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TECHNOLOGY CHARACTERISTICS AND POLICY INCENTIVES AFFECT CONSUMERS' PURCHASING INTENTION THROUGH PERCEIVED VALUE AND PERCEIVED RISK

AS CARACTERÍSTICAS TECNOLÓGICAS E OS INCENTIVOS POLÍTICOS INFLUENCIAM A INTENÇÃO DE COMPRA DOS CONSUMIDORES POR MEIO DO VALOR PERCEBIDO E DO RISCO PERCEBIDO

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Yi Guo*
***Suan Sunandha Rajabhat University, Thailand
s64584945041@ssru.ac.th

Niyom Suwandej*
***Suan Sunandha Rajabhat University, Thailand
niyom.su@ssru.ac.th

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Abstract
Technological advancements and government support have become critical factors influencing consumers' purchasing decisions for new energy vehicles (NEVs). This paper aims to explore how technical characteristics and policy incentives affect consumers' purchase intentions through the mediating roles of perceived value and perceived risk. A quantitative analysis was conducted using a partial least squares structural equation model (PLS-SEM) based on data collected from 366 valid questionnaires targeting current and potential NEV consumers in Guangxi. The results indicate that technical characteristics and policy incentives positively influence perceived value, while they negatively influence perceived risk. Additionally, perceived value has a positive impact on purchase intention, whereas perceived risk has a negative impact. Furthermore, perceived value and perceived risk play significant mediating roles in the relationships between technical characteristics, policy incentives, and purchase intention. This paper provides empirical evidence to support NEV companies in product development and market promotion while offering valuable insights for the formulation and optimization of government policies.

Keywords: Technical Characteristics. Policy Incentives. Perceived Value. Perceived Risk. Purchase Intention. PLS-SEM.

Resumo
Os avanços tecnológicos e o apoio governamental tornaram-se fatores críticos que influenciam as decisões de compra dos consumidores em relação aos veículos movidos a energia alternativa (NEVs). Este artigo tem como objetivo explorar como as características técnicas e os incentivos políticos afetam as intenções de compra dos consumidores por meio dos papéis mediadores do valor percebido e do risco percebido. Foi realizada uma análise quantitativa utilizando um modelo de equações estruturais de mínimos quadrados parciais (PLS-SEM), com base em dados coletados a partir de 366 questionários válidos direcionados a consumidores atuais e potenciais de NEVs em Guangxi. Os resultados indicam que as características técnicas e os incentivos políticos influenciam positivamente o valor percebido, enquanto influenciam negativamente o risco percebido. Além disso, o valor percebido tem um impacto positivo na intenção de compra, ao passo que o risco percebido tem um impacto negativo. Ademais, o valor percebido e o risco percebido desempenham papéis mediadores significativos nas relações entre características técnicas, incentivos políticos e intenção de compra. Este artigo fornece evidências empíricas para apoiar as empresas de NEV no desenvolvimento de produtos e na promoção de mercado, ao mesmo tempo em que oferece insights valiosos para a formulação e otimização de políticas governamentais.

Palavras-chave: *Características Técnicas. Incentivos Políticos. Valor Percebido. Risco Percebido. Intenção de Compra. PLS-SEM.*

1 INTRODUCTION

Over the past decade, technological innovation has continuously driven the transformation and upgrading of the new energy vehicle (NEV) industry. Market demand for NEVs has shifted from functional products to intelligent products, with emerging technologies such as autonomous driving and intelligent connectivity becoming key areas for countries seeking to gain a competitive edge in the NEV sector (Xiao & Qi, 2024). Intelligence and networking have become the focal point for major automotive companies following vehicle electrification (Zhao, 2023). Advances in intelligence, networking, and security technologies have made driving more convenient, safe, and comfortable while enabling personalized services, all of which enhance consumers' positive perceptions and purchasing intentions toward NEVs.

Simultaneously, governments worldwide have introduced a series of policy incentives aimed at promoting the adoption and development of NEVs. The most notable policies attracting consumer attention include purchase subsidies, vehicle purchase tax exemptions, exemptions from driving restrictions, and preferential purchasing policies (Wu *et al*., 2023). Furthermore, infrastructure development, such as the construction of charging stations, and related incentive policies guiding NEV usage can effectively stimulate consumer purchasing behavior (Chen *et al*., 2019). Against this backdrop, consumers face multifaceted influences from both technical characteristics and policy incentives when making decisions about purchasing NEVs.

Relevant studies have explored the impact of technical characteristics and policy incentives on consumer behavior. Research conducted by Ozaki & Sevastyanova (2011) highlights that safety and comfort in electric vehicles are paramount concerns for consumers during their purchasing decisions. Empirical studies by Mi *et al*. (2018) reveal that government policies, such as tax reductions, purchase subsidies, and the development of relevant infrastructure, effectively motivate individuals to buy vehicles. Furthermore, Sheng & Xie (2019) found that factors such as performance, safety, brand reputation, and government incentives play a crucial role in shaping consumers' purchasing intentions regarding NEVs. However, there is still a lack of systematic research on how technical characteristics and policy incentives influence consumer behavior through the mediating variables of perceived value and perceived risk. As psychological factors affecting consumers' purchase intentions, perceived value and perceived risk can effectively explain how technological and policy factors shape consumer purchasing decisions through emotional and cognitive pathways.

