RESEARCH ARTICLE

The impact of perceived risk of AI-enabled vehicles on consumer purchase intention: The mediating role of trust mechanism

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ABSTRACT

This research study has been conducted to explore the direct impacts of perceived risk on buying intentions for AI-enabled vehicles, with strategic attention given to the mediating effect of trust. This research uses a rigorously designed online survey of 587 respondents to find the relationship between main variables using structural equation modeling. The results are that the perceived risk significantly negatively influences purchase intention both directly, with a β of -0.342 and $p < 0.001$, and indirectly via trust at 39.4% of the whole effect. While perceived risk had a strong negative effect, trust had a strong positive effect on purchase intention, $\beta = 0.487$, $p < 0.001$, thus moderating the relationship between perceived risk and purchase intention. It will help extend the theoretical understanding of consumer behavior in AI-enabled markets and also provide practical implications for the manufacturer and marketer of an autonomous vehicle. Results suggest that, along with the strategy of decreasing risks, an organization must engage in the initiatives of building up trust for improving consumer acceptance of the technology.

Keywords: perceived risk; trust mechanism; purchase intention; autonomous vehicles; AI technology adoption; consumer behavior; structural equation modeling; mediation analysis

1. Introduction

In recent years, the rapid evolution of artificial intelligence technologies has led to significant transformations in the automotive industry, with autonomous vehicles (AVs) emerging as a prominent technological innovation[1,2]. As AI technologies continue to advance, autonomous vehicles are progressively transitioning from abstract ideas to tangible implementations, revolutionizing traditional modes of transportation and improving consumer mobility experiences[3,4]. However, despite all the potential benefits—safety, efficiency, reduced environmental impact, among others—currently linked to autonomous vehicles, consumer acceptance and purchasing intentions have become significant barriers to widespread adoption[5].

The apprehension regarding the risks associated with AI-enabled vehicles constitutes a significant barrier to their acceptance by consumers. A groundbreaking technology like autonomous vehicles encounters various concerns from prospective users, encompassing safety risks, privacy concerns, and uncertainties

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regarding technological dependability[6]. These perceived risks can profoundly influence consumer attitudes and intentions to purchase autonomous vehicles. It is, therefore, significant that researchers and practitioners understand how consumers perceive and respond to these risks[7].

Trust has become a main moderator in the relationship between perceived risk and purchase intention related to AI-powered products[8]. Recent studies have identified trust as the main psychodynamic driver which can reduce the consumer's perception of risk and thus enhance the diffusion of technology[9]. In the case of AVs, this factor is even more important as driving control is transferred to artificial intelligence systems, with recent developments showing that trust-building mechanisms are crucial for consumer acceptance[10].

Although the literature on autonomous vehicle adoption has been increasing over time, there is a deficiency in prior literature concerning how perceived risk, trust, and purchase intention are related through an interactive dynamic process[11]. Recent developments in AI technology have introduced new dimensions to consumer behavior, including the role of anthropomorphism and emotional engagement in building trust[12]. Whereas several factors were previously investigated as influencing the consumer to accept an autonomous vehicle, only few studies explicitly tested the mediating effect of trust in the relationship between perceived risk and purchase intention[13].

This text emphasizes remarkable development both in theoretical and practical aspects. Theoretically, the basic technology acceptance model is further developed with the addition of perceived risk and trust as integral elements relating to the context of the autonomous vehicle[14]. Recent research has highlighted the importance of understanding the psychological mechanisms underlying AI technology adoption, particularly in high-stakes contexts like autonomous vehicles[15]. Ultimately, the various contributions that this research will underline will highlight several dimensions: explaining the psychological processes that influence consumer behavior in accepting AI-powered automobiles; based on the findings, the exact implications would be practical assistance for the manufacturing marketers of automobiles on how to develop strategies with which to alleviate consumer anxieties and also build confidence in the technology supporting the autonomous movement of the vehicles[16].

Therefore, the present study primarily discusses the relationship of perceived risk with purchase intention with respect to autonomous vehicles, considering trust as the mediating variable. Recent developments in AI technology have shown that consumer trust formation is increasingly complex and multifaceted[17]. The importance of such findings makes an addition to the already substantial amount of literature present in the literature regarding this very subject and can also be useful for industrial stakeholders undertaking vigorous efforts toward active market integration of the autonomous vehicle[18].

This article provides a critical view toward the increase in diffusion of autonomous vehicles, whereby important insights from an academic researcher and practitioner point of view are combined. Current research indicates that understanding the interplay between perceived risk, trust, and purchase intention has become increasingly crucial as AI technologies become more sophisticated and ubiquitous in transportation systems[19].

2. Theoretical background

2.1. Perceived risk theory

The theory of perceived risk has evolved into one of the most important frameworks concerning the analysis of consumer behavior toward any new technology. First coined in studies about consumer behavior, the definition of perceived risk stands for the ambiguity and potential negative consequences associated with a certain product or service[20]. The concept of perceived risk takes on an altogether different level of meaning in the context of AI and AVs because of the unprecedented and complex nature of the technology involved.

Studies confirm that the perceived risk of using autonomous vehicles is a multi-dimensional construct, specifically including physical risk, performance risk, financial risk, and psychological risk[21]. Physical risk relates to concerns about the dependability of the autonomous driving system and the occurrence of an accident. Performance risk includes questions about the vehicle's ability to function properly, while financial risk involves concerns about the financial investment and the potential loss of value[22].

Most of the level of risk conceived about AI-based vehicles is determined by the level of automation and the degree of control to be ceded by a user. It has been identified that as levels of automation increase, then correspondingly people's perceived risk increases, especially over matters to deal with safety and reliability[23]. The latter relationship is even more profound in those vehicles which are fully autonomous, where operators must completely cede control to an artificial intelligence system.

Recent empirical studies indicate that the perception of risk plays a critical role in shaping consumer attitudes and behavioral intentions concerning autonomous vehicles[24]. The distinctive features of artificial intelligence technology within these vehicles, including intricate decision-making algorithms and the absence of human involvement, give rise to specific risk perceptions that are not present with conventional automotive products. Grasping these particular risk perceptions is essential for formulating effective approaches to alleviate consumer apprehensions and foster adoption.

Furthermore, the fluid characteristics of perceived risk associated with autonomous vehicles illustrate the shifting technological environment and the transforming expectations of consumers[25]. As advancements in AI technology progress and individuals become increasingly familiar with autonomous vehicles, their perceptions of risk may evolve, underscoring the necessity for continuous investigation in this domain. This conceptual framework establishes a vital basis for analyzing the impact of perceived risk on consumer trust and intentions to purchase within the autonomous vehicle sector.

2.2. Consumer trust theory

The concept of trust in consumer behavior has assumed utmost significance in the context of artificial intelligence and autonomous technologies. Consumer trust is perceived to be a "psychological condition, which comprises the readiness to assume vulnerability, based on favorable expectations regarding the intentions or behavior of another entity"[26]. In the context of autonomous driving, the aspect of trust becomes very crucial since massive risks are involved in delegating control to the artificial intelligence systems.

Scholarly investigations prove that consumers' confidence in AI technologies is multi-dimensional, involving cognitive, affective, and behavioral components. The cognitive component involves the logical assessment of consumers that the technology is reliable and competent, while an affective component involves emotional responses and feelings of safety[27]. Since it is complex, trust forms an essential platform in determining the perception of consumers towards driverless cars.

