] emphasized that VAM highlights consumers' subjective value experiences, extending beyond the functional attributes of technology to incorporate emotional and psychological factors. By integrating perceived benefit and perceived sacrifice, VAM serves as a robust theoretical framework for capturing user behavioral intentions in complex technological environments [25]. This comprehensive analytical approach enhances VAM's explanatory power, particularly in emerging information and communication technology (ICT) contexts. As illustrated in Table 1, VAM has been widely applied across various domains, including internet of things (IoT) services, self-service technologies, fitness wearables, and healthcare technology [26–29]. Liao et al. [30], based on the VAM model, comprehensively considered perceived benefits and perceived sacrifice to explore the relationship between perceived value and E-learning. In the context of new technology adoption, perceived value has a more significant impact on predicting individuals' actual behavioral intentions compared to attitudes toward technology adoption [31,32]. Consumers are able to assess the perceived value they gain, which allows for a more accurate formation of their intention to use new technologies [33,34].

AIDVs represent a high level of integration between automation and artificial intelligence technologies. The adoption of such technologies is often accompanied by significant risks and uncertainties. When considering the adoption of AIDVs, users must evaluate both the perceived benefit (e.g., convenience, comfort) and the perceived sacrifice (e.g., technical failures, privacy concerns). The VAM provides a comprehensive theoretical framework for examining the adoption of such technologies. It facilitates a deeper understanding of how users perceive the value of AIDVs and how these value perceptions influence their purchase intentions.

Table 1. Prior research on VAM.

Research Context	Perceived Value		Scholar
	Perceived Benefit	Perceived Sacrifice	
AI-based intelligent products	Usefulness; Enjoyment	Technicality; Perceived Fee	Sohn and Kwon [19]
Smart Home Service	Facilitating Conditions Usefulness; Enjoyment	Privacy Risk; Perceived Fee Innovation Resistance; Technicality	Kim et al. [23]
Sharing Platform	Ease of Use	Transaction Costs; Risk	Liang et al. [26]
Fitness Wearables	Perceived Usefulness Perceived Social Image Perceived Health Increase Perceived Enjoyment	Perceived Privacy Risk Perceived Fee	Mathavan et al. [27]
Smart Product-Service Systems	Perceived Usefulness Perceived Flexibility Perceived Reliability	Perceived Fee Perceived Technicality	Yu and Sung [28]
Internet Health Care Technology	Perceived Usefulness Perceived Enjoyment	Perceived Complexity Perceived Risk	Bian et al. [29]
E-Learning	Perceived Usefulness Perceived Enjoyment	Perceived Fee Perceived Risk	Liao et al. [30]
Chatbot Technology	Perceived Usefulness Perceived Enjoyment	Perceived Risk	Al-Abdullatif [31]
E-wallet	Perceived usefulness Enjoyment Facilitating condition	Privacy Risk; Monetary Risk Innovative Resistance Technicality	Ju et al. [32]
PropTech Service	Usefulness; Enjoyment	Technicality: Perceived fee	Kim and Kim [33]
Financial Robo-advisors	Perceived Financial Benefit	Perceived Financial Risk Perceived Privacy Risk	Hong et al. [34]

2.2. Brand Credibility

According to Innovation Diffusion Theory (IDT), consumers often rely on external signals when adopting new technologies, with brand credibility being a key signaling factor. Brand credibility can be defined as consumers' perception of a brand's reliability and consistency, reflecting their level of trust in the brand and its associated products or services [35]. It plays a crucial role in reducing perceived risk arising from insufficient product or service knowledge while simultaneously enhancing perceived value [36]. In consumer purchase decision-making, higher brand credibility typically leads to more positive brand evaluations. Strong brand trust increases consumers' willingness to accept brand-related information, thereby strengthening their confidence in purchasing the brand's products [22,37,38]. Brand credibility is particularly critical in emerging technology sectors. Autonomous driving technology, as an emerging innovation, is often associated with high perceived risks, including concerns about technological reliability and safety, which can significantly impact consumer purchase intentions. In this context, consumers tend to rely on a brand's credibility to mitigate perceived risks associated with new technologies. Specifically, in high-risk technological product domains, consumers are more inclined to trust companies with high brand credibility to reduce uncertainty and fear of unfamiliar technologies. Enhancing brand credibility can effectively strengthen consumer trust in the safety and reliability of technology-driven products, thereby increasing their acceptance and purchase intention.

3. Research Hypotheses and Model

Building upon prior research on the VAM, this study develops a consumer-centric research framework. Through a systematic literature analysis, perceived usefulness and perceived enjoyment are categorized as sub-dimensions of perceived benefit, while perceived risk and perceived fee are defined as sub-dimensions of perceived sacrifice. Additionally, given the critical role of brand credibility in consumer behavior research, it is incorporated as a key variable in the proposed model, as illustrated in Figure 1.

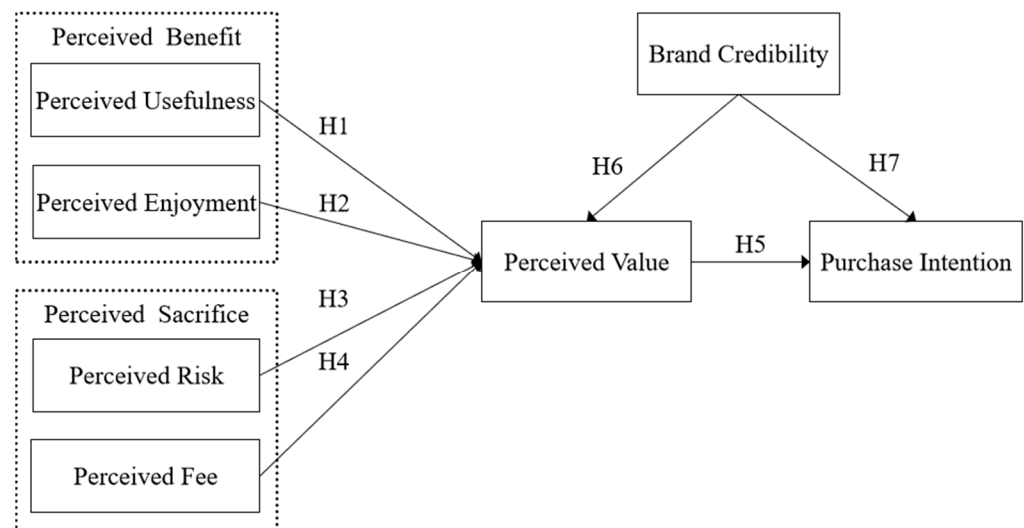


Figure 1. Research Model.

3.1. Perceived Benefit

Perceived benefit refers to the advantages or value that consumers perceive when using a product or service. This concept is generally defined as consumers' positive evaluation of a product or service, reflecting the favorable outcomes derived from their usage experience [39]. Peter and Olson [40] further emphasized that perceived benefit is not only a rational assessment of a product's or service's functional attributes but also an emotion-driven evaluation shaped by individuals' subjective perceptions of how well the product or service fulfills their needs and expectations. In this study, perceived benefit is categorized into two key dimensions: perceived usefulness and perceived enjoyment.

3.1.1. Perceived Usefulness

Perceived usefulness (PU) refers to users' subjective assessment of the overall value of a new technology or service, particularly its potential to enhance personal work efficiency or daily life [41]. Venkatesh [42] defined perceived usefulness as the functional capability of a technology to improve productivity, fulfill needs, or solve problems. In the field of information systems and technology research, perceived usefulness is widely recognized as a key driving force behind technology adoption [18]. Kettinger et al. [43] further emphasized that perceived usefulness not only directly influences perceived value but also indirectly affects technology adoption decisions by shaping users' attitudes and behavioral intentions. Empirical studies suggested that perceived usefulness plays a critical role in the market acceptance of emerging technologies, particularly in domains such as innovative online services and mobile payment platforms [44]. Liao et al. [30] found that perceived usefulness is a significant predictor of perceived value in e-learning systems. Moreover, Kim and Kyung [45] emphasized that perceived usefulness not only reflects the practical value of new technology in individuals' daily lives but also serves as a crucial factor in enhancing work efficiency and convenience. Recent research by Ju et al. [32] demonstrated

that perceived usefulness significantly influences e-wallet adoption by enhancing consumers' perceived value, thereby reinforcing the belief that e-wallet systems offer superior advantages over traditional payment methods. Similarly, AIDVs not only improve road safety but also reduce drivers' cognitive and physical burdens, offering greater convenience in both work and daily life. Therefore, users' perception of usefulness will directly impact their overall perceived value of this technology, consequently influencing their adoption intentions. Building on the theoretical framework and empirical analysis of the existing literature, this study proposes the following hypothesis.