Based on the Stimulus-Organism-Response (SOR) theory, this study constructs a research model and hypotheses to explore how technical characteristics and policy incentives influence consumers' purchase intentions through the mediating roles of perceived value and perceived risk. This study expands the application of SOR theory within the domain of consumer behavior toward NEVs, offering a novel perspective on the psychological mechanisms driving consumer purchase decisions. Furthermore, it provides empirical support for policymakers in designing effective policy measures and for enterprises in refining technical strategies to strengthen market competitiveness.

2 LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 SOR theory

SOR theory is the stimulus-organism-response theory. It mainly explains that stimulus, as an external factor, will have an impact on people's psychology, and then prompt people to produce corresponding reactions. This reaction can be an internal change or an external behavior. Internal changes usually refer to subjective attitudes, and behavioral reactions refer to the behavior of individuals approaching or avoiding something (Luo & Lv, 2019). When applied to the field of consumer behavior, it can be summarized as stimulus-perception-response, and the three variables are respectively interpreted as various external environmental factors-people's emotional state and emotional response-approach or avoidance behavior. In this study, "S" represents technical characteristics and policy incentives, "O" represents perceived value and perceived risk, and "R" represents consumers' purchase intention.

2.2 Technical characteristics and perceived value

Technical characteristics can enhance consumers' perceived value. Kuang (2023) suggests that the technical features of NEVs can elevate their innovative value, providing consumers with a comfortable and enjoyable consumption experience, thereby enhancing the emotional benefits associated with NEV ownership. Similarly, Wang *et al*. (2023) argue that consumers' perceptions of NEVs are largely shaped by the experiential effects of the product itself, which subsequently influences their perceived value of these vehicles. Therefore, we propose the following hypothesis:

H1: Technical characteristics have a positive impact on perceived value.

2.3 Perceived value and purchase intention

Perceived value can enhance consumers' purchase intention. In the context of NEVs, Chen *et al*. (2019) established that perceived value plays a crucial role in shaping purchase intention, identifying it as a key determinant influencing consumer decisions. Similarly, Kim M.-K.*et al*. (2018), through an analysis of survey data from 285 South Korean drivers, found that perceived value is a critical factor in driving consumers' willingness to purchase electric vehicles. They also highlighted that environmental awareness and economic incentive policies significantly amplify the impact of perceived value on purchase intention. Wang *et al*. (2024) investigated the purchasing intentions of consumers interested in mid-to high-end NEVs, revealing that perceived value positively affects purchase intentions. Therefore, we propose the following hypothesis:

H2: Perceived value has a positive impact on consumers' purchase intention.

2.4 Technical characteristics, perceived value and purchase intention

Technical characteristics can enhance perceived value, thereby strengthening consumers' purchasing intentions. Drawing from technology acceptance theory and SOR theory, Wang *et al*. (2023) identified that perceived value serves as a mediator between the product attributes of NEVs and consumer purchase intention. In line with the perceived benefit-risk framework, Chen *et al*. (2019) demonstrated that the technical features of NEVs, including aspects like battery performance and intelligence level, influence consumers' perceptions of quality and emotional value, ultimately driving their purchasing intention. Therefore, we propose the following hypothesis:

H3: Perceived value mediates the relationship between technical characteristics and purchase intention.

2.5 Technical characteristics and perceived risk

Technical characteristics can reduce consumers' perceived risk. Du (2022) took luxury mid-size SUV car consumers as the research object to explore the impact of automobile product attributes on consumers' purchasing intention, and found that the technical characteristics of the car have a significant negative impact on perceived risk. Xie (2023) studied the impact of the innovative characteristics of NEVs on the diffusion effect, revealed the influence mechanism between innovative characteristics and diffusion effect, and found that the relative advantage of innovation has a significant negative impact on perceived risk. Therefore, we propose the following hypothesis:

H4: Technical characteristics have a negative impact on perceived risk.

2.6 Perceived risk and purchase intention

Perceived risk can reduce consumers' purchasing intentions. Wang & Li (2013) argued that consumers' perceived risk negatively impacts their willingness to purchase NEVs, with financial, physical, and functional risks playing a particularly significant role. Yin *et al*. (2019) developed and validated a theoretical model examining the factors influencing consumers' willingness to buy NEVs, confirming that perceived risk significantly reduces purchase intention. Xu G. *et al*. (2020), applying the SOR framework, found a negative correlation between perceived risk and consumers' willingness to purchase electric vehicles. Similarly, Ren (2024) developed a research framework with four dimensions: attitude, ability, situation, and perceived risk, and found that perceived risk negatively affects consumers' willingness to purchase NEVs. Therefore, we propose the following hypothesis:

H5: Perceived risk has a negative impact on consumers' purchase intention.

2.7 Technical characteristics, perceived risk and purchase intention

Technical characteristics can reduce perceived risk, thereby enhancing consumers' purchasing intentions. Mei (2023) examined the impact of product factors and consumer perceptions on the purchase intentions of NEV consumers and found that perceived risk significantly mediated the relationship. Du (2022) focused on luxury mid-size SUV consumers and discovered that perceived risk served as a mediating factor between the car's functional attributes and consumers' purchase intention. Therefore, we propose the following hypothesis:

H6: Perceived risk mediates the relationship between technical characteristics and purchase intention.