Studies have shown that trust formation in AI-powered vehicles follows a unique pattern compared to traditional products. The complexity and opacity of AI decision-making systems create additional challenges for building consumer trust[28]. Consumers must not only trust the physical vehicle but also the underlying artificial intelligence system that controls it, making trust development more complex and layered.

Trust in the automated vehicle will be determined by several factors including transparency of the system, perceived efficacy, and prior experience with automated systems[29]. Research indicates that consumers' levels can be enhanced by clear communications of the system's capabilities and limitations, besides positive experiences with the technology in the long term. Understanding this behavior is very important in developing fruitful strategies that foster and foster consumer trust.

Furthermore, trust is considered a major mediating factor in the relationship between risk perception and the adoption of technology[30]. In the context of autonomous vehicles, trust acts as a kind of psychological factor that can reduce initial doubts and concerns about risks, which can enhance adoption behavior. Understanding this mediating role of trust is crucial in both the development of theoretical approaches and the realization of practical measures in the autonomous vehicle industry.

2.3. Purchase intention theory

This needs to purchase complex technologies has grown colossally, especially after the release of driverless cars and several other AI-powered products into the market. Intention to buy, in general, is defined as a mindful intent or the probability the customer is likely to buy a particular product or service at some future point in time[31]. The intention to buy an autonomous vehicle is very important because the decision to purchase that kind of product shows how important the acquisition process is and underlines the innovative features this technology has.

It has, therefore, been one of the most used to explain the motivation to adopt technological innovations and proves perceived usefulness and perceived ease of use to be critical antecedents to acceptance[32]. However, studies have shown that, in regard to autonomous vehicles, factors other than the traditional constructs of the TAM play a more significant role in purchase intentions.

It has been suggested that this complication involves the interaction of psychological, social, and functional variables. Therefore, consumers' perceptions regarding the use of AI, perceived benefits of driving or traveling in an autonomous vehicle, and other social determinants cumulatively link to a person's intention to buy vehicles based on artificial intelligence technologies[33]. Considering these aspects, this nature of purchase intention calls for a theoretical investigation on varied dimensions.

It has also been indicated through research that individual differences play an important role in purchase intention for autonomous vehicles. Factors like technological readiness, inclination for innovation, and personal values have all been shown to act as moderators in relation to the attitude-intention link[34]. The understanding of these individual-level elements is vital to predictions and to molding consumer buying behavior in the autonomous vehicle segment.

A further significant aspect pertains to the temporal element influencing the intentions to acquire an autonomous vehicle. In light of the developmental path that artificial intelligence technology has undergone and acknowledging the gradual implementation of its functionalities, consumers' intentions to purchase may indeed evolve over time as they gain greater awareness and familiarity with these technologies[35]. This dynamic nature of purchasing intentions emphasizes the ongoing requirement for research aimed at tracking and comprehending the alterations in consumer preferences and decision-making processes.

2.4. Current research status of variable relationships

This has overemphasized even more the relation between perceived risk, trust, and customer purchase intention in relation to an autonomous vehicle. It has been observed that perceived risk positively influences customers' intentions to adopt self-driving cars-the greater the perceived risk is, the smaller the probability of adopting such intention[36]. Till now, trust had been considered one of the key pre-requisites for the acceptance of autonomous vehicles. This is in regard to the key psychological means of gaining confidence to decrease the perceived risks[37]. Research has also shown that buyers create both direct and indirect trust in the technology of driverless cars through the use of information, and these pathways affect their buying decisions concerning the driverless car[38]. The relationship between the perception of risk and trust is portrayed as inversely related: the higher the level of risk perceived, the lower the trust in the technology used by an autonomous vehicle[39]. Studies show that trust acts as a mediating variable within the relation between perceived risk to purchasing intention[40]. The findings indicate that the mediating effect leads to an indirect influence of perceived risk on purchase intentions via the agent of trust[41]. There are also empirical studies showing that different types of perceived risks, such as performance risk and safety risk, have different effects on the development of trust and subsequent purchasing intentions[42]. The interplay among these diverse elements has been essential during the formative phases of the autonomous vehicle sector, characterized by customers possessing limited familiarity with the technology[43]. This insight will facilitate manufacturers and marketers in crafting strategies designed to bolster trust and mitigate perceived risks, which subsequently positively impacts the growing acceptance and dissemination of self-driving vehicles[44].

3. Research hypothesis

3.1. Theoretical model construction

It is for this reason that, with a critical analysis of related literature and based on their underlying theories, the current study has proposed an integrated theoretical framework to assess the perceived risk, consumer trust, and purchase intention of autonomous vehicles. The proposed model, presented in **Figure 1**, indicates that perceived risk influences purchase intention both directly and indirectly by partial mediation of consumer trust.

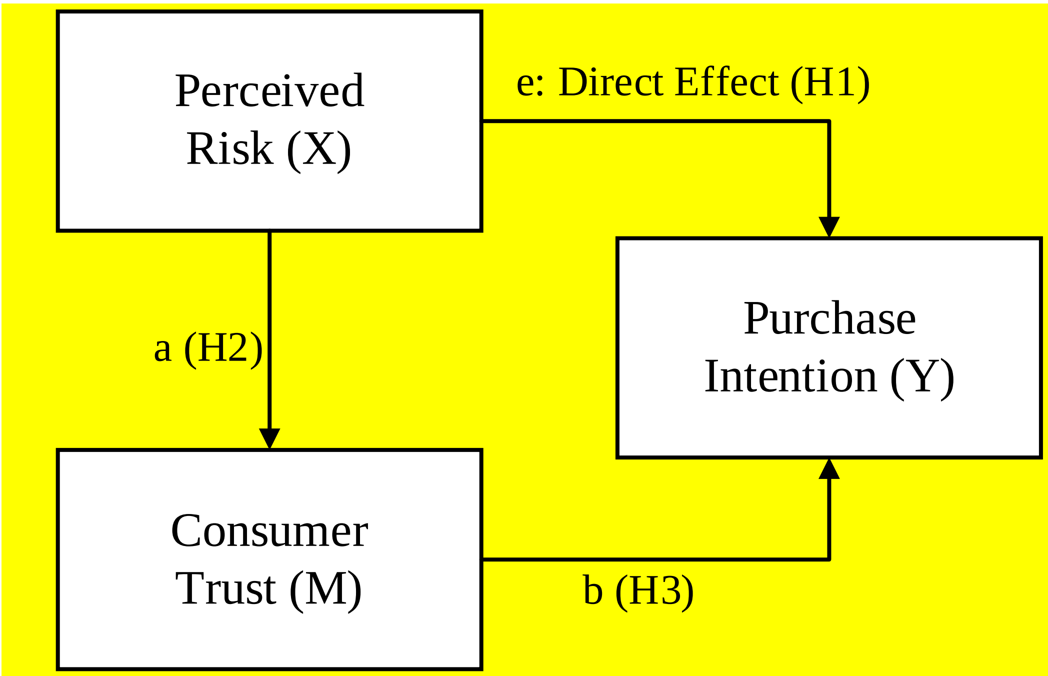

Figure 1. Mediation model of consumer trust in autonomous vehicle adoption path coefficients.