H1. *Perceived usefulness has a positive impact on the perceived value of AIDVs.*

3.1.2. Perceived Enjoyment

Perceived Enjoyment refers to the pleasure and satisfaction consumers experience while using a technology or service [18]. Chi et al. [46] defined perceived enjoyment as the degree of happiness and pleasure users feel during online-to-offline (O2O) transactions, emphasizing that this enjoyment not only enhances consumers' emotional experiences but also fosters a positive evaluation of the technology. When users derive enjoyment from interacting with an information technology system, they are generally more inclined to engage with it actively and increase their long-term usage frequency [33,47]. Furthermore, Huang [48] found that experience-oriented users of autonomous vehicles (AVs) tend to seek novel and diverse sensory experiences and are more willing to accept the risks associated with such technology. In the context of AIDVs, human-machine interaction and in-vehicle entertainment experiences, such as intelligent cockpit adjustments, dynamic navigation recommendations, and personalized cabin environments, contribute to users' emotional satisfaction. This enjoyment not only enhances users' perceived value of the technology but may also significantly increase their intention to use and adopt it. Building on the theoretical framework and empirical analysis of the existing literature, this study proposes the following hypothesis.

H2. *Perceived enjoyment has a positive impact on the perceived value of AIDVs.*

3.2. Perceived Sacrifice

Perceived Sacrifice refers to the negative costs or disadvantages perceived by consumers when adopting a particular technology or product, encompassing all the expenditures associated with its use. Zeithaml [20] proposed that perceived sacrifice consists of two main components: monetary sacrifice and non-monetary sacrifice. Monetary sacrifice primarily refers to the direct financial costs consumers incur when purchasing a product or service, while non-monetary sacrifice includes the time, effort, risk, and potential dissatisfaction that consumers experience during the usage process, all of which represent indirect non-financial costs [18,49]. Research has shown that perceived sacrifice is particularly related to the complexity and potential risks associated with a technology, and it has a significant negative impact on perceived value [45,50]. In this study, perceived sacrifice is further subdivided into two core dimensions: perceived risk and perceived fee.

3.2.1. Perceived Risk

Stone et al. [51] defined perceived risk as the uncertainty consumers face when purchasing a product or service, along with their subjective assessment of the potential negative consequences associated with that uncertainty. Perceived risk stems from various sources, including uncertainties related to product quality, functionality, price fluctuations, brand reputation, and after-sales service. In the adoption of emerging technological products, perceived risk is particularly prominent, as consumers often lack sufficient knowledge and

trust in these technologies, leading to heightened anxiety and hesitation in their adoption decisions [52]. Safety concerns remain a primary factor influencing consumer acceptance of autonomous driving technology. One of the key psychological barriers is that consumers may perceive a loss of control over vehicle speed and road conditions when using autonomous vehicles, leading to a higher perceived risk. This perceived risk not only weakens consumer trust in intelligent driving technology but may also have a negative impact on perceived value [53]. In the context of public transportation, personal safety and data privacy risks are critical factors influencing users' adoption decisions regarding autonomous driving technologies [54,55]. Given the complexity and uncertainty associated with advanced autonomous driving technologies, consumers may perceive multiple forms of risk when adopting such systems, including safety risks, technological reliability concerns, and operational complexity. A higher perceived risk of autonomous driving technology typically leads to a significant decrease in perceived value. Based on the aforementioned theoretical and empirical studies, this research proposes the following hypothesis:

H3. *Perceived risk has a negative impact on the perceived value of AIDVs.*

3.2.2. Perceived Fee

Perceived fee refers to the total negative costs or sacrifices that users perceive when utilizing a technology or service. These costs typically encompass financial expenses, time investment, and effort exerted. In the field of technology adoption, the perceived fee is regarded as a critical negative factor influencing user behavior, particularly in the context of highly complex technological products or services, where its impact is especially pronounced [56]. In the electric vehicle sector, consumers' purchase intentions are often significantly constrained by perceived fees, particularly due to high initial purchase costs and frequent maintenance requirements [57]. Moreover, the complexity of the technology itself and the difficulty of operation may also be perceived by consumers as additional costs, further affecting their willingness to adopt the technology [18,30]. Kim and Kyung [45] argued that when consumers perceive a technological product or service as requiring substantial time, financial, or psychological investment, their perceived value tends to decline, subsequently impacting their adoption intentions. Advanced autonomous vehicles not only demand a steep learning curve and adaptation from users but also impose substantial financial costs related to purchasing, maintenance, and system upgrades. Based on the above literature and theoretical analysis, this study proposes the following hypothesis:

H4. *Perceived fee has a negative impact on the perceived value of AIDVs.*

3.3. Perceived Value

Perceived value refers to consumers' subjective assessment formed through the comprehensive evaluation of their expectations, perceived benefits, and perceived costs associated with a product or service. Zeithaml [20] defined perceived value as the balance between the benefits consumers gain from purchasing a product or service and the resources they invest, including time, money, and effort. Woodruff [58] further elaborated that perceived value encompasses not only the functional attributes of a product or service but also consumers' emotional states, overall evaluation of the offering, and the sacrifices made to acquire it. As a key variable in measuring technology adoption and usage, perceived value has been extensively applied in consumer behavior research, particularly in the context of information technology (IT) adoption and usage [27,59]. In the electric vehicle (EV) sector, the impact of perceived value on purchase intention has been widely validated [60]. Wang et al. [61] argued that perceived value influences consumers' purchasing decisions by shaping their perceptions of EVs' ease of use and usefulness. Similarly,

Zhang et al. [62] found that information related to EVs' environmental performance and technological attributes enhances consumers' perceived value and trust, significantly promoting purchase intention. Additionally, Hu et al. [63] demonstrated a positive correlation between consumers' perceptions of economic, environmental, and psychological benefits and their perceived value, which in turn significantly increases their purchase intention. Therefore, perceived value not only shapes consumers' attitudes toward autonomous driving technology but also influences their perceptions of usability, efficiency, and safety, ultimately determining their purchase decisions. Based on the above literature, this study proposes the following hypothesis:

H5. *Perceived value has a positive impact on the intention to AIDVs.*

3.4. Brand Credibility, Perceived Value and Purchase Intention

Enhancing brand credibility is beneficial in increasing consumers' trust in the brand and its products, as well as their perceived value [64]. When customers perceive a brand as trustworthy and reliable, they are more likely to purchase its products [65]. Wang and Yang [66] investigated the impact of brand credibility on consumers' purchase intentions within the Chinese automotive industry and found that the higher the brand credibility, the stronger the consumers' willingness to purchase. In the context of advanced autonomous vehicles, brand credibility is especially critical, and its core can be captured through two key attributes: trustworthiness and expertise [67]. Trustworthiness refers to consumers' confidence in whether the company can fulfill its promises regarding the safety, performance, and other aspects of autonomous vehicles. Expertise, on the other hand, pertains to consumers' belief in the company's technical and professional capabilities to deliver on those promises. Given that autonomous driving technology has not yet been fully mainstreamed, consumers often experience considerable uncertainty and perceived risk regarding its safety and technological maturity. In such a context, brand credibility can effectively alleviate consumers' concerns about the technology's safety and reliability, reduce their perception of risk regarding emerging technologies, and enhance their perceived value of the technology. Therefore, brand credibility not only strengthens consumers' confidence in advanced autonomous vehicles but also likely contributes to the formation of their purchase intentions. Based on the above literature, this study proposes the following hypotheses:

H6. *Brand credibility has a positive impact on the perceived value of AIDVs.*

H7. *Brand credibility has a positive impact on the purchase intention of AIDVs.*

4. Research Methodology

4.1. Instrument Design

Based on the research hypotheses, this study selected seven constructs: perceived usefulness, perceived enjoyment, perceived risk, perceived fee, perceived value, brand credibility, and purchase intention. To ensure the validity and reliability of the scales, a review of existing well-established scales was conducted, and these scales were adapted and designed in accordance with the specific characteristics of AIDVs. The measurement items for perceived usefulness were adapted from Liao et al. [30] and Kim and Kyung [45]. Perceived enjoyment was measured using scales developed by Kim and Kim [33] and Chi et al. [46]. The measurement items for perceived risk were revised based on Yang et al. [11] and Hong et al. [34], while the perceived fee was assessed using the scales proposed by Xu et al. [57] and Kim and Kyung [45]. The measurement of perceived value was derived from Zhang et al. [62] and Hu et al. [63]. Brand credibility was measured following the methods

of Guo and Luo [22] and Erdem and Swait [35]. Lastly, purchase intention was assessed based on the studies of Wang et al. [60] and Zhang et al. [62]. All measurement items were evaluated using a five-point Likert scale, where 1 represents strongly disagree, and 5 represents strongly agree. The specific constructs and their corresponding measurement items are detailed in Table 2.

Table 2. Measurement scale.