2.8 Policy incentives and perceived value

Policy incentives can enhance consumers' perceived value. Zhang (2024) classified policies related to the use of NEVs into two categories: priority rights and preferential policies. The research revealed that both priority rights and preferential policies have a substantial positive effect on perceived value. Notably, preferential policies play a crucial role in enhancing consumers' evaluation of the value of NEVs. In a similar vein, Wang & Xiong (2023) investigated potential consumer groups for NEVs in Jilin Province, concluding that both subsidy and non-subsidy policies positively influence consumers' perceived value. Therefore, we propose the following hypothesis:

H7: Policy incentives have a positive impact on perceived value.

2.9 Policy incentives, perceived value and purchase intention

Policy incentives can enhance consumers' perceived value, thereby strengthening consumers' purchasing intentions. Cai *et al.* (2022) examined the influence of government incentive policies on the intention to purchase pure electric vehicles and concluded that such policies significantly affect consumers' purchase intentions by shaping their perceptions of price and welfare value. Wang & Xu (2021) highlighted that perceived value partially mediates the relationship between reducing purchase costs and consumers' willingness to buy, as well as between the provision of charging subsidies and consumers' purchase intentions. Therefore, we propose the following hypothesis:

H8: Perceived value mediates the relationship between policy incentives and purchase intention.

2.10 Policy incentives and perceived risk

Policy incentives can reduce consumers' perceived risk. Kuang (2023), using NEVs as a case study, discovered that publicity and promotional policies lower consumers' perceived risks. Additionally, fiscal and tax incentive policies exert an even more pronounced effect on reducing these risks, while technology and infrastructure policies also contribute to mitigating perceived risks. Wang & Xiong (2023) explored the influence of NEV consumption promotion policies in Jilin Province on potential consumers' purchasing intentions, finding that both subsidy and non-subsidy policies affect perceived risk. Similarly, Li *et al.* (2021) examined how various policies for promoting NEV consumption influence potential consumers' purchasing intentions and concluded that publicity policies, as well as road right policies, significantly reduce perceived risk. Therefore, we propose the following hypothesis:

H9: Policy incentives have a negative impact on perceived risk.

2.11 Policy incentives, perceived risk and purchase intention

Policy incentives can reduce consumers' perceived risk, thereby enhancing consumers' purchasing intentions. Li *et al*. (2021) employed a structural equation model to assess the impact of NEV consumption promotion policies on potential consumers, revealing that perceived risk mediates the relationship between these policies and purchase intention. Additionally, Li *et al*. (2023) emphasized the diversity of policy incentives within the dual carbon framework, which includes regulatory measures, supportive infrastructure, technological advancements, and economic incentives, with perceived risk acting as a mediator between these policies and consumers' purchase intentions. Therefore, we propose the following hypothesis:

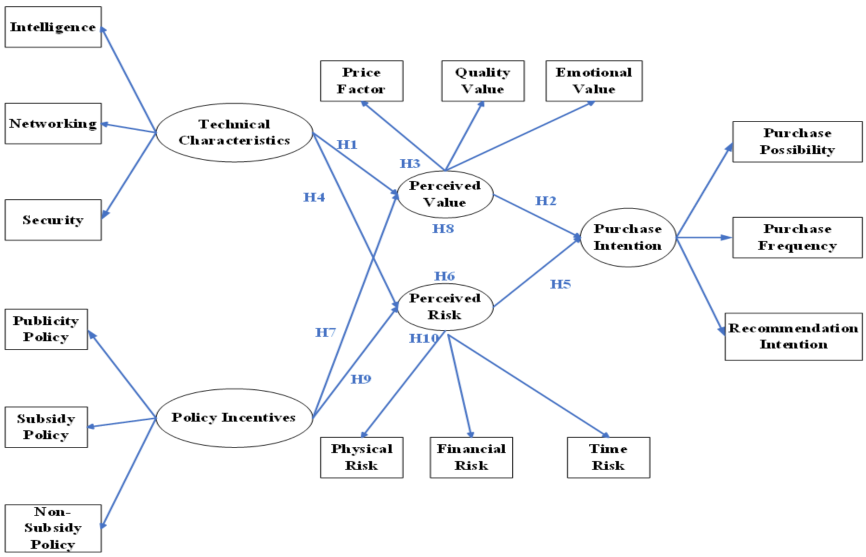
H10: Perceived risk mediates the relationship between policy incentives and purchase intention.

2.12 Research model

Based on the literature review and research hypotheses, the conceptual model of consumers' purchasing intention for NEVs is shown in Figure 1.

Figure 1

Conceptual model



3 METHODOLOGY

3.1 Participants and sample design

The target population consists of both current and potential NEV consumers aged 18 to 60 in Guangxi, with a particular focus on individuals from Liuzhou, Nanning, and Guilin. In order to break through the geographical limitations, this paper used the Questionnaire Star online platform to distribute electronic questionnaires in Nanning, Guilin, and Liuzhou at the same time. The researchers collected a total of 422 questionnaires. After eliminating invalid questionnaires, a total of 366 valid questionnaires were obtained, with an effective recovery rate of 86.7%.