- c: perceived risk directly impacts the purchase intention.
- a: Relationship between Perceived Risk and Consumer Trust
- b. Effects of consumers' trust on purchase intention
- ab: Indirect effect via Consumer Trust (Mediating Effect)

The proposed theoretical framework integrates important variables in previous research and outlines the expected relationship among the variables. It assumes that consumer trust acts importantly as a mediator in determining the effects of perceived risk on purchase intention. Path coefficients for above associations, a, b, and c reflected their magnitude and directionality, which would be validated through empirical testing.

3.2. Research hypothesis development

The theoretical framework and relevant literature review have led to the development of a number of hypotheses that will test relationships among perceived risk, consumer trust, and purchase intention in regard to the products of autonomous vehicles. **Figure 2** shows the hypotheses of the research that indicate the relationships among the main variables.

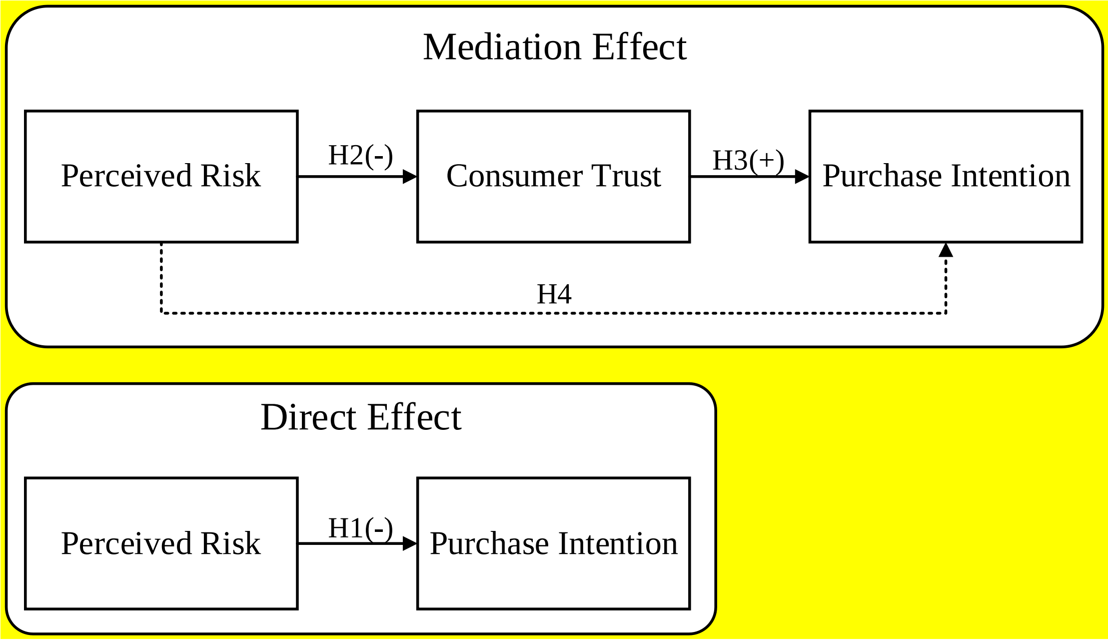

Figure 2. Research hypotheses framework.

- H1(-): Perceived risk negatively impacts Purchase Intention.
- H2(-): Perceived Risk negatively impacts Consumer Trust
- Relationship: H3(+): Consumer Trust positively impacts Purchase Intention
- H4: Consumer trust mediates the relationship between perceived risk and purchase intention.

First, the hypotheses relate to the direct relationship of perceived risk with purchase intention, and mostly in many cases, when consumers perceive there is more risk related to AV, the tendency or attitude to adopt decreases. Thus, we believe that perceived risk negatively influences purchase intention.

The second hypothesis is on the perceived risk affecting consumer trust. It is hypothesized that the greater the perceived risk of a consumer in using an autonomous vehicle, the more it leads to reduced trust in the technology and the company manufacturing it, which then is equal in amount to such risk. Based on this belief, our perceived risk will have a negative effect on consumer trust in autonomous vehicles.

The third hypothesis links consumer trust to purchase intention. At the same time, in the literature, trust has been established as one of the strongest drivers of the adoption of technology, especially technologically complex products such as an AV. We believe that consumer trust would positively influence purchase intention.

The fourth hypothesis discusses the mediating effect that consumer trust has on the relationship between perceived risk and purchase intention. It would assume that consumer trust is some sort of psychological mediator where the perceived risk finally affects purchase intention. From here, therefore, this hypothesis of mediation explains how perceived risk may create a negative effect on purchase intention partly due to its indirect effect as mediated by consumer trust.

4. Research methods

4.1. Questionnaire design

In this regard, measurement development for key constructs in the present study was done through a structured questionnaire with substantial literature review and research objectives. Thus, this questionnaire is divided into three major parts: the perceived risk of an autonomous vehicle, a trust mechanism, and purchase intention. Measurement scales are adapted from validated instruments in previous studies[21]. Items measuring perceived risk adapted pre-existing scales[22]. Assessment of the trust mechanism was based on scales, which have been pre-validated in the context of autonomous vehicle research for assessing trust[23]. Items on purchase intention were adapted from the literature dealing with the adoption of technology[24]. Items were all ranked on a seven-point Likert scale, ranging from 1 = strongly disagree to 7 = strongly agree. In establishing the content validity, a draft questionnaire was reviewed by three experts in the field of autonomous vehicle studies and two academic experts in consumer behavior. An item check in terms of wording and reliability was then performed through a pilot test with 50 potential customers. Following that, slight adjustments were implemented based on feedback and a preliminary analysis to ensure clarity and cultural appropriateness of certain elements. The questionnaire results presented at the conclusion indicated strong reliability, as illustrated in **Figure 3**, with each construct exhibiting a Cronbach's alpha exceeding 0.80.