Constructs	Description	References
Perceived Usefulness (PU)	1. AIDVs can reduce traffic accidents. 2. AIDVs can make travel more convenient. 3. AIDVs can improve travel efficiency. 4. AIDVs can enhance travel safety.	Liao et al. [30] Kim and Kyung [45]
Perceived Enjoyment (PE)	1. AIDVs can bring me pleasure. 2. AIDVs allow me to enjoy activities like watching videos. 3. AIDVs enable me to freely use smart devices while on the move. 4. AIDVs provide a more relaxed travel experience.	Kim and Kim [33] Chi et al. [46]
Perceived Risk (PR)	1. I am concerned about AIDVs being involved in traffic accidents. 2. I worry that AIDVs may not perform as well as human drivers in emergency situations. 3. I am concerned that my personal information might be leaked.	Yang et al. [11] Hong et al. [33]
Perceived Fee (PF)	1. The purchase price of AIDVs is too high. 2. The maintenance cost of AIDVs is too high. 3. The repair cost of AIDVs is too high. 4. The insurance cost of AIDVs is too high.	Xu et al. [57] Kim and Kyung [45]
Perceived Value (PV)	1. The driving experience offered by AIDVs is more valuable than that of traditional vehicles. 2. I believe the technological innovation of AIDVs increases their overall value. 3. The convenience of AIDVs makes me feel they are valuable. 4. The additional features and services offered by AIDVs make them more valuable than traditional cars.	Zhang et al. [62] Hu et al. [63]
Brand Credibility (BC)	1. I believe the brand can fulfill its promises. 2. I think the brand's products are trustworthy. 3. I believe the brand is reliable.	Guo and Luo [22] Erdem and Swait [35]
Purchase Intention (PI)	1. I will consider buying AIDVs when I purchase a car next time. 2. I would be willing to buy AIDVs when I purchase a car next time. 3. I am more inclined to buy AIDVs compared to traditional cars. 4. I would recommend AIDVs to my relatives and friends.	Wang et al. [60] Zhang et al. [62]

4.2. Data Collection

This study designed and administered a survey questionnaire through the online survey platform Wenjuanxing. The target population consisted of individuals with driving experience in Shandong Province. Because this region has a large population and is a major province for automobile manufacturing and sales. The survey was conducted from 19 August 2024 to 9 September 2024. To ensure data quality, questionnaires that were incomplete, had excessively short response times, or contained identical responses across all items were deemed invalid. A total of 390 questionnaires were collected, of which 337 were valid. Data processing and analysis were conducted using SPSS 28.0 and AMOS 28.0. Specifically, SPSS 28.0 was employed to analyze the sample characteristics and to perform reliability and validity assessments, while AMOS 28.0 was utilized for confirmatory factor analysis (CFA) and structural equation modeling (SEM) path analysis to test the proposed hypotheses.

Regarding sample characteristics, male respondents accounted for 58.75%, while female respondents represented 41.25%. In terms of age distribution, the largest group of respondents, 73.6%, were aged between 20 and 40 years. The sample generally exhibited a high level of education, with approximately 85% of respondents holding a college or undergraduate degree. In terms of household monthly income, the largest proportion of respondents (56%) earned between USD 1000 and USD 2000. Additionally, respondents were asked to identify well-known brands associated with advanced driving assistance systems, with Huawei being the most frequently mentioned, followed by Lixiang. Descriptive statistics are presented in Table 3.

As shown in Figure 2, 41% of respondents (138 individuals) reported having experience with advanced driver assistance systems, while 59% (199 individuals) had not used them. Figure 3 indicates a diverse array of motivations for owning AIDVs. 60% of respondents believed that they could reduce parking hassles, 63% felt that they enhanced driving safety, and 76% emphasized the convenience of travel. Moreover, all respondents (337 individuals, 100%) agreed that AIDVs could alleviate driving burdens and fatigue. This suggests that the convenience and benefits of AIDVs are widely recognized among the respondents.

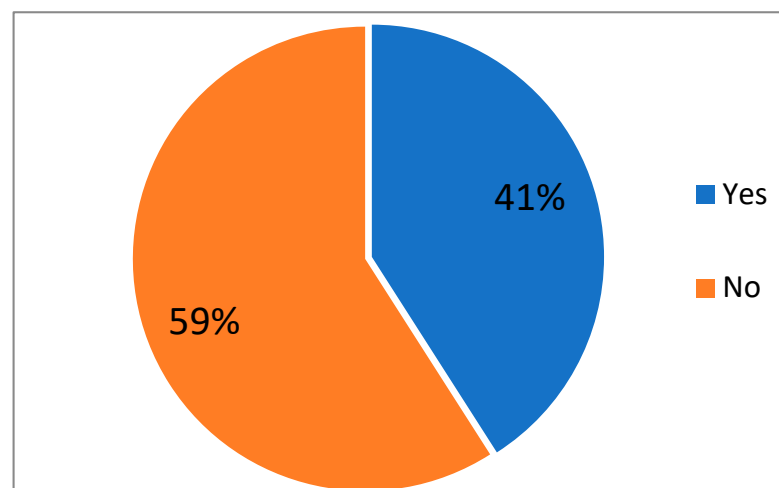


Figure 2. Experience with Advanced Driver Assistance Systems.

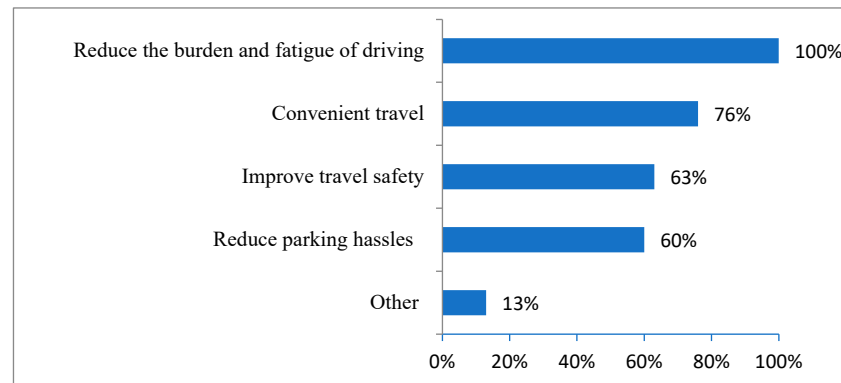


Figure 3. Motivations for Owning AIDVs.

Table 3. Demographic features.

Items	Types	Numbers	Percentage (%)
Gender	Male	198	58.75
	Female	139	41.25
Age	20–30 years old	132	39.2
	31–40 years old	116	34.4
	41–50 years old	70	20.8
	Above 50 years old	19	5.6
Education level	High school graduates	16	4.7
	Junior colleges	153	45.4
	Four-year colleges	133	39.5
	Graduate schools and above	35	10.4
Average monthly Income	Below USD 1000	60	17.8
	USD 1000~USD 2000	189	56.1
	USD 2000~USD 3000	65	19.3
	More than USD 3000	23	6.8
Brand type	Huawei	91	27
	Lixiang	78	23.1
	Tesla	59	17.5
	Xiaopeng	53	15.8
	Weilai	31	9.2
	Other	25	7.4

4.3. Structural Equation Modeling (SEM) Analysis

4.3.1. Measurement Modeling

This study first conducted an exploratory factor analysis (EFA). As shown in Table 4, the factor analysis extracted seven constructs, with a total explained variance of 70.5%, which significantly exceeds the critical threshold of 50%, indicating strong representativeness of the identified factors. Furthermore, the factor loadings for all measurement items were greater than 0.5, while cross-loadings were below 0.4, demonstrating good construct validity of the scale.

Table 4. Cross-loadings.

Construct	Component						
	PI	PV	PE	PU	PF	BC	PR
PI1	0.806	0.102	0.129	0.148	−0.105	0.112	0.078
PI2	0.806	0.231	0.102	0.051	−0.112	0.204	0.124
PI4	0.777	0.205	0.140	0.132	−0.083	0.151	0.154
PI3	0.723	0.121	0.124	0.185	−0.130	0.200	0.208
PV4	0.131	0.845	0.071	0.121	−0.127	0.027	0.084
PV3	0.153	0.811	0.160	0.239	−0.130	0.093	0.117
PV1	0.198	0.767	0.153	0.211	−0.176	0.104	0.036
PV2	0.165	0.710	0.172	0.188	−0.214	0.069	−0.001
PE2	0.050	0.164	0.829	−0.004	−0.013	0.056	0.031
PE1	0.044	0.092	0.828	0.066	−0.064	0.040	0.033
PE4	0.152	0.128	0.749	0.139	−0.115	0.090	0.148
PE3	0.262	0.088	0.708	0.208	−0.148	0.120	0.090
PU2	0.095	0.168	−0.001	0.783	−0.088	0.108	0.125
PU4	0.159	0.087	0.078	0.753	−0.124	0.174	0.113
PU1	0.166	0.241	0.122	0.730	−0.119	0.194	0.128
PU3	0.075	0.238	0.212	0.701	−0.126	−0.002	0.001
PF3	−0.028	−0.130	−0.026	−0.100	0.805	−0.031	0.063
PF4	−0.071	−0.159	−0.042	−0.017	0.801	0.048	−0.205
PF1	−0.094	−0.118	−0.099	−0.138	0.757	−0.138	−0.087
PF2	−0.193	−0.139	−0.149	−0.162	0.672	−0.029	−0.027
BC3	0.132	0.053	0.078	0.136	−0.059	0.855	0.079
BC1	0.180	0.086	0.140	0.141	−0.070	0.834	0.083
BC2	0.239	0.094	0.050	0.121	−0.006	0.793	0.140
PR1	0.134	0.103	0.062	0.003	−0.123	0.127	0.817
PR2	0.164	0.041	0.066	0.108	−0.029	0.133	0.809
PR3	0.123	0.037	0.118	0.195	−0.056	0.026	0.769
Eigenvalues	2.914	2.900	2.731	2.658	2.591	2.362	2.187
Variance %	11.209	11.155	10.504	10.223	9.966	9.084	8.413
Cumulative%	11.209	22.364	32.868	43.091	53.057	62.140	70.553

Note: PU = Perceived Usefulness, PE = Perceived Enjoyment, PR = Perceived Risk, PF = Perceived Fee, PV = Perceived Value, BC = Brand Credibility, PI = Purchase intention.