3.2 Measurement

This study employed established measurement scales for variables from both domestic and international sources, modifying the items to align with the specific context of Chinese consumers. The technical characteristics scale contains 10 items, using the three dimensions of intelligence, networking and security to measure this variable, referring to the scale of Zhang *et al*. (2023). The policy incentive scale contains 12 items, and uses three dimensions of publicity policy, subsidy policy, and non-subsidy policy to measure this variable, referring to the scales of Kuang (2023) and Li *et al*. (2021). The perceived value scale consists of 15 items and measures the variable through three dimensions including price factors, quality value, and emotional value, adapted from Chen *et al*. (2019) and Wang *et al*. (2024). The perceived risk scale consists of 15 items and measures the variable through three dimensions including physical risk, financial risk, and time risk, adapted from Chen *et al*. (2019) and Li (2022). The purchase intention scale consists of 12 items and measures the variable through three dimensions including purchase likelihood, purchase frequency, and recommendation intention, adapted from Zhang *et al*. (2023) and Zhang (2024).

4 DATA ANALYSIS AND RESULTS

This study constructs a PLS-SEM model and employs Smart PLS 4.0 software to conduct validity and reliability tests as well as path coefficient analysis to verify the proposed hypotheses.

4.1 Reliability and convergent validity analysis

Internal consistency reliability is commonly evaluated through Cronbach's alpha (CA) and composite reliability (CR). According to Cronbach (1951), the acceptable threshold for Cronbach's alpha is greater than 0.70. Hair, Jr. *et al*. (2016) argued that a

CR value above 0.70 is necessary to demonstrate an acceptable level of internal consistency. As presented in Table 1 and Table 2, the Cronbach's alpha values for all first-order constructs exceed 0.70, while the second-order constructs also meet this threshold, demonstrating that the scale possesses satisfactory internal consistency. Composite reliability (CR) assesses the extent to which the observed variables collectively explain the corresponding latent variables. According to the data in Table 1 and Table 2, the CR values for each construct surpass 0.70, further confirming the strong internal consistency of the measurement model.

As a general guideline, the standardized factor loading should be at least 0.708, as this value squared equals 0.50, meaning that the latent variable explains at least 50% of the variance in each indicator (Hair *et al*., 2019). Furthermore, the AVE value should be no less than 0.50, signifying that the construct accounts for over half of the variance observed in its indicators (Hair Jr. *et al*., 2016). According to Table 1 and 2, all external loadings for the observed variables in both the first-order and second-order structures of this study surpass 0.708, indicating that the measurement model meets the established evaluation criteria. all constructs in this study exhibit AVE values greater than 0.50, confirming that the measurement model demonstrates strong convergent validity.

Table 1

Reliability and validity analysis for first-order constructs

	Loading	T	P	Cronbach's alpha	rho_a	rho_c	AVE
I1 <- I	0.850	43.166	0.000	0.824	0.824	0.895	0.739
I2 <- I	0.877	63.668	0.000				
I3 <- I	0.853	48.279	0.000				
N1 <- N	0.853	41.737	0.000	0.808	0.808	0.887	0.723
N2 <- N	0.864	47.522	0.000				
N3 <- N	0.832	37.465	0.000				
S1 <- S	0.830	44.995	0.000	0.851	0.853	0.900	0.693
S2 <- S	0.775	25.959	0.000				
S3 <- S	0.875	55.849	0.000				
S4 <- S	0.846	49.614	0.000				
PUP1 <- PUP	0.865	47.547	0.000	0.838	0.839	0.902	0.755
PUP2 <- PUP	0.872	64.512	0.000				
PUP3 <- PUP	0.868	61.946	0.000				
SP1 <- SP	0.897	63.821	0.000	0.900	0.901	0.93	0.769
SP2 <- SP	0.887	54.554	0.000				
SP3 <- SP	0.892	58.470	0.000				
SP4 <- SP	0.831	32.266	0.000				
NSP1 <- NSP	0.737	25.659	0.000	0.868	0.871	0.905	0.656