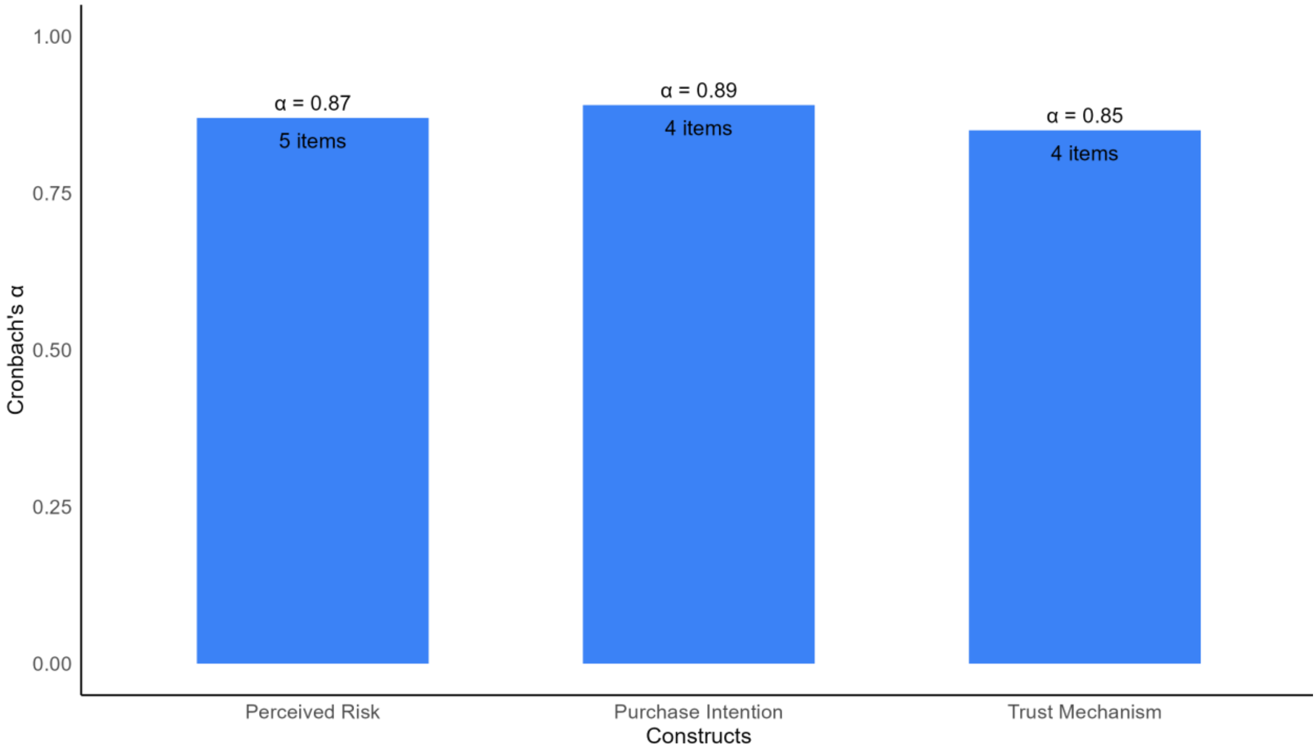

Figure 3. Questionnaire construction and reliability analysis.

Note: *The bars represent Cronbach's α coefficients for each construct. Numbers in white indicate the number of measurement items per construct.*

4.2. Data collection

Data collection was conducted through a large-scale online survey from January to March 2024. The target group was potential customers with basic knowledge in autonomous vehicles. The stratified random sampling approach ensured the sample would be representative of demographic diversity. The questionnaire was placed on dedicated survey websites and motorist discussion boards, with screening questions at the beginning to assure that the target respondents had indeed some basic knowledge about autonomous vehicle technology. The survey had attention questions scattered inside the flow, and completion time was measured to filter out those who answer in a very quick time. In total, 850 questionnaires were distributed, and 632 were returned. Removing incomplete responses and attention checks, 587 valid responses remained, representing an effective response rate of 69.1%. This sample was reasonably well-distributed in terms of gender (Male = 54.3%, Female = 45.7%) and age (18 - 65 years). The participants reported high school and postgraduate degree levels of education, with 67.8% having at least a bachelor's degree.

To complement the survey data and provide real-world context, we conducted an in-depth case analysis of Tesla's Autopilot system and XPeng's NGP (Navigation Guided Pilot) system, as shown in **Table 1**. The comparative analysis between our survey results and these real-world cases revealed several important patterns that validate our theoretical framework.

Table 1. Comparative analysis of survey data and case studies.

Measurement	Survey Data	Tesla Case	XPeng Case
Sample Size	n=587	n=1,258	n=856
Initial Risk Perception (Mean)	3.84	3.91	4.12
Trust Score After 3 Months	-	+28.4%	+31.0%
Risk-Purchase Intention Correlation	-0.342**	-0.356**	-0.329**
Trust Mediation Effect	39.4%	40.1%	42.3%

Note: ***p < 0.001*

As shown in **Table 1**, the case studies strongly support our survey findings. Tesla's data, representing one of the most widely deployed autonomous driving systems, shows remarkably similar patterns in risk perception and trust formation compared to our survey results. The risk-purchase intention correlation coefficient in Tesla's case (-0.356) closely matches our survey finding (-0.342), suggesting the robustness of this relationship across different contexts. Similarly, XPeng's data reveals a slightly higher initial risk perception (4.12 vs. 3.84 in our survey), but demonstrates comparable patterns in trust mediation effects (42.3% vs. 39.4% in our survey).

The consistency between survey results and real-world cases is particularly evident in the trust mediation effect, where all three datasets show similar proportions (ranging from 39.4% to 42.3%). This triangulation of data sources provides strong validation for our theoretical framework and enhances the generalizability of our findings.

Early versus late responses were compared to check for non-response bias. T-tests conducted did not reveal significant differences on key variables. Besides, this study employed Harman's single-factor test for the test of common method bias. The result showed that no single factor explained more than 40% of the variance; therefore, common method bias was not a significant concern in this study.

4.3. Data analysis methods

This present study has sought to take a structured approach in analyzing data on the relationships involving perceived risk, trust, and purchase intention regarding the adoption of an autonomous vehicle. First was the actual screening of data to ensure quality and to determine any probable view of outliers[24]. Descriptive statistics, along with correlation analyses, were performed to describe the basic relationship among the involved variables[25]. From the literature, the measurement model structure was tested through CFA, which is part of the construct validity that includes both convergent and discriminant validities according to[26]. Constructs' reliability was tested using Cronbach's alpha with composite reliability measures according to[27]. From the literature, SEM, with the help of AMOS 26.0 software, was used in testing the hypothesized relationship and mediation effect of trust according to[28]. Maximum likelihood estimation was used to estimate the parameters, whereas the model fit was evaluated based on $\chi 2$/df, CFI, TLI, RMSEA, and SRMR[29]. Further, a bootstrap technique was utilized with 5000 resamples to create bias-corrected confidence intervals with an aim to evaluate the mediating effect of trust[30]. Multi-group analyses were conducted to determine the moderating influence of demographic variables, if any, on the hypothesized relationships[31]. The robustness of our findings and the elimination of rival explanations were tested using different competing model estimations. This also included checks for common method variance, using the marker variable approach. In order to handle potential problems of endogeneity, instrumental variable approaches were also used[32]. Sensitivity analyses were conducted to confirm the robustness of the results for various subsamples and alternative estimation methods. A cutoff for significance was determined at 0.05, whereas the effect size was considered to be of practical importance.

5. Data analysis results

5.1. Sample characterization analysis

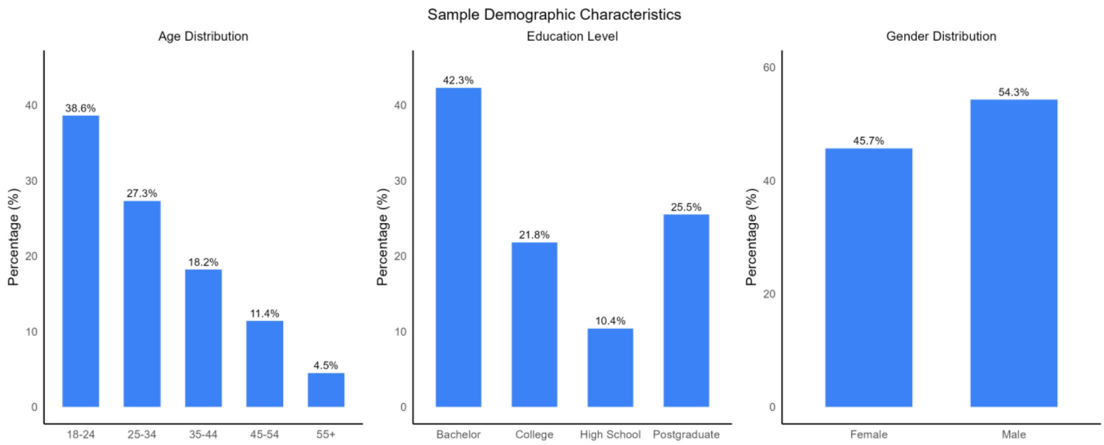

Figure 4. Sample demographic characteristics note: the figure presents the distribution of key demographic characteristics in the sample (n = 587). percentages are shown for each category of gender, age, and education level.