Given the presence of latent variables in this study, a confirmatory factor analysis (CFA) was further conducted to assess the extent to which the measurement variables reflect the latent variables, thereby verifying the accuracy of questionnaire items in capturing the corresponding model variables. The results of the CFA are presented in Tables 5 and 6. Table 5 shows the standardized factor loadings (λ), Cronbach's alpha coefficients, composite reliability (CR), and average variance extracted (AVE). According to standard thresholds, λ must exceed 0.5, Cronbach's alpha must be greater than 0.6, CR must be above 0.6, and AVE must be greater than 0.5. In this study, all λ values exceed 0.6, Cronbach's alpha coefficients are above 0.7, CR values exceed 0.7, and AVE values are greater than 0.5,

indicating strong internal consistency and reliability. In addition, discriminant validity was assessed by comparing the square root of AVE for each construct with the correlation coefficients between constructs. Table 6 presents the results of discriminant validity analysis, demonstrating that the square root of AVE for all seven latent variables exceeded the correlation coefficients between constructs. This finding suggests that the model exhibits satisfactory discriminant validity.

Table 5. Confirmatory factor analysis results.

Construct	Items	λ	CR	AVE	α
(PU)	PU1	0.827	0.821	0.536	0.820
	PU2	0.718			
	PU3	0.648			
	PU4	0.725			
(PE)	PE1	0.734	0.834	0.553	0.834
	PE2	0.744			
	PE3	0.752			
	PE4	0.757			
(PR)	PR1	0.752	0.785	0.55	0.783
	PR2	0.778			
	PR3	0.692			
(PF)	PF1	0.736	0.803	0.507	0.801
	PF2	0.654			
	PF3	0.701			
	PF4	0.755			
(PV)	PV1	0.816	0.880	0.647	0.878
	PV2	0.731			
	PV3	0.872			
	PV4	0.794			
(BC)	BC1	0.834	0.849	0.652	0.843
	BC2	0.772			
	BC3	0.815			
(PI)	PI1	0.769	0.873	0.637	0.873
	PI2	0.846			
	PI3	0.767			
	PI4	0.809			

Note: Model fit statistics: $\chi^2 = 440.65$, $df = 278$, $\chi^2/df = 1.585$, CFI = 0.86, GFI = 0.914, IFI = 0.961, NFI = 0.9, RMR = 0.041, and RMSEA = 0.042.

In summary, the confirmatory factor analysis model employed in this study is both rigorous and scientifically sound, effectively supporting the construct validity, reliability, and discriminant validity of the measurement scale.

Table 6. Discriminant validity of the constructs.

	PI	BC	PV	PF	PR	PU	PE
PI	0.798						
BC	0.523	0.807					
PV	0.521	0.312	0.805				
PF	−0.374	−0.209	−0.475	0.747			
PR	0.464	0.358	0.288	−0.281	0.742		
PU	0.481	0.45	0.594	−0.408	0.376	0.732	
PE	0.436	0.32	0.442	−0.318	0.306	0.401	0.747

Notes: The square root of AVE is in bold on diagonals. Off diagonals are Pearson correlation of constructs.

4.3.2. Path Analysis

This study used AMOS 28.0 to conduct structural equation modeling (SEM) analysis on data from 337 valid questionnaires. The SEM analysis diagram is provided in Appendix A Figure A1. The model fit indices and results are presented in Table 7. As shown in Table 7, all model fit indices meet the recommended thresholds, indicating that the theoretical model demonstrates a good fit with the observed data. To test the structural model shown in Figure 1, this study performed path analysis using AMOS 28.0, with the results provided in Table 8 and the path coefficients illustrated in Figure 4.

Table 7. SEM model fit test results.

Model Fit Indicators	Optimization Criteria	Statistical Value	Fit
CMIN	—	542.476	—
DF	—	286	—
CMIN/DF	<3	1.897	Good
NFI	>0.8	0.877	Good
RFI	>0.8	0.860	Good
IFI	>0.9	0.938	Good
TLI	>0.9	0.929	Good
CFI	>0.9	0.937	Good
RMSEA	<0.08	0.052	Good

Table 8. Significance test of the path coefficients.

	Path			β	S.E.	C.R.	<i>p</i> -Value	Hypothesis
H1	PV	<---	PU	0.408	0.069	5.651	***	Accepted
H2	PV		PE	0.202	0.056	3.315	***	Accepted
H3	PV	<---	PR	0.013	0.062	0.205	0.838	Rejected
H4	PV	<---	PF	−0.247	0.054	−3.590	***	Accepted
H5	PI	<---	PV	0.451	0.064	7.374	***	Accepted
H6	PV	<---	BC	0.032	0.050	0.560	0.576	Rejected
H7	PI	<---	BC	0.402	0.056	6.530	***	Accepted

Note: *** $p < 0.001$.

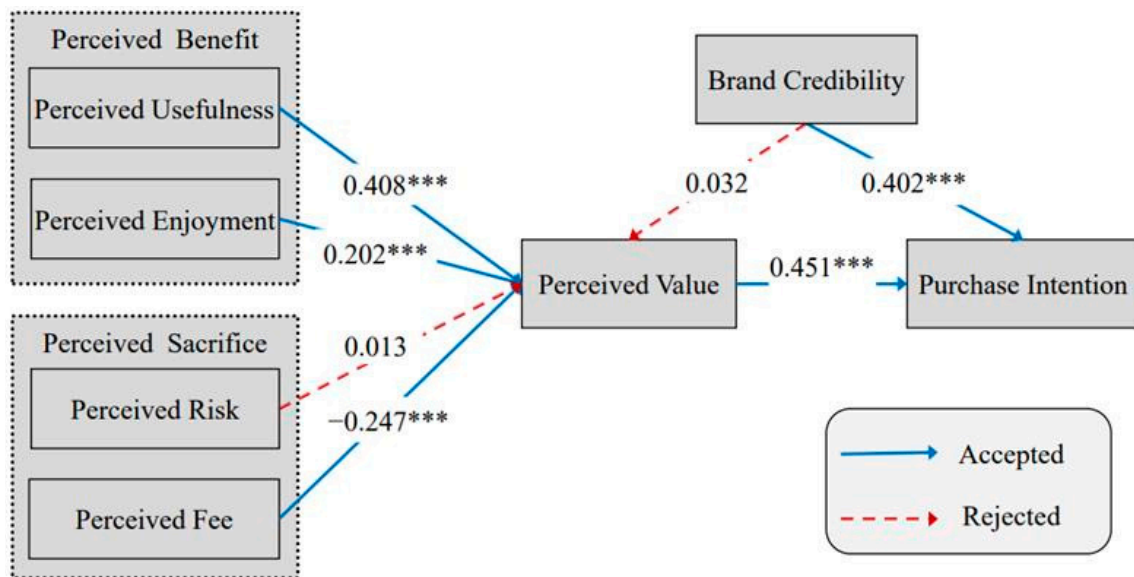


Figure 4. Standardized path coefficient results (***) significant at p -value < 0.001 .

The empirical results indicate that H1 is supported, demonstrating that perceived usefulness ($\beta = 0.408$, $p < 0.001$) has a significant positive impact on perceived value. This finding aligns with prior studies. The advanced perception and decision-making capabilities of AIDVs, along with their high degree of automation, effectively reduce driving complexity, alleviate driver burden, and enhance consumers' perceived value of the technology. Similarly, H2 is supported, as perceived enjoyment ($\beta = 0.202$, $p < 0.001$) exhibits a significant positive effect on perceived value, consistent with the conclusions of Zhu et al. [7]. As a critical emotional driver, perceived enjoyment significantly enhances consumers' overall experience with AIDVs, thereby strengthening their perception of the value of the technology. However, H3 is not supported, as perceived risk ($\beta = 0.013$, $p > 0.05$) does not have a significant impact on perceived value. This result diverges from some existing studies, suggesting that consumers' concerns about potential risks associated with AIDVs do not substantially diminish their overall value assessment of the product. The findings also confirm that H4 is supported, indicating that perceived fee ($\beta = -0.247$, $p < 0.001$) has a significant negative impact on perceived value. This result is consistent with previous research, further highlighting consumers' high sensitivity to price when making purchasing decisions for high-tech products. Moreover, H5 is supported, as perceived value ($\beta = 0.451$, $p < 0.001$) has a significant positive effect on purchase intention, reinforcing its central role in consumer behavior models. In the high-tech domain of AIDVs, perceived value serves as a key driver of consumer decision-making by integrating multiple dimensions of advantages. Regarding brand credibility, H7 is supported, as brand credibility has a significant positive impact on purchase intention ($\beta = 0.402$, $p < 0.001$). However, H6 is not supported since the effect of brand credibility on perceived value ($\beta = 0.032$, $p > 0.05$) is not significant. This may be attributed to the fact that when assessing the value of a product, consumers tend to prioritize its functionality and economic attributes over its external brand reputation.

5. Discussion and Implication

This study, based on the theoretical framework of Perceived Value and Brand Credibility, employs the VAM model to explore the formation mechanism of consumer purchase intentions toward advanced intelligent driving vehicles (AIDVs). Through the development of a questionnaire and empirical analysis, we validated the effectiveness of the hypothesized paths, thereby deepening the understanding of consumer behavior in the field of

intelligent driving technology. The following section provides a detailed discussion of the main research findings.