NSP2 <- NSP	0.824	29.860	0.000				
NSP3 <- NSP	0.800	31.611	0.000				
NSP4 <- NSP	0.842	50.867	0.000				
NSP5 <- NSP	0.842	41.938	0.000				
PRF1 <- PRF	0.822	41.896	0.000	0.881	0.884	0.914	0.679
PRF2 <- PRF	0.811	40.027	0.000				
PRF3 <- PRF	0.880	78.081	0.000				
PRF4 <- PRF	0.836	47.328	0.000				
PRF5 <- PRF	0.768	32.911	0.000				
QV1 <- QV	0.827	41.077	0.000	0.862	0.863	0.901	0.644
QV2 <- QV	0.766	25.963	0.000				
QV3 <- QV	0.790	29.791	0.000				
QV4 <- QV	0.799	32.015	0.000				
QV5 <- QV	0.830	42.552	0.000				
EV1 <- EV	0.846	42.907	0.000	0.889	0.890	0.919	0.693
EV2 <- EV	0.858	62.429	0.000				
EV3 <- EV	0.823	41.008	0.000				
EV4 <- EV	0.839	47.817	0.000				
EV5 <- EV	0.794	34.293	0.000				
PHR1 <- PHR	0.858	41.076	0.000	0.910	0.911	0.933	0.736
PHR2 <- PHR	0.865	45.088	0.000				
PHR3 <- PHR	0.885	55.183	0.000				
PHR4 <- PHR	0.834	46.244	0.000				
PHR5 <- PHR	0.847	45.529	0.000				
FR1 <- FR	0.802	33.948	0.000	0.859	0.861	0.899	0.640
FR2 <- FR	0.797	33.699	0.000				
FR3 <- FR	0.813	34.064	0.000				
FR4 <- FR	0.767	28.948	0.000				
FR5 <- FR	0.820	35.969	0.000				
TR1 <- TR	0.751	24.504	0.000	0.864	0.867	0.902	0.649
TR2 <- TR	0.827	40.772	0.000				
TR3 <- TR	0.848	53.585	0.000				
TR4 <- TR	0.813	33.844	0.000				
TR5 <- TR	0.785	28.573	0.000				
PP1 <- PP	0.774	27.512	0.000	0.873	0.881	0.913	0.726
PP2 <- PP	0.852	46.399	0.000				
PP3 <- PP	0.891	69.646	0.000				
PP4 <- PP	0.886	64.489	0.000				
PF1 <- PF	0.854	44.087	0.000	0.850	0.854	0.899	0.691
PF2 <- PF	0.870	51.471	0.000				
PF3 <- PF	0.769	31.508	0.000				
PF4 <- PF	0.829	37.174	0.000				
RI1 <- RI	0.873	47.034	0.000	0.891	0.894	0.924	0.754
RI2 <- RI	0.893	65.196	0.000				
RI3 <- RI	0.892	63.265	0.000				
RI4 <- RI	0.813	32.862	0.000				

Note: I=Intelligence, N=Networking, S=Security, PUP=Publicity policy, SP=Subsidy policy, NSP=Non-subsidy policy, PRF=Price factor, QV=Quality value, EV=Emotional value, PHR=Physical risk, FR=Financial risk, TR=Time risk, PP=Purchase possibility, PF=Purchase frequency, RI= Recommendation intention.

Table 2

Reliability and validity analysis for second-order constructs

	Loading	T	P	Cronbach's alpha	rho_a	rho_c	AVE
I <- TC	0.821	30.475	0.000	0.771	0.771	0.867	0.686
N <- TC	0.836	30.467	0.000				
S <- TC	0.826	40.433	0.000				
PUP <- POI	0.857	52.950	0.000	0.810	0.810	0.888	0.725
SP <- POI	0.845	45.084	0.000				
NSP<- POI	0.852	49.250	0.000				
PRF <- PV	0.841	41.735	0.000	0.806	0.807	0.886	0.721
QV <- PV	0.868	57.843	0.000				
EV <- PV	0.839	40.468	0.000				
PHR <- PR	0.852	47.502	0.000	0.799	0.800	0.882	0.714
FR <- PR	0.844	35.239	0.000				
TR <- PR	0.839	41.041	0.000				
PP <- PI	0.835	43.771	0.000	0.784	0.785	0.874	0.699
PF <- PI	0.849	46.436	0.000				
RI<- PI	0.823	33.486	0.000				

Note: TC=Technical characteristics, POI=Policy incentives, PV=Perceived value, PR=Perceived risk, PI=Purchase intention.

4.2 Discriminant validity analysis

According to Fornell & Larcker (1981), discriminant validity is established when the square root of the average variance extracted (AVE) for each latent variable exceeds its correlation coefficient with any other latent variables. As presented in Tables 3 and 4, the measurement model exhibits satisfactory discriminant validity.

Table 3

Fornell-Larcker criterion of first-order constructs

	I	N	S	PUP	SP	NSP	PRF	QV	EV	PHR	FR	TR	PP	PF	RI
I	0.860														
N	0.535	0.850													
S	0.512	0.540	0.832												
PUP	0.305	0.362	0.447	0.869											
SP	0.28	0.346	0.342	0.587	0.877										
NSP	0.258	0.335	0.344	0.602	0.578	0.810									
PRF	0.433	0.358	0.432	0.413	0.344	0.390	0.824								
QV	0.336	0.402	0.356	0.431	0.398	0.415	0.613	0.803							
EV	0.436	0.457	0.462	0.473	0.433	0.435	0.541	0.602	0.833						
PHR	-0.371	-0.401	-0.404	-0.388	-0.402	-0.379	-0.254	-0.22	-0.276	0.858					
FR	-0.376	-0.374	-0.395	-0.393	-0.37	-0.369	-0.260	-0.258	-0.328	0.584	0.800				
TR	-0.366	-0.422	-0.387	-0.401	-0.41	-0.378	-0.229	-0.207	-0.326	0.573	0.558	0.805			
PP	0.382	0.296	0.355	0.399	0.351	0.368	0.446	0.460	0.418	-0.394	-0.387	-0.345	0.852		
PF	0.366	0.339	0.370	0.409	0.435	0.368	0.431	0.444	0.464	-0.411	-0.426	-0.429	0.582	0.831	
RI	0.352	0.397	0.359	0.368	0.350	0.361	0.459	0.412	0.435	-0.427	-0.400	-0.461	0.530	0.550	0.868

Table 4

Fornell-Larcker criterion of second-order constructs

	TC	POI	PV	PR	PI
TC	0.828				
POI	0.476	0.851			
PV	0.580	0.573	0.849		
PR	-0.556	-0.538	-0.365	0.845	
PI	0.514	0.530	0.619	-0.575	0.836

The heterotrait-monotrait ratio (HTMT) measures the discrimination between latent variables, and usually requires the HTMT value to be less than 0.90, and should be less than 0.85 under stricter standards (Hair *et al*., 2019). As illustrated in Tables 5 and 6, the HTMT values for all latent variables within both the first-order and second-order structures are below the threshold of 0.85. This finding suggests that the measurement model demonstrates acceptable discriminant validity.