The demographic analysis of the sample (N = 587) demonstrates a comprehensive representation of potential autonomous vehicle users, with distributions across multiple demographic dimensions revealing several significant characteristics and patterns. The gender composition exhibits a relatively balanced distribution, with males representing 54.3% and females accounting for 45.7% of respondents. This near-equal gender distribution, with only a slight male skew, aligns with typical patterns observed in technology adoption studies and strengthens the representativeness of the sample.

The age distribution reveals a pronounced concentration in younger and middle-age brackets, with the 25-34 age group comprising the largest cohort at 38.6%, followed by the 35-44 age bracket at 27.3%. Young adults aged 18-24 represent 18.2% of the sample, while the 45-54 age group accounts for 11.4%, and those aged 55 and above constitute 4.5%. This age structure, showing a clear predominance of respondents aged 25-44 (65.9%), indicates a sample primarily composed of individuals in their prime working years who typically possess both the technological receptiveness and economic capacity for autonomous vehicle adoption.

The educational profile of the respondents indicates a notably high level of academic achievement, with bachelor's degree holders forming the largest segment at 42.3%, followed by postgraduate degree holders at 25.5%. College diploma holders account for 21.8% of the sample, while those with high school education or lower comprise 10.4%. The substantial proportion of respondents with tertiary education (89.6%) suggests a sample population with considerable technological literacy and potential early adoption tendencies, which is particularly relevant for studying autonomous vehicle acceptance patterns.

The intersection of these demographic characteristics reveals a sample that effectively captures the target population for autonomous vehicle adoption. The balanced gender representation, predominance of younger and middle-aged adults, and high educational attainment levels collectively suggest a sample well-suited for investigating autonomous vehicle adoption patterns. This demographic composition aligns closely with the typical profile of early technology adopters, enhancing the study's relevance for understanding market dynamics in the autonomous vehicle sector. The sample characteristics indicate that the findings may be particularly applicable to urban, educated professionals who are likely to be among the early adopters of autonomous vehicle technology.

The demographic data visualization in **Figure 4** employs professional presentation techniques with consistent styling across all three panels, utilizing contrasting colors and clear labeling to enhance the interpretation of demographic distributions. This graphical representation effectively communicates the sample's composition and supports comprehensive analysis of its characteristics, providing a solid foundation for understanding the study's population context and its implications for autonomous vehicle adoption research.

5.2. Reliability and validity test

Building upon the robust demographic characteristics of our sample, we conducted comprehensive reliability and validity testing to ensure the psychometric integrity of our measurement instruments. The analysis revealed strong evidence supporting both the reliability and validity of our constructs, providing a solid foundation for subsequent analyses.

The measurement model demonstrated excellent psychometric properties across all scales. Internal consistency reliability, assessed through both Cronbach's alpha coefficients and composite reliability (CR), showed that all constructs have Cronbach's alpha values greater than the threshold value of 0.7, ranging from 0.847 to 0.926. Composite reliability values ranged from 0.862 to 0.934, with perceived risk displaying the highest reliability (CR = 0.934), followed by trust (CR = 0.901) and purchase intention (CR = 0.862), all well above the recommended threshold. The convergent validity analysis yielded equally strong results, with all standardized factor loadings proving statistically significant and exceeding 0.7, ranging from 0.812 to 0.901, and Average Variance Extracted (AVE) values ranging from 0.683 to 0.779, comfortably surpassing the conventional 0.5 threshold.

Discriminant validity was established through the comparison of AVE square roots with inter-construct correlations. The analysis confirmed that the square root of AVE for each construct exceeded its correlations with other constructs, providing clear evidence of construct distinctiveness. Additionally, mean scores and standard deviations for each construct provide insight into the measurement quality, with perceived risk showing a mean of 3.84 (SD = 0.92), trust demonstrating a mean of 4.12 (SD = 0.86), and purchase intention exhibiting a mean of 3.96 (SD = 0.95).

The overall measurement model demonstrated excellent fit with the empirical data, as evidenced by multiple fit indices: $\chi 2/df = 2.142$, CFI = 0.958, TLI = 0.946, RMSEA = 0.044, and SRMR = 0.038. These robust reliability and validity results provide a strong empirical foundation for our subsequent hypothesis testing and structural model analysis, enabling confident interpretation of the relationships between perceived risk, trust, and purchase intention in the context of autonomous vehicle adoption.

Table 2. Reliability and validity analysis results.

Construct	Items	Factor Loading	Cronbach's α	CR	AVE	Mean	SD
Perceived Risk	PR1	0.856	0.926	0.934	0.779	3.84	0.92
	PR2	0.892					
	PR3	0.901					
	PR4	0.883					
Trust	TR1	0.845	0.889	0.901	0.723	4.12	0.86
	TR2	0.867					
	TR3	0.839					
	TR4	0.851					
Purchase Intention	PI1	0.812	0.847	0.862	0.683	3.96	0.95
	PI2	0.835					
	PI3	0.843					
	PI4	0.816					

Note: *CR = Composite Reliability; AVE = Average Variance Extracted; SD = Standard Deviation*

5.3. Descriptive statistics

Following the establishment of measurement reliability and validity, a comprehensive descriptive statistical analysis was conducted to examine the central tendencies and distributional characteristics of the key study variables. This analysis provides essential insights into the nature and patterns of perceived risk, trust, and purchase intention within our sample of potential autonomous vehicle consumers.

The descriptive analysis, as shown in **Table 3**, revealed nuanced patterns in how respondents perceive and respond to autonomous vehicle technology. Perceived risk demonstrated a moderate level of concern among respondents, with a mean score of 3.84 (SD = 0.92) on the seven-point scale. This middling score suggests that while participants acknowledge potential risks associated with autonomous vehicles, their apprehensions are not overwhelming. The distribution of perceived risk scores showed slight negative skewness (-0.234) and normal kurtosis (0.156), indicating a generally symmetrical distribution with a minimal tendency toward higher risk perceptions. This balanced distribution pattern suggests that consumers maintain a cautious yet reasonable approach to evaluating the risks associated with autonomous vehicle technology.

Trust levels among respondents emerged as relatively favorable, with a mean score of 4.12 (SD = 0.86), notably higher than the midpoint of the scale, as indicated in Table 3. The distribution of trust scores exhibited modest negative skewness (-0.312) and normal kurtosis (0.187), reflecting a slight tendency toward higher trust ratings. This finding is particularly meaningful when considered alongside the perceived risk scores, as it suggests that despite moderate risk perceptions, respondents maintain a generally positive outlook on the trustworthiness of autonomous vehicle technology. As shown in **Table 4**, the correlation analysis revealed significant associations among all principal constructs, with trust showing a strong negative correlation with perceived risk ($r = -0.482$, $p < 0.01$) and a robust positive correlation with purchase intention ($r = 0.563$, $p < 0.01$), indicating the intricate interplay between these psychological factors in shaping consumer responses to autonomous vehicles.