5.1. Determinants of Perceived Value

Perceived usefulness has a significant positive impact on perceived value, which aligns with findings from the existing literature [7,68]. This suggests that an increase in perceived usefulness enhances individuals' overall value perception of AIDVs. Propagation [69] argued that the driver assistance features of intelligent vehicles contribute to enhancing user satisfaction with AIDVs, further building trust in the brand. With the rapid advancement of connected and automated vehicle technology, cooperative control among vehicles has significantly improved traffic efficiency and safety. By integrating multimodal sensors (e.g., LiDAR, cameras, and radar) with artificial intelligence algorithms, AIDVs can accurately perceive their surrounding environment and assess traffic conditions in real-time, enabling autonomous driving decision-making. This technology has substantially reduced the risk of traffic accidents caused by human factors, providing users with significant practical value [70]. The Autonomous Emergency Braking (AEB) function can swiftly intervene when a potential collision risk is detected, actively decelerating or stopping the vehicle to avoid a collision or reduce injury from a crash. Compared to traditional vehicles, AIDVs offer enhanced convenience by assisting users with dynamic route planning, autonomous parking, adaptive cruise control, and lane-change assistance, thereby reducing cognitive, psychological, and physical fatigue during driving [71]. Furthermore, by minimizing the complexity of driving operations through high levels of automation, AIDVs significantly alleviate the driver's burden and enhance consumers' perception of their value.

Perceived enjoyment has a significant positive impact on perceived value, a finding consistent with the research [7]. Zhu et al. [7] found that perceived enjoyment surpassed functional utility value and was identified as a key factor in shaping the value perception of autonomous vehicles. For traditional vehicles, functional utility is a critical determinant in user decision-making. In contrast, AIDVs tend to emphasize entertainment and information features more than traditional vehicles. As a key emotional driver, perceived enjoyment significantly enhances consumers' experience evaluation of AIDVs, thereby strengthening their overall perception of the vehicle's value. This effect is not only reflected in the direct experience of technological functions but also permeates the psychological enjoyment and satisfaction derived from the driving experience. AIDVs, through innovative human-machine interaction designs and diverse entertainment features—such as multi-screen interaction, natural voice commands, and immersive audio-visual experiences—greatly enrich the consumer travel experience [61]. Modern consumers now perceive cars not merely as traditional modes of transportation but as mobile private spaces. The in-car entertainment systems and smart cabins equipped in AIDVs can automatically play music, movies, or podcasts suited to the passengers' preferences, injecting enjoyment into the otherwise monotonous driving process. These entertainment functions not only fulfill the consumers' functional needs but also evoke emotional pleasure during use.

Perceived fee has a significant negative impact on perceived value. This finding is consistent with existing research [28,56], further highlighting consumers' high sensitivity to price in their purchase decisions for high-tech products. Specifically, in the field of intelligent driving vehicles, the negative effect of the perceived fee not only reflects the significant influence of economic cost on consumer decision-making but also reveals a major obstacle that needs to be overcome in current technology and market promotion efforts. In the Chinese new energy vehicle market, the current adoption rate of advanced intelligent driving configurations is uneven. According to data from the National Information Center, 74% of passenger vehicles in China are priced between USD 11,000 and USD 30,000.

However, the penetration rate of advanced intelligent driving systems within this price range is nearly zero. In contrast, these systems are primarily found in mid-to-high-end models priced above USD 35,000, a price range that is significantly higher than the psychological expectations of average consumers. As a result, the acceptance of these features is relatively low, with consumers generally perceiving the value of such technologies as not being aligned with their high prices. When consumers lack sufficient trust in the reliability and safety of the technology, even if the potential value of the features is substantial, they are unlikely to overcome the psychological barriers posed by high prices.

5.2. The Non-Significant Effect of Perceived Risk

The results of this study indicate that perceived risk does not have a significant effect on perceived value. This finding differs from some conclusions in the existing literature. Traditional perspectives suggest that perceived risk (such as concerns about technological failures, data privacy breaches, etc.) typically has a negative impact on consumers' acceptance of high-tech products [72,73]. However, in the context of this study, consumers' concerns about the potential risks associated with AIDVs do not appear to significantly undermine their overall value assessment of the product. Zhu et al. [74] pointed out that both perceived benefit and perceived sacrifice significantly influence users' interest in autonomous vehicles, but the role of perceived risk in actual purchase decisions is relatively weaker. This suggests that, while consumers may be more sensitive to risk at the interest level, they are more likely to weigh the product's features and overall value when making purchase decisions. The positive perceptions of the functional benefits and experiences associated with AIDVs may, to some extent, offset the negative impact of perceived risk. As technology becomes more widespread and market education continues to progress, consumers' awareness and risk tolerance regarding advanced intelligent driving technology may improve. Studies indicate that the potential consumer base for AIDVs generally exhibits a high level of acceptance toward emerging technologies and holds a certain level of confidence in technological evolution [75]. AIDVs, by enhancing driving safety, convenience, and entertainment experiences, encourage consumers to focus more on the potential benefits rather than the associated risks. For example, advanced driver assistance systems can significantly reduce the risk of traffic accidents and enhance travel efficiency, making these tangible and positive functions central to consumer decision-making [45]. Research has shown that as the level of vehicle automation increases, consumers' attitudes and perceptions of safety tend to decrease significantly [76,77]. Empirical analyses by Behnood et al. [68] and Zhu et al. [7] have demonstrated that, compared to fully autonomous vehicles (FAVs), partially autonomous vehicles (PAVs) exhibit higher acceptance rates. AIDVs operate in a human-vehicle shared control state; if the system allows users to take over the vehicle whenever they wish, they are more likely to trust AIDVs [78].

5.3. The Relationship Between Perceived Value and Purchase Intention

The results of this study show that perceived value has a significant positive impact on purchase intention, confirming the central role of perceived value in consumer behavior models. Technological advancements alone do not guarantee the widespread acceptance of autonomous vehicles, as consumers' value perceptions are based on their subjective evaluations of the product or service. When consumers perceive a higher overall value of a product, their purchase intention increases accordingly. In particular, within the high-tech domain of AIDVs, perceived value, by integrating multiple advantageous features, becomes a key driver in the consumer decision-making process. The convenience and safety provided by AIDVs significantly enhance consumers' daily travel experiences. For example, advanced driving functions reduce driver fatigue and lower the risk of accidents,

offering consumers a heightened sense of comfort and security. This practical advantage occupies a central position in consumer value assessments. In addition to concerns about driving safety and convenience, consumers also expect AIDVs to provide entertaining and personalized features (e.g., smart home connectivity, AR navigation, etc.), which further increase the overall weight of perceived value. AIDVs not only represent an upgrade in transportation methods but also symbolize consumers' aspirations for a future technology-driven lifestyle.

5.4. The Role of Brand Credibility

The results of this study indicate that brand credibility has a significant positive impact on purchase intention, but its effect on perceived value is not significant. This finding reveals the unique role that brand credibility plays in the consumer purchasing process for AIDVs while also suggesting that its influence on perceived value is limited.

The significant positive effect of brand credibility on purchase intention validates its important role in consumer behavior models. The complexity and technological barriers of high-tech products cause consumers to place greater reliance on brand credibility when making decisions. Consumers are more likely to choose brands they perceive as reliable and reputable, as brand credibility significantly reduces their perceived risk and increases their confidence in the product's performance and after-sales service. Furthermore, brand credibility can stimulate purchase intention through emotional connections with consumers. Research indicates that consumers often view trusted brands as symbols of identity or extensions of their values, particularly in high-investment decisions such as purchasing AIDVs, where this emotional connection plays a crucial role in influencing purchase intention [62].

Despite the significant effect of brand credibility on purchase intention, its impact on perceived value is not significant, which contrasts with prior research findings [37,66]. This may be due to consumers' greater focus on the product's functional and economic aspects when evaluating its value rather than on the brand's external reputation. AIDVs, as high-tech products, typically derive their perceived value from specific performance indicators (such as safety, convenience, and entertainment) and long-term economic benefits, with brand credibility playing more of a supportive role in this process. Liu et al. [79] suggested that brand credibility is more likely to directly influence consumer behavior decisions rather than indirectly affecting purchase intention through perceived value. Additionally, consumers may perceive brand credibility as an independent decision-making criterion rather than a core component of product value. This independence is particularly evident in high-tech domains, where technological performance and innovation are often the primary focus of consumer evaluations.

5.5. Implications

First, companies should focus on enhancing consumers' perceived value of AIDVs. Among the various components of perceived value, perceived usefulness and perceived enjoyment play key roles in promoting purchase intention. To achieve this, companies can organize on-site test drive events that allow consumers to personally experience the intelligent and connected technologies of AIDVs, thereby deepening their emotional recognition and sense of identification with the product. In addition, companies should continuously optimize product functionality, particularly by driving innovative breakthroughs in autonomous driving, human-machine interaction, and infotainment systems. Given the significant role of perceived enjoyment in shaping consumers' perceived value, researchers and practitioners should prioritize highlighting the pleasurable and enjoyable experiences offered by AIDVs. Emphasizing the enjoyment aspect of autonomous vehicles will help

increase consumer acceptance. Integrating features that enhance the driving experience and create positive emotions into marketing strategies can help craft a more attractive and consumer-centered narrative for autonomous driving.