Table 5

HTMT discriminant validity of first-order constructs

	I	N	S	PUP	SP	NSP	PRF	QV	EV	PHR	FR	TR	PP	PF	RI
I															
N	0.655														
S	0.611	0.650													
PUP	0.366	0.440	0.532												
SP	0.325	0.406	0.392	0.673											
NSP	0.304	0.398	0.399	0.703	0.653										
PRF	0.509	0.423	0.501	0.480	0.387	0.445									
QV	0.396	0.480	0.416	0.506	0.451	0.479	0.699								
EV	0.508	0.539	0.531	0.548	0.484	0.492	0.610	0.685							
PHR	0.428	0.467	0.459	0.443	0.444	0.426	0.285	0.248	0.307						
FR	0.447	0.447	0.464	0.461	0.422	0.426	0.301	0.301	0.375	0.659					
TR	0.433	0.505	0.451	0.468	0.464	0.434	0.263	0.238	0.372	0.640	0.638				
PP	0.451	0.351	0.411	0.462	0.393	0.425	0.506	0.528	0.473	0.441	0.446	0.394			
PF	0.437	0.407	0.433	0.483	0.497	0.428	0.497	0.518	0.533	0.465	0.499	0.495	0.671		
RI	0.411	0.466	0.412	0.426	0.391	0.408	0.520	0.469	0.488	0.471	0.455	0.521	0.594	0.631	

Table 6

HTMT discriminant validity of second-order constructs

	TC	POI	PV	PR	PI
TC					
POI	0.601				

PV	0.736	0.708		
PR	0.708	0.669	0.454	
PI	0.662	0.665	0.778	0.727

4.3 Structural equation model test

The primary criteria for assessing the structural model in PLS-SEM include the coefficient of determination (R^2), predictive relevance (Q^2), and the significance of the path coefficient. R^2 represents the extent to which the variance of an endogenous latent variable is accounted for by its corresponding predictive latent variables. Chin (1998) provides a more detailed classification: an R^2 value of 0.67 or above signifies strong explanatory power, values between 0.33 and 0.67 represent moderate explanatory power, and values from 0.19 to 0.33 indicate weak explanatory power. If the R^2 is below 0.19, it suggests minimal explanatory ability with limited practical significance. According to Hair *et al*. (2019), as a general guideline, Q^2 values greater than 0, 0.25, and 0.50 are indicative of small, medium, and large levels of predictive relevance, respectively.

As shown in Table 7, the R^2 values for perceived value, perceived risk, and purchase intention all fall within the moderate explanatory power level. All Q^2 values in the model are greater than zero, indicating that the model has a certain level of predictive relevance.

Table 7

R^2 and Q^2 Test

	R^2	R^2adjusted	Q^2 (=1-SSE/SSO)
PV	0.450	0.447	0.319
PR	0.406	0.403	0.285
PI	0.524	0.521	0.363

4.4 Significance of path coefficients

The path coefficient quantifies the direct relationship between latent variables, making its magnitude and significance crucial components in evaluating the structural model. In PLS-SEM, the Bootstrapping technique is commonly applied to repeatedly sample the original dataset, usually 5000 times or more according to Hair Jr. *et al*. (2021), to compute the standard error of the path coefficient. This iterative process enables the calculation of the t-value and the corresponding confidence intervals. In this study, 5000 resampling iterations were performed to test the statistical significance of the path coefficients. The results, including path coefficients, t-values, and p-values for the structural model, are presented in Figure 2 and Table 8.