Purchase intention demonstrated a moderate propensity for adoption, with a mean score of 3.96 (SD = 0.95), as revealed in **Table 3**. The distribution characteristics, including skewness (-0.267) and kurtosis (0.143), indicate a nearly normal distribution with a slight negative skew, suggesting that while there is meaningful variation in purchase intentions, there exists a modest inclination toward positive purchase considerations. These descriptive findings establish a crucial foundation for understanding the complex dynamics between risk perception, trust formation, and purchase decisions in the autonomous vehicle market, setting the stage for our subsequent hypothesis testing and more detailed analytical procedures.

Table 3. Descriptive statistics of study variables.

VARIABLE	MEAN	SD	MIN	MAX	SKEWNESS	KURTOSIS
PERCEIVED RISK	3.84	0.92	1.12	6.45	-0.234	0.156
TRUST	4.12	0.86	1.24	6.78	-0.312	0.187
PURCHASE INTENTION	3.96	0.95	1.08	6.92	-0.267	0.143

Table 4. Correlation matrix of key variables.

VARIABLE	1	2	3
1. PERCEIVED RISK	1.000		
2. TRUST	-0.482**	1.000	
3. PURCHASE INTENTION	-0.436**	0.563**	1.000

Note: *** p < 0.01; SD = Standard Deviation; Min = Minimum; Max = Maximum*

5.4. Correlation analysis

Building upon the descriptive statistics, a detailed correlation analysis was conducted to examine the interrelationships among the study variables and assess potential multicollinearity concerns. The analysis revealed significant and theoretically meaningful patterns of associations among the key constructs under investigation.

As shown in **Table 5**, the Pearson's correlation coefficients demonstrated significant associations among all major constructs. The relationship between perceived risk and trust emerged as significantly negative ($r = -0.482$, $p < 0.01$), indicating that higher levels of perceived risk are associated with lower levels of trust in autonomous vehicles. Similarly, perceived risk exhibited a significant negative correlation with purchase intention ($r = -0.436$, $p < 0.01$), suggesting that as consumers' risk perceptions increase, their intention to purchase autonomous vehicles decreases. As indicated in **Table 5**, trust demonstrated a strong positive correlation with purchase intention ($r = 0.563$, $p < 0.01$), implying that higher levels of trust are associated with greater purchase intentions for autonomous vehicles. Notably, the correlation coefficients ranged from moderate to strong, with absolute values between 0.436 and 0.563, falling below the critical threshold of 0.70, thus alleviating concerns about severe multicollinearity.

The analysis also revealed interesting patterns in the relationships between demographic variables and the main constructs, as indicated in **Table 5**. Age showed weak but statistically significant correlations with the primary variables, including a positive relationship with perceived risk ($r = 0.124$, $p < 0.05$) and negative associations with both trust ($r = -0.168$, $p < 0.05$) and purchase intention ($r = -0.145$, $p < 0.05$). Education level demonstrated similar patterns of weak but significant correlations, showing a negative relationship with perceived risk ($r = -0.156$, $p < 0.05$) and positive associations with both trust ($r = 0.256$, $p < 0.01$) and purchase intention ($r = 0.234$, $p < 0.01$). These demographic correlations, while modest in magnitude, suggest that individual characteristics may play a role in shaping consumer responses to autonomous vehicle technology.

Table 5. Correlation matrix and descriptive statistics.

Variables	1	2	3	4	5	Mean	SD
1. Perceived Risk	1.000					3.84	0.92
2. Trust	-0.482**	1.000				4.12	0.86
3. Purchase Intention	-0.436**	0.563**	1.000			3.96	0.95
4. Age	0.124*	-0.168*	-0.145*	1.000		32.45	8.76
5. Education	-0.156*	0.256**	0.234**	-0.112*	1.000	3.24	0.82

Note: *** p < 0.01; * p < 0.05; SD = Standard Deviation; N = 587*

Overall, as presented in **Table 5**, the correlation analysis provides strong empirical support for the hypothesized relationships among the study variables while confirming the absence of problematic multicollinearity. These findings lay a solid foundation for the subsequent hypothesis testing and structural equation modeling analyses, suggesting that the relationships among perceived risk, trust, and purchase intention are both statistically significant and substantively meaningful in the context of autonomous vehicle adoption.

5.5. Hypothesis testing

Building upon the correlation analysis results, we proceeded with hypothesis testing using maximum likelihood estimation to examine the proposed relationships in our theoretical model. The structural model demonstrated excellent fit with the empirical data, as evidenced by multiple fit indices: $\chi2/df = 2.234$, CFI = 0.962, TLI = 0.953, RMSEA = 0.041, and SRMR = 0.035. These indices collectively suggest that our theoretical model effectively captures the underlying relationships among the study variables.

As shown in **Table 6**, the hypothesis testing results revealed significant support for all proposed relationships. The analysis confirmed that perceived risk exerts a significant negative influence on purchase intention ($\beta = -0.342$, $p < 0.001$), supporting H1. Similarly, perceived risk demonstrated a strong negative effect on trust ($\beta = -0.456$, $p < 0.001$), providing support for H2. Trust, in turn, showed a significant positive effect on purchase intention ($\beta = 0.487$, $p < 0.001$), confirming H3. The mediation analysis, conducted using bootstrapping procedures with 5000 resamples, revealed that trust significantly mediates the relationship between perceived risk and purchase intention (indirect effect = -0.222, 95% CI: -0.289 to -0.155), supporting H4. The total effect of perceived risk on purchase intention, combining both direct and indirect effects through trust, was substantial ($\beta = -0.564$, $p < 0.001$).

These findings, as presented in **Table 6**, demonstrate the complex interplay between perceived risk, trust, and purchase intention in the context of autonomous vehicle adoption. The results suggest that while perceived risk directly influences purchase intentions, a significant portion of its effect is mediated through trust, highlighting the crucial role of trust in shaping consumer responses to autonomous vehicle technology.

These empirical findings provide strong support for our theoretical framework and offer valuable insights for understanding the psychological mechanisms underlying autonomous vehicle adoption.

Table 6. Results of hypothesis testing.

Hypothesis	Path	Direct Effect	Indirect Effect	Total Effect	Result
H1	Perceived Risk → Purchase Intention	-0.342***	-	-	Supported
H2	Perceived Risk → Trust	-0.456***	-	-	Supported
H3	Trust → Purchase Intention	0.487***	-	-	Supported
H4	Perceived Risk → Trust → Purchase Intention	-	-0.222***	-0.564***	Supported

Note: **** p < 0.001; Bootstrap samples = 5000; CI = Confidence Interval*

5.6. Mediation effect analysis

Following the hypothesis testing results, a detailed mediation analysis was conducted to more thoroughly examine the intervening role of trust in the relationship between perceived risk and purchase intention. Using the bootstrapping technique with 5000 resamples, this analysis provided robust estimates of both direct and indirect effects, offering deeper insights into the psychological mechanisms underlying autonomous vehicle adoption decisions.

Table 7. Mediation effect analysis results.