Second, the purchase and insurance costs of high-end intelligent autonomous vehicles remain psychological barriers in consumers' decision-making process. Companies should actively collaborate with governments to seek policy support in order to reduce consumer purchase costs, thus enhancing the product's competitiveness and appeal. Additionally, companies should strengthen partnerships with insurance and automotive service providers to establish a more comprehensive after-sales service system, alleviating consumers' concerns about the potential additional expenses associated with owning high-end intelligent autonomous vehicles.

Finally, the key to enhancing purchase intention through brand credibility lies in building and maintaining a strong brand reputation. Brand reputation development requires not only strong product capabilities but also the creation of a fan culture around the brand. This culture helps fans form their own communities, shaping a clear brand image and value system. The establishment of fan culture is a goal for all brands, as positive word-of-mouth and organic recommendations from brand followers become the most effective advertisements for the brand's credibility.

5.6. Limitations and Future Research

This study primarily targeted users with driving experience, which facilitated their understanding of the described functionalities of intelligent vehicles. However, to enhance the generalizability of the findings, future research could distribute surveys through platforms or communities where intelligent vehicle users are concentrated, thereby increasing the diversity of data sources. Additionally, employing stratified sampling could further improve the representativeness of the survey sample. Since this study was conducted exclusively in Shandong Province, regional differences may exist in the findings. To strengthen the representativeness and generalizability of the research, future studies could extend the investigation to other regions for comparative analysis.

Furthermore, this study adopted a cross-sectional design, collecting data at a single time point. Longitudinal studies could provide deeper insights into how perceived value and purchase intention evolve over time, offering a more dynamic understanding of the adoption process. For instance, future research could compare consumers' perceptions before and after experiencing autonomous vehicles, providing manufacturers with key insights into user behavior evolution that could inform product optimization and marketing strategies.

Lastly, this study focused exclusively on AIDVs. Future research could expand the scope to include fully autonomous vehicles for comparative analysis, allowing for a more comprehensive examination of consumer perceptions at different levels of automation. This approach would help uncover broader consumer attitudes toward autonomous driving technologies and provide manufacturers with detailed data on user preferences at various technological stages, thereby supporting technology development and market positioning strategies.

6. Conclusions

With the advent of the era of automotive intelligence, advanced intelligent driving technologies have gradually become a core area of competition among major automotive companies. These technologies integrate cutting-edge innovations, including intelligent connectivity, autonomous driving, human-machine interaction, and entertainment fea-

tures, aiming to provide consumers with a more intelligent, comfortable, and luxurious driving experience.

This study examines the impact mechanism of perceived value and brand credibility on the purchase intention of AIDVs from the perspective of consumer perception. The core innovation of this research lies in the application of the Value-Based Adoption Model (VAM) to the domain of advanced intelligent driving for the first time, systematically revealing the multidimensional driving factors of perceived value and their influence on consumer behavior. This study extends the application scope of the VAM model and provides a novel theoretical perspective for understanding consumer attitudes toward emerging technologies. Based on the VAM framework, this study constructs a comprehensive theoretical model and validates it through structural equation modeling (SEM) using questionnaire survey data. The findings indicate that perceived usefulness and perceived enjoyment significantly enhance consumers' perceived value, whereas perceived fee exerts a negative impact, suggesting that consumers often struggle to overcome the psychological barriers associated with high pricing. Compared to fully autonomous vehicles, AIDVs are more familiar to consumers and enjoy higher acceptance levels. Consequently, perceived risk does not exert a significant influence on perceived value at the current stage of advanced autonomous driving. Furthermore, brand credibility significantly influences consumers' purchase intention but does not have a significant effect on perceived value. This may be attributed to the fact that consumers prioritize the functional and economic attributes of the product itself over its external brand reputation when evaluating its value. Perceived value exerts a significant positive impact on purchase intention, reaffirming its central role in consumer behavior models. Notably, technological advancements alone do not guarantee the widespread acceptance of autonomous vehicles (AVs), as consumers' value perceptions are shaped by their subjective evaluations of products or services. Therefore, enhancing consumers' perceived value of AIDVs and establishing a strong brand reputation is crucial for boosting purchase intention. By elucidating the mechanisms of perceived value and brand credibility, this study not only fills a gap in the existing literature but also provides scientific insights for technology enterprises to optimize product design, formulate market strategies, and enhance consumer trust.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

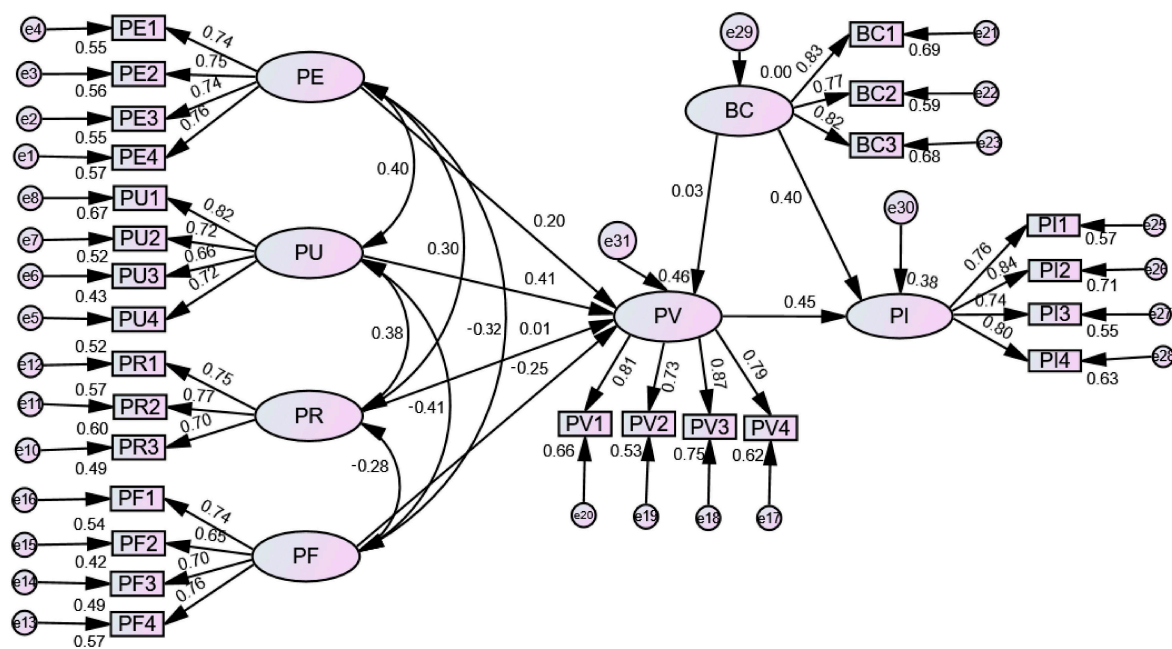


Figure A1. SEM Analysis Diagram.

References

- Wang, X.; Li, K.; Chehri, A. Multi-Sensor Fusion Technology for 3D Object Detection in Autonomous Driving: A Review. *IEEE Trans. Intell. Transp. Syst.* **2023**, *25*, 1148–1165. [\[CrossRef\]](#)
- Liang, J.; Tian, Q.; Feng, J.; Pi, D.; Yin, G. A Polytopic Model-Based Robust Predictive Control Scheme for Path Tracking of Autonomous Vehicles. *IEEE Trans. Intell. Veh.* **2023**, *9*, 3928–3939. [\[CrossRef\]](#)
- Rammohan, A. Revolutionizing Intelligent Transportation Systems with Cellular Vehicle-to-Everything (C-V2X) Technology: Current Trends, Use Cases, Emerging Technologies, Standardization Bodies, Industry Analytics and Future Directions. *Veh. Commun.* **2023**, *43*, 100638. [\[CrossRef\]](#)
- J.D. Power. Available online: <https://china.jdpower.com/zh-hans> (accessed on 12 June 2024).
- 2024 Autonomous Driving Industry Research Report. Available online: http://www.jazzyyear.com/study_info.html?id=139 (accessed on 20 January 2025).
- 2024 McKinsey China Automotive Consumer Insights Report. Available online: <https://www.mckinsey.com.cn> (accessed on 30 January 2025).
- Zhu, G.; Chen, Y.; Zheng, J. Partially Autonomous Vehicles (PAVs) vs. Fully Autonomous Vehicles (FAVs): A Comparative Study with Adoption Models. *Technol. Soc.* **2024**, *79*, 102698. [\[CrossRef\]](#)
- Bansal, P.; Kockelman, K.M.; Singh, A. Assessing Public Opinions of and Interest in New Vehicle Technologies: An Austin Perspective. *Transp. Res. Part C Emerg. Technol.* **2016**, *67*, 1–14. [\[CrossRef\]](#)
- Wu, M.; Wang, N.; Yuen, K.F. Can autonomy level and anthropomorphic characteristics affect public acceptance and trust towards shared autonomous vehicles? *Technol. Forecast. Soc.* **2023**, *189*, 122384. [\[CrossRef\]](#)
- Xie, R.; An, L.; Yasir, N. How Innovative Characteristics Influence Consumers' Intention to Purchase Electric Vehicle: A Moderating Role of Lifestyle. *Sustainability* **2022**, *14*, 4467. [\[CrossRef\]](#)
- Yang, Y.; Wang, Y.; Liu, J.; Lee, K. An Empirical Study on the Structural Assurance Mechanism for Trust Building in Autonomous Vehicles Based on the Trust-in-Automation Three-Factor Model. *Sustainability* **2024**, *16*, 8258. [\[CrossRef\]](#)
- Jing, P.; Huang, F.; Xu, G.; Wang, W. Analysis of Autonomous Driving Payment Willingness and Influencing Factors. *J. Chang'an Univ. (Nat. Sci. Ed.)* **2021**, *41*, 90–102. [\[CrossRef\]](#)
- Adu-Gyamfi, G.; Song, H.; Obuobi, B.; Nketiah, E.; Wang, H.; Cudjoe, D. Who Will Adopt? Investigating the Adoption Intention for Battery Swap Technology for Electric Vehicles. *Renew. Sustain. Energy Rev.* **2022**, *156*, 111979. [\[CrossRef\]](#)
- Deng, M.; Guo, Y.; Guo, Y.; Wang, C. The Role of Technical Safety Riskiness and Behavioral Interventions in the Public Acceptance of Autonomous Vehicles in China. *J. Transp. Eng. Part A Syst.* **2023**, *149*, 04022122. [\[CrossRef\]](#)
- Coad, A.; De Haan, P.; Woersdorfer, J.S. Consumer Support for Environmental Policies: An Application to Purchases of Green Cars. *Ecol. Econ.* **2009**, *68*, 2078–2086. [\[CrossRef\]](#)