Figure 2

The path coefficients of the structural model

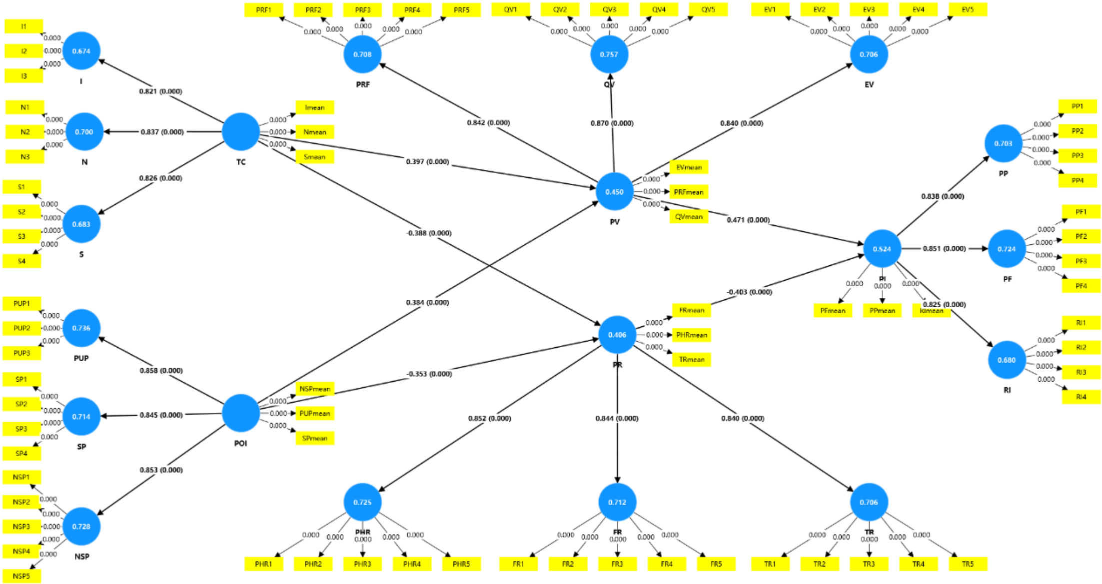


Table 8

The path coefficients and their significance levels from the PLS-SEM

	Original sample	Sample mean	Standard deviation	T statistics	P values
TC -> PV	0.397	0.397	0.041	9.779	0.000
TC -> PR	-0.388	-0.387	0.045	8.549	0.000
POI -> PV	0.384	0.383	0.042	9.203	0.000
POI -> PR	-0.353	-0.353	0.046	7.669	0.000
PV -> PI	0.471	0.471	0.037	12.894	0.000
PR -> PI	-0.403	-0.403	0.039	10.225	0.000

From Table 8 we can see the size and significance of the path coefficients, which can verify whether the research hypotheses are valid. Empirical results indicate that technical characteristics exert a significantly positive influence on perceived value ($\beta=0.397$, $P<0.001$), thereby supporting H1. Additionally, perceived value has a significant and positive effect on purchase intention (β=0.471, $P < 0.001$), confirming H2. The relationship between technical characteristics and perceived risk is found to be significantly negative (β= -0.388, $P<0.001$), thus validating H4. Furthermore, perceived risk exhibits a significantly negative impact on purchase intention (β= -0.403, $P<0.001$), supporting H5. Policy incentives also show a significantly positive effect on perceived value (β=0.384, $P<0.001$), leading to the confirmation of H7. Lastly, policy incentives demonstrate a significant negative effect on perceived risk (β= -0.353, $P<0.001$), supporting H9.

4.5 Mediation effect analysis

PLS-SEM, as a variance-based analytical method, is particularly appropriate for exploratory research and is capable of accurately estimating mediation effects, as noted by Hair Jr. *et al*. (2021). The original data are sampled 5000 times by Bootstrap and a 95% confidence interval is constructed.

As shown in Table 9, the indirect effect of technical characteristics on purchase intention through perceived value is 0.187, with a bias-corrected 95% confidence interval [0.143, 0.236], which does not contain zero. This indicates that the indirect effect is statistically significant, thereby supporting H3. Similarly, the indirect effect of technical characteristics on purchase intention through perceived risk is 0.156, with a bias-corrected 95% confidence interval [0.111, 0.208], which also excludes zero, confirming the significance of the indirect effect and supporting H6. Furthermore, the indirect effect of policy incentives on purchase intention via perceived value is 0.181, with a bias-corrected 95% confidence interval [0.136, 0.233], which does not contain zero, thus verifying the significance of the indirect effect and supporting H8. Lastly, the indirect effect of policy incentives on purchase intention through perceived risk is 0.143, with a bias-corrected 95% confidence interval [0.096, 0.192], which excludes zero, indicating a significant indirect effect and supporting H10.

Table 9

Results of the mediation effect test

	Effec	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics	P values	2.50%	97.50%
TC -> PV -> PI	Indirect effec	0.187	0.187	0.024	7.770	0.000	0.143	0.236
TC -> PR -> PI	Indirect effec	0.156	0.156	0.025	6.300	0.000	0.111	0.208
POI -> PV -> PI	Indirect effec	0.181	0.180	0.025	7.345	0.000	0.136	0.233
POI -> PR -> PI	Indirect effec	0.143	0.142	0.025	5.805	0.000	0.096	0.192
TC -> PI	Total indirect effect	0.344	0.343	0.031	11.133	0.000	0.284	0.406
POI -> PI	Total indirect effect	0.323	0.323	0.033	9.797	0.000	0.259	0.387