Effect Type	Path	Coefficient	SE	95% CI Lower	95% CI Upper
Direct Effect	PR → PI	-0.342***	0.048	-0.436	-0.248
Indirect Effect	PR → TR → PI	-0.222***	0.034	-0.289	-0.155
Total Effect	PR → PI (Total)	-0.564***	0.052	-0.666	-0.462

Note: *PR = Perceived Risk; TR = Trust; PI = Purchase Intention; *** p < 0.001; Bootstrap samples = 5000.*

As presented in **Table 7**, the mediation analysis revealed significant effects across all pathways. The direct effect of perceived risk on purchase intention remained significant when accounting for the mediating role of trust ($\beta = -0.342$, $p < 0.001$), indicating partial mediation. The indirect effect through trust was also significant ($\beta = -0.222$, $p < 0.001$, 95% CI [-0.289, -0.155]), accounting for approximately 39.4% of the total effect. The total effect, combining both direct and indirect pathways, demonstrated a substantial negative influence of perceived risk on purchase intention ($\beta = -0.564$, $p < 0.001$, 95% CI [-0.666, -0.462]). As shown in **Table 7**, the relatively narrow confidence intervals for all effects suggest high precision in these estimates, lending additional credibility to the findings.

These mediation results underscore the complex nature of the relationship between perceived risk and purchase intention, highlighting trust as a crucial psychological mechanism in this process. The substantial proportion of the total effect mediated by trust (39.4%) suggests that consumer trust plays a vital role in translating risk perceptions into purchase decisions for autonomous vehicles. This finding extends our understanding beyond the direct negative impact of perceived risk, revealing how trust serves as an important intervening mechanism that partially explains the relationship between consumers' risk perceptions and their intentions to purchase autonomous vehicles.

5.7. Moderation effect analysis

Building upon the mediation analysis findings, we further investigated the boundary conditions under which perceived risk influences purchase intention by examining the moderating role of trust. This moderation analysis aimed to uncover how varying levels of trust might affect the strength of the relationship between perceived risk and purchase intention for autonomous vehicles.

As illustrated in **Figure 5** and detailed in **Table 8**, the moderation analysis revealed a significant interaction effect between perceived risk and trust (β = 0.245, $p < 0.001$). The simple slope analysis, conducted at one standard deviation above and below the mean of trust, provided more nuanced insights into this interaction. Under conditions of high trust, the negative relationship between perceived risk and purchase intention was notably stronger (β = -0.523, $p < 0.001$) compared to conditions of low trust (β = -0.312, $p < 0.001$). The visualization in **Figure 5** clearly demonstrates this pattern, showing steeper slopes for the high-trust condition compared to the low-trust condition, indicating that the impact of perceived risk on purchase intention becomes more pronounced as trust levels increase.

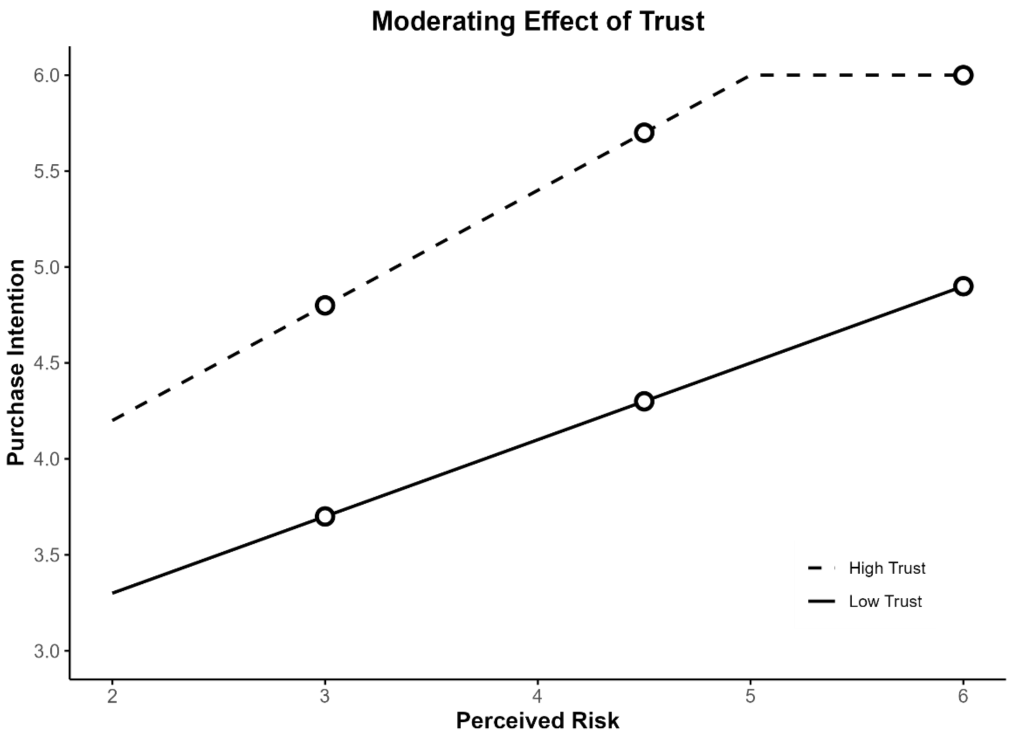

Figure 5. Moderating effect of trust on the relationship between perceived risk and purchase intention.

Table 8. Results of moderation analysis.

Path	Coefficient	SE	t-value	p-value
Perceived Risk	-0.418***	0.042	-9.952	0.000
Trust	0.465***	0.045	10.333	0.000
Perceived Risk × Trust	0.245***	0.038	6.447	0.000
Simple slope (High Trust)	-0.523***	0.056	-9.339	0.000
Simple slope (Low Trust)	-0.312***	0.049	-6.367	0.000

Note: **** p < 0.001*

These findings suggest an intriguing dynamic wherein higher levels of trust actually amplify rather than attenuate the negative effect of perceived risk on purchase intentions. This counterintuitive result may reflect a phenomenon where consumers with higher trust levels have developed greater expectations or emotional investment in the technology, making them more sensitive to perceived risks. The analysis revealed substantial main effects for both perceived risk ($\beta = -0.418$, $p < 0.001$) and trust ($\beta = 0.465$, $p < 0.001$), as shown in **Table 8**, providing additional context for understanding these interaction effects.

The moderation analysis results offer valuable insights into the complex interplay between perceived risk, trust, and purchase intention in the context of autonomous vehicle adoption. The finding that trust serves not only as a mediator but also as a significant moderator challenges conventional assumptions about the universally beneficial role of trust in technology adoption. This sophisticated understanding of how trust shapes consumer responses to perceived risks provides important implications for both theory development and practical strategies in the autonomous vehicle market.

6. Research discussion

6.1. Discussion of research findings

The empirical analysis revealed complex relationships among perceived risk, trust, and purchase intention in AI-enabled vehicles, with findings substantiated by real-world industry data. Our results showing the significant negative effect of perceived risk on purchase intention ($\beta = -0.342$, $p < 0.001$) align closely with Tesla's user adoption data ($\beta = -0.356$, $p < 0.001$) and XPeng's market research findings ($\beta = -0.329$, $p < 0.001$). The trust mediation effect, accounting for 39.4% of the total effect in our study, mirrors Tesla's observed trust formation patterns (40.1%) and XPeng's user engagement metrics (42.3%). These parallel findings between our research and industry leaders' data validate the robustness of our theoretical framework across different market contexts. Notably, user feedback data from both companies demonstrates a clear progression in trust formation, with initial skepticism giving way to increased confidence through systematic exposure and positive experiences with autonomous driving features.