16. Jain, N.K.; Bhaskar, K.; Jain, S. What Drives Adoption Intention of Electric Vehicles in India? An Integrated UTAUT Model with Environmental Concerns, Perceived Risk and Government Support. *Res. Transp. Bus. Manag.* **2022**, *42*, 100730. [\[CrossRef\]](#)
17. Wang, F.; Zhang, Z.; Lin, S. Purchase Intention of Autonomous Vehicles and Industrial Policies: Evidence from a National Survey in China. *Transp. Res. Part A Policy Pract.* **2023**, *173*, 103719. [\[CrossRef\]](#)
18. Kim, H.W.; Chan, H.C.; Gupta, S. Value-Based Adoption of Mobile Internet: An Empirical Investigation. *Decis. Support Syst.* **2007**, *43*, 111–126. [\[CrossRef\]](#)
19. Sohn, K.; Kwon, O. Technology Acceptance Theories and Factors Influencing Artificial Intelligence-Based Intelligent Products. *Telemat. Inform.* **2020**, *47*, 101324. [\[CrossRef\]](#)
20. Zeithaml, V.A. Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *J. Mark.* **1988**, *52*, 2–22. [\[CrossRef\]](#)
21. Molinillo, S.; Japutra, A.; Ekinici, Y. Building Brand Credibility: The Role of Involvement, Identification, Reputation and Attachment. *J. Retail. Consum. Serv.* **2022**, *64*, 102819. [\[CrossRef\]](#)
22. Guo, W.; Luo, Q. Investigating the Impact of Intelligent Personal Assistants on the Purchase Intentions of Generation Z Consumers: The Moderating Role of Brand Credibility. *J. Retail. Consum. Serv.* **2023**, *73*, 103353. [\[CrossRef\]](#)
23. Kim, Y.; Park, Y.; Choi, J. A Study on the Adoption of IoT Smart Home Service: Using Value-Based Adoption Model. *Total Qual. Manag. Bus. Excell.* **2017**, *28*, 1149–1165. [\[CrossRef\]](#)
24. Kahneman, D.; Tversky, A. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* **1979**, *47*, 263–291. [\[CrossRef\]](#)
25. Kim, I.S.; Jang, J.A.; Kim, J. Understanding User Acceptability Towards Robo Taxi Based on Value-Based Adoption Model. *J. Korea Inst. Intell. Transp. Syst.* **2023**, *22*, 291–310. [\[CrossRef\]](#)
26. Liang, T.P.; Lin, Y.L.; Hou, H.C. What Drives Consumers to Adopt a Sharing Platform: An Integrated Model of Value-Based and Transaction Cost Theories. *Inf. Manag.* **2021**, *58*, 103471. [\[CrossRef\]](#)
27. Mathavan, B.; Vafaei-Zadeh, A.; Hanifah, H.; Ramayah, T.; Kurnia, S. Understanding the Purchase Intention of Fitness Wearables: Using Value-Based Adoption Model. *Asia-Pac. J. Bus. Adm.* **2024**, *16*, 101–126. [\[CrossRef\]](#)
28. Yu, Y.; Sung, T.J. A Value-Based View of the Smart PSS Adoption: A Study of Smart Kitchen Appliances. *Serv. Bus.* **2023**, *17*, 499–527. [\[CrossRef\]](#)
29. Bian, D.; Xiao, Y.; Song, K.; Dong, M.; Li, L.; Millar, R.; Li, G. Determinants Influencing the Adoption of Internet Health Care Technology among Chinese Health Care Professionals: Extension of the Value-Based Adoption Model with Burnout Theory. *J. Med. Internet Res.* **2023**, *25*, e37671. [\[CrossRef\]](#)
30. Liao, Y.-K.; Wu, W.-Y.; Le, T.Q.; Phung, T.T.T. The Integration of the Technology Acceptance Model and Value-Based Adoption Model to Study the Adoption of E-Learning: The Moderating Role of e-WOM. *Sustainability* **2022**, *14*, 815. [\[CrossRef\]](#)
31. Al-Abdullatif, A.M. Modeling Students' perceptions of chatbots in learning: Integrating technology acceptance with the value-based adoption model. *Educ. Sci.* **2023**, *13*, 1151. [\[CrossRef\]](#)
32. Jingnan, J.; Teo, P.-C.; Ho, T.C.F.; Ling, C.H. The Behavioral Intention of Young Malaysians Towards Cashless Society: Value-Based Adoption Model. *Cogent Bus. Manag.* **2023**, *10*, 2244756. [\[CrossRef\]](#)
33. Kim, J.; Kim, J. An Integrated Analysis of Value-Based Adoption Model and Information Systems Success Model for PropTech Service Platform. *Sustainability* **2021**, *13*, 12974. [\[CrossRef\]](#)
34. Hong, X.; Pan, L.; Gong, Y.; Chen, Q. Robo-advisors and investment intention: A perspective of value-based adoption. *Inf. Manag.* **2023**, *60*, 103832. [\[CrossRef\]](#)
35. Erdem, T.; Swait, J. Brand credibility, brand consideration, and choice. *J. Consum. Res.* **2004**, *31*, 191–198. [\[CrossRef\]](#)
36. Vidyanata, D.; Sunaryo, S.; Hadiwidjojo, D. The Role of Brand Attitude and Brand Credibility as a Mediator of the Celebrity Endorsement Strategy to Generate Purchase Intention. *J. Apl. Manag.* **2022**, *16*, 402–411. [\[CrossRef\]](#)
37. Jeng, S. The Influences of Airline Brand Credibility on Consumer Purchase Intentions. *J. Air Transp. Manag.* **2016**, *55*, 1–8. [\[CrossRef\]](#)
38. Wang, S.; Liao, Y.; Wu, W.; Le, K.B.H. The Role of Corporate Social Responsibility Perceptions in Brand Equity, Brand Credibility, Brand Reputation, and Purchase Intentions. *Sustainability* **2021**, *13*, 11975. [\[CrossRef\]](#)
39. Gutman, J. A Means-End Chain Model Based on Consumer Categorization Processes. *J. Mark.* **1982**, *46*, 60–72. [\[CrossRef\]](#)
40. Peter, J.P.; Olson, P. *Understanding Consumer Behavior*; Richard D. Irwin: Homewood, IL, USA, 1994.
41. Rogers, E.M. *Diffusion of Innovations*, 4th ed.; The Free Press: New York, NY, USA, 1995.
42. Venkatesh, V. Creation of Favorable User Perceptions: Exploring the Role of Intrinsic Motivation. *MIS Q.* **1999**, *23*, 239–260. [\[CrossRef\]](#)
43. Kettinger, W.J.; Park, S.H.; Smith, J. Understanding the Consequences of Information Systems Service Quality on IS Service Reuse. *Inf. Manag.* **2009**, *46*, 335–341. [\[CrossRef\]](#)
44. Rafique, H.; Almagrabi, A.O.; Shamim, A.; Anwar, F.; Bashir, A.K. Investigating the Acceptance of Mobile Library Applications with an Extended Technology Acceptance Model (TAM). *Comput. Educ.* **2020**, *145*, 103732. [\[CrossRef\]](#)