5 DISCUSSION AND CONCLUSIONS

This study reveals that technical characteristics have a significant positive impact on perceived value (β=0.397), a conclusion that is consistent with the findings of Wang *et al*. (2023). The technical attributes of NEVs, including intelligence, connectivity, and safety, were seen as enhancing consumers' perceived value across dimensions such as price, quality, and emotional appeal. Perceived value has a significant positive impact on purchasing intention (β=0.471), a conclusion that is consistent with the findings of Kim M.-K. *et al*. (2018). Consumers' perceptions of price, quality, and emotion can enhance their purchasing intention from the perspectives of purchase possibility, purchase frequency, and willingness to recommend. Perceived value mediates the relationship between technical characteristics and purchase intention (β=0.187), a conclusion that is consistent with the findings of Chen *et al*. (2019). Technical characteristics significantly influence consumers' purchasing intentions through perceived value. Technical characteristics have a significant negative impact on perceived risk (β= -0.388), a conclusion that is consistent with the findings of Du (2022). Technical characteristics such as intelligence, networking, and safety in NEVs contribute to reducing perceived risks related to physical harm, financial concerns, and time. Perceived risk has a significant negative impact on purchase intention (β= -0.403), a conclusion that is consistent with the findings of Wang & Li (2013). Consumers' perceptions about finance, physical health, and time can reduce their willingness to buy from the perspectives of purchase possibility, purchase frequency, and willingness to recommend. Perceived risk mediates the relationship between technical characteristics and purchase intention (β=0.156), a conclusion that is consistent with the findings of Mei (2023). Technical characteristics significantly influence consumers' purchasing intentions through perceived risk. Policy incentives have a significant positive impact on perceived value (β=0.384), a conclusion that is consistent with the findings of Zhang (2024). Various incentive policies, including publicity, subsidy, and non-subsidy policies for NEVs, can enhance consumers' perceived value in terms of price, quality, and emotional appeal. Perceived value mediates the relationship between policy incentives and purchase intention (β=0.181), a conclusion that is consistent with the findings of Wang and Xu (2021). Policy incentives significantly influence consumers' purchasing intentions through perceived value. Policy incentives have a significant negative impact on perceived risk (β= -0.353), a conclusion that is consistent with the findings of Wang and Xiong (2023). Incentive policies, including publicity, subscription, and non-subsidy policies for new energy vehicles, help mitigate consumers' perceived risks in terms of physical harm, financial concerns, and time. Perceived risk mediates the relationship between policy incentives and purchase intention (β=0.143), a conclusion that is consistent with the findings of Li *et al*. (2021). Policy incentives significantly influence consumers' purchasing intentions through perceived risk.

The empirical results indicate that both technical characteristics and policy incentives exert a significant influence on perceived value and perceived risk. Additionally, perceived value positively affects purchase intention, while perceived risk has a negative impact. Notably, perceived value and perceived risk serve as crucial mediating variables in the relationship between technical characteristics, policy incentives, and purchase intention. These findings enrich the theoretical explanation of how external stimuli affect purchasing decisions in consumer behavior research, deepen the understanding of the new energy vehicle consumption decision-making mechanism, and also provide important decision-making references for governments and enterprises in the promotion of new energy vehicles.

REFERENCES

Cai, J. H., Li, S. Q., & Jia, L. S. (2022). Research on the relationship between government incentive policies and the purchase intention of pure electric vehicles: Based on the theory of consumer perceived value. *Science and Technology and Economy*, 4, 71–75.

Chen, K., Gu, R., & Hu, J. (2019). Study on the willingness to purchase new energy vehicles based on the perceived benefit-perceived risk framework. *Journal of Nanjing Tech University (Social Science Edition)*, 2, 61–70, 112.

Chen, K., Ren, C., Gu, R., & Zhang, P. (2019). Exploring purchase intentions of new energy vehicles: From the perspective of frugality and the concept of "mianzi". *Journal of Cleaner Production*, 230, 700–708.

Chin W. W. (1998). The partial least squares approach to structural equation modeling. *Modern methods for business research*. Lawrence Erlbaum Associates.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, 16(3), 297–334.

Du, Y. Q. (2022). The impact of automobile product attributes on consumer purchasing intention: A case study of luxury mid-sized SUVs [Master's thesis, Shanghai University of Finance and Economics].

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, 18(1), 39–50.

Hair Jr., J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*. Springer Nature.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24.

Hair, Jr., J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: Part I – method. *European Business Review*, 28(1), 63–76.

Kim, M.-K., Oh, J., Park, J.-H., & Joo, C. (2018). Perceived value and adoption intention for electric vehicles in Korea: Moderating effects of environmental traits and government supports. *Energy*, 159, 799–809.

Kuang Yuanyuan. (2023). Research on the market vitality stimulation mechanism of low-carbon supply chain products [Master's thesis, Suzhou University of Science and Technology].

Li, C., Ye, L. L., & Wang, L. P. (2021). The impact of new energy vehicle consumption promotion policies on potential consumers’ purchase intentions. *China Management Science*, 10, 151–164.

Li, W. L. (2022). Research on the subsidy model of the new energy vehicle industry in Shenzhen [Master's thesis, Harbin Institute of Technology].

Li, X. D., He, S. K., Dai, Q. C., & Mou, B. (2023). The impact of multiple policies on consumers’ purchase intention of new energy vehicles under the dual carbon background. *Journal of Chongqing University of Technology (Natural Science)*, 11, 362–371.

Luo, Z. W. & Lv, L. X. (2019). The impact of cause marketing on consumer attitudes and its theoretical explanation. *Advances in Psychological Science*, 4, 737–747.

Mei, J. Y. (2023). Research on the influencing factors of consumers’ purchasing new energy vehicles [Master's thesis, Shanghai University of Finance and Economics].

Mi, L. Y., Yu, X. Y., & Yang, J. (2018). Research on the influencing factors of knowledge-based consumers' new energy vehicle purchasing behavior: An exploration based on grounded theory. *Enterprise Economy*, 4, 19–26.

Ozaki, R., & Sevastyanova, K. (2011). Going hybrid: An analysis of consumer purchase motivations. *Energy Policy*, 39(5), 2217–2227.

Ren, Y. T. (2024). Analysis of new energy vehicle marketing strategies from the perspective of consumer purchasing intentions. *E-Commerce Letters