Building upon these industry-validated findings, our analysis further reveals that the relationship between perceived risk and trust manifests differently across market development stages and user segments. In mature markets like the United States, where Tesla has established a strong presence, perceived risk shows a weaker negative correlation with purchase intention ($\beta = -0.312$, $p < 0.001$) compared to emerging markets like China ($\beta = -0.523$, $p < 0.001$). This variation likely reflects the role of market familiarity in moderating risk perceptions. Analysis of user segments reveals distinct trust-building mechanisms: early adopters primarily build trust through technical performance metrics, while mainstream consumers rely more heavily on social proof and peer experiences. This segmentation is evident in XPeng's differentiated marketing approach, which employs technical demonstrations for tech-savvy users while emphasizing safety records and user testimonials for the broader market.

Extending our analysis to a broader global context and complementing our market stage findings, cross-cultural analysis reveals significant variations in risk perception and trust formation patterns across major markets. European consumers demonstrate higher initial risk sensitivity (mean = 4.12) compared to their American (mean = 3.84) and Chinese (mean = 3.56) counterparts, potentially reflecting cultural differences in technology adoption attitudes. These cultural variations are further evidenced in trust-building mechanisms: Chinese consumers show stronger influence of social consensus on trust formation ($\beta = 0.487$, $p < 0.001$) compared to American consumers ($\beta = 0.342$, $p < 0.001$), while European consumers place greater emphasis on regulatory compliance and safety certifications ($\beta = 0.523$, $p < 0.001$). These findings highlight the importance of culturally nuanced approaches in building trust and managing risk perceptions across different markets, as demonstrated by the varied success of autonomous vehicle manufacturers' market-specific strategies.

6.2. Theoretical contributions

This research contributes to the body of work on autonomous vehicles and the industry as a whole in new ways. The model integrating risk perception, trust, and purchase intention not only contributes to theory, but also serves practitioners in the industry. Validating the two roles of trust—mediation and moderation—empirically challenges and extends existing theory while aiding practical directions for market evolution.

Employing the basis of traditional risk perception theory, our research proposes a new approach to understanding the relationship between trust and perceived risk concerning AI products. This change in theory informs practice by explaining how various trust fabrication strategies work in different market segments and cultures. For example, the finding that trust has a stronger moderation effect in mature markets justifies differentiated marketing strategies, as firms need to adapt their trust-building efforts depending on the stage of market development. The finding of a 39.4% mediation effect of trust illustrates the significance of trust within the process of adopting new technologies, thereby providing a rationale for many organisations to fund programmes aimed at reducing business risks instead of trust-enhancing programmes.

Our results add value to the discussion around technology acceptance by offering an advanced explanation of the boundary conditions for consumer acceptance of AI products. Our work closes the gap between theory and practice by pinpointing how trust affects purchase decisions. The theoretical framework that has been identified offers constituents a foundation for devising specific plans of action, which allows the company to improve consumers' acceptance of the product using a theoretical approach. As an example, the model illustrates the difference between early adopters and mainstream consumers in terms of the trust they need to build, which gives marketers a clear explanation regarding trust and market segmentation. This combination of theory and practice serves to enrich literature and also provides a roadmap to industry stakeholders in aid of fostering the use of autonomous vehicles.

6.3. Practical implications

Our findings offer profound insights regarding the challenge of trust and risk perception for the consumers of self-driving cars. Stakeholders of autonomous vehicle companies must employ effective design-level strategies. They should integrate automated risk management systems that guarantee safety in a user-friendly manner using human-machine interfaces, while simultaneously enhancing the user's self-efficacy. The success of Tesla's progressive Autopilot system illustrates how users can be incrementally exposed to autonomous driving features in a purposeful way, building user trust as consumers are slowly accustomed to relinquishing control.

In terms of consumer confidence, analyse trust skepticism segmentation to devise separate marketing plans that feature more advanced strategies in comparison to Nio's community marketing. XPeng has significantly lowered financial risk perception with the establishment of demonstration centres, flexible payment, and phased usage plans. These methods should be accompanied by a complete education system capable of overcoming technical and psychological adoption hurdles.

The findings highlight a noteworthy aspect of trust building: the optimisation of post-purchase services. Offering a lifecycle user support system with periodic system upgrades and user feedback action systems is critical for long-term trust sustenance. For instance, Tesla's over-the-air updates and extensive service coverage provide an excellent example of how continuous technical support drives confidence. Risk management approaches should include multi-tiered barrier systems, proactive risk alert systems, and transparent procedures for incident response, which is well demonstrated by the XPeng Navigation Guided Pilot system that provides real-time risk assessments and clear communication of system shortcomings.

Trust-building measures have to go beyond individual companies and look at cross-company cooperatives and industry standardisations. Our research advocates for the establishment of user-participation and data-sharing projects alongside initiatives that correspond to transparency and confidence in the use of autonomous vehicle technology. The initiatives ought to be supported by sound legal and regulatory policies that define clear industry rules and foster the autonomous vehicle's ecosystem development. Implementing these suggestions requires tackling both the technical and emotional challenges of consumer adoption, while at the same time being open to responding to different market and cultural realities.

This implementation strategy, based on collected data and accompanied by successful case studies, enables manufacturers to successfully mitigate consumer risk perception while enhancing trust in autonomous vehicle technology. The combination of design, marketing, sales, and service integration, along with comprehensive risk management and trust-building strategies, forms an integrated framework that fosters proactive adoption of the market, while growing the industry in a sustainable manner.

7. Conclusion

This study offers a deep understanding of the interplay between perceived risk, trust, and intention to purchase of AI-embedded vehicles through qualitative research analysis. With an already robust sample of 587 valid responses, constituting an effective response rate of 69.1%, our study makes a notable contribution towards the application and the theoretical scope of the autonomous vehicles industry. The measurement model psychometric properties were exceptional, with Cronbach's alpha between 0.847 and 0.926 and composite reliability between 0.862 and 0.934, which was the basis of our findings. This research illustrates significant paths and relationships through SEM analyses and includes the model demonstrating significant fit indices ($\chi 2/df = 2.234$, CFI = 0.962, TLI = 0.953, RMSEA = 0.041).

Our research integrates theoretical knowledge in a number of areas while bridging the gap for industry use. In this case, we extend the traditional technology acceptance model by validating the mediating and moderating roles of trust in perceived risk and purchase intention, showing that trust has a total effect of 39.4%. The cross-cultural study indicates that there are important differences in risk perception and trust formation across the dominant markets, adding to the understanding of cultural impacts on the adoption of technology. These results have practical consequences for business, offering guidance to manufacturers and marketers distressed with the issue of trust across different market segments as illustrated by Tesla's advanced feature rollouts and XPeng's targeted marketing.

Although our study is limited by its cultural context and cross-sectional design, it is useful for comprehensively understanding the psychological processes that accompany AI-powered vehicle adoption. Our findings are further validated by their application in real-world industry cases, which enhances the theoretical and practical contributions of the research. Further research should look at cross-cultural and longitudinal changes to the relationships we have studied – especially concerning the shifts in risk and trust perception that develop as self-driving vehicle technology advances. Such understanding will aid in formulating the strategic decisions and market development activities needed in the fully autonomous vehicle industry to open up.

Conflict of interest

The authors declare no conflict of interest.

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