45. Kim, E.; Kyung, Y. Factors Affecting the Adoption Intention of New Electronic Authentication Services: A Convergent Model Approach of VAM, PMT, and TPB. *IEEE Access* **2023**, *11*, 13859–13876. [\[CrossRef\]](#)
46. Chi, Y.S.; Kang, M.Y.; Choi, J.I. A Study of O2O-Commerce Consumers' Word-of-Mouth Intentions Based on the Value-Based Adoption Model: The Comparison of Korean and Chinese Consumers. *Int. Telecommun. Policy Rev.* **2016**, *23*, 81–116.
47. Zhang, Y.; Zhang, B.; Chen, J.; Zhang, Y.; Wu, Y.; Zhou, L. How to Promote People to Use Autonomous Vehicles? A Latent Congruence Path Model. *Transp. Lett.* **2023**, *16*, 416–427. [\[CrossRef\]](#)
48. Huang, T. Psychological Factors Affecting Potential Users' Intention to Use Autonomous Vehicles. *PLoS ONE* **2023**, *18*, e0282915. [\[CrossRef\]](#)
49. Roostika, R. Mobile Internet Acceptance among University Students: A Value-Based Adoption Model. *Int. J. Res. Manag. Technol.* **2012**, *2*, 221–228.
50. Yoon, S.; Oh, J. A Theory-Based Approach to the Usability of Augmented Reality Technology: A Cost-Benefit Perspective. *Technol. Soc.* **2022**, *68*, 101860. [\[CrossRef\]](#)
51. Stone, R.N.; Grønhaug, K. Perceived Risk: Further Considerations for the Marketing Discipline. *Eur. J. Mark.* **1993**, *27*, 39–50. [\[CrossRef\]](#)
52. Bearth, A.; Siegrist, M. Are Risk or Benefit Perceptions More Important for Public Acceptance of Innovative Food Technologies: A Meta-Analysis. *Trends Food Sci. Technol.* **2016**, *49*, 14–23. [\[CrossRef\]](#)
53. Schoettle, B.; Sivak, M. *Public Opinion about Self-Driving Vehicles in China, India, Japan, the US, the UK, and Australia*; University of Michigan, Ann Arbor, Transportation Research Institute: Ann Arbor, MI, USA, 2014.
54. Bucher, E.; Fieseler, C.; Fleck, M.; Lutz, C. Authenticity and the Sharing Economy. *Acad. Manag. Discov.* **2018**, *4*, 294–313. [\[CrossRef\]](#)
55. Hong, J.H.; Kim, B.C.; Park, K.S. Optimal Risk Management for the Sharing Economy with Stranger Danger and Service Quality. *Eur. J. Oper. Res.* **2019**, *279*, 1024–1035. [\[CrossRef\]](#)
56. Vafaei-Zadeh, A.; Wong, T.K.; Hanifah, H.; Teoh, A.P.; Nawaser, K. Modelling Electric Vehicle Purchase Intention among Generation Y Consumers in Malaysia. *Res. Transp. Bus. Manag.* **2022**, *43*, 100784. [\[CrossRef\]](#)
57. Xu, G.; Wang, S.; Li, J.; Zhao, D. Moving Towards Sustainable Purchase Behavior: Examining the Determinants of Consumers' Intentions to Adopt Electric Vehicles. *Environ. Sci. Pollut. Res.* **2020**, *27*, 22535–22546. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Woodruff, R.B. Customer Value: The Next Source for Competitive Advantage. *J. Acad. Mark. Sci.* **1997**, *25*, 139–153. [\[CrossRef\]](#)
59. Hsu, C.L.; Lin, J.C.C. Exploring Factors Affecting the Adoption of Internet of Things Services. *J. Comput. Inf. Syst.* **2018**, *58*, 49–57. [\[CrossRef\]](#)
60. Wang, L.; Wei, L.; Zhou, X.; Xiao, W. The Impact of Consumer Perception on the Purchase Intention of Mid-to-High-End New Energy Vehicles: The Moderating Role of Individual Innovativeness. *Bus. Manag.* **2024**, *8*, 92–101. [\[CrossRef\]](#)
61. Wang, Z.X.; Jantan, A.H.B.; Wu, R.X.; Gong, Y.; Cao, M.R.; Wong, P.P.W.; Wang, L. Exploring Consumers' Intention toward Domestic Energy-Saving Vehicles: Some Insights from China. *Front. Psychol.* **2022**, *13*, 927709. [\[CrossRef\]](#)
62. Zhang, W.; Wang, S.; Wan, L.; Zhang, Z.; Zhao, D. Information Perspective for Understanding Consumers' Perceptions of Electric Vehicles and Adoption Intentions. *Transp. Res. Part D Transp. Environ.* **2022**, *102*, 103157. [\[CrossRef\]](#)
63. Hu, X.; Zhou, R.; Wang, S.; Gao, L.; Zhu, Z. Consumers' Value Perception and Intention to Purchase Electric Vehicles: A Benefit-Risk Analysis. *Res. Transp. Bus. Manag.* **2023**, *49*, 101004. [\[CrossRef\]](#)
64. Chakraborty, U.; Bhat, S. The Effects of Credible Online Reviews on Brand Equity Dimensions and Its Consequence on Consumer Behavior. *J. Promot. Manag.* **2018**, *24*, 57–82. [\[CrossRef\]](#)
65. Bougoure, U.S.; Russell-Bennett, R.; Fazal-E-Hasan, S.; Mortimer, G. The Impact of Service Failure on Brand Credibility. *J. Retail. Consum. Serv.* **2016**, *31*, 62–71. [\[CrossRef\]](#)
66. Wang, X.; Yang, Z. The Effect of Brand Credibility on Consumers' Brand Purchase Intention in Emerging Economies: The Moderating Role of Brand Awareness and Brand Image. *J. Glob. Mark.* **2010**, *23*, 177–188. [\[CrossRef\]](#)
67. Sweeney, J.; Swait, J. The Effects of Brand Credibility on Customer Loyalty. *J. Retail. Consum. Serv.* **2008**, *15*, 179–193. [\[CrossRef\]](#)
68. Behnood, A.; Haghani, M.; Golafshani, E.M. Determinants of Purchase Likelihood for Partially and Fully Automated Vehicles: Insights from Mixed Logit Model with Heterogeneity in Means and Variances. *Transp. Res. Part A Policy Pract.* **2022**, *159*, 119–139. [\[CrossRef\]](#)
69. Antonialli, F.; Cavazza, B.H.; Gandia, R.M.; Nicolai, I.; de Miranda Neto, A.; Sugano, J.Y.; Zambalde, A.L. Autonomous Vehicles, Are They 'Riding' in a Blue Ocean? In *12th European Conference on Innovation and Entrepreneurship ECIE 2017, Paris, France, 21–22 September 2017*; Academic Conferences International Limited: Reading, UK, 2018; Volume 36, pp. 2–3.
70. Liang, J.; Li, Y.; Yin, G.; Xu, L.; Lu, Y.; Feng, J.; Cai, G. A MAS-Based Hierarchical Architecture for the Cooperation Control of Connected and Automated Vehicles. *IEEE Trans. Veh. Technol.* **2022**, *72*, 1559–1573. [\[CrossRef\]](#)
71. Hengstler, M.; Enkel, E.; Duelli, S. Applied Artificial Intelligence and Trust—The Case of Autonomous Vehicles and Medical Assistance Devices. *Technol. Forecast. Soc. Change* **2016**, *105*, 105–120. [\[CrossRef\]](#)

72. Ribeiro, M.A.; Gursoy, D.; Chi, O.H. Customer Acceptance of Autonomous Vehicles in Travel and Tourism. *J. Travel Res.* **2022**, *61*, 620–636. [[CrossRef](#)]
73. Liu, H.; Yang, R.; Wang, L.; Liu, P. Evaluating Initial Public Acceptance of Highly and Fully Autonomous Vehicles. *Int. J. Hum.-Comput. Interact.* **2019**, *35*, 919–931. [[CrossRef](#)]
74. Zhu, G.; Chen, Y.; Zheng, J. Modelling the acceptance of fully autonomous vehicles: A media-based perception and adoption model. *Transp. Res. Part F Traffic Psychol. Behav.* **2020**, *73*, 80–91. [[CrossRef](#)]
75. Kenesei, Z.; Ásványi, K.; Kökény, L.; Jászberényi, M.; Miskolczi, M.; Gyulavári, T.; Syahrivar, J. Trust and Perceived Risk: How Different Manifestations Affect the Adoption of Autonomous Vehicles. *Transp. Res. Part A Policy Pract.* **2022**, *164*, 379–393. [[CrossRef](#)]
76. Hewitt, C.; Politis, I.; Amanatidis, T.; Sarkar, A. Assessing Public Perception of Self-Driving Cars: The Autonomous Vehicle Acceptance Model. In Proceedings of the 24th International Conference on Intelligent User Interfaces, New York, NY, USA, 17–20 March 2019; pp. 518–527. [[CrossRef](#)]
77. Wali, B.; Santi, P.; Ratti, C. Modeling Consumer Affinity Towards Adopting Partially and Fully Automated Vehicles—The Role of Preference Heterogeneity at Different Geographic Levels. *Transp. Res. Part C Emerg. Technol.* **2021**, *129*, 103276. [[CrossRef](#)]
78. Sun, X.F.; Zhao, Y.; Lyu, C.M. Influencing Mechanism of Human-Computer Interaction Trust in Autonomous Vehicles. *J. Northeast. Univ. (Nat. Sci.)* **2022**, *43*, 1305–1313. [[CrossRef](#)]
79. Liu, X.; Zheng, X. The persuasive power of social media influencers in brand credibility and purchase intention. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 15. [[CrossRef](#)]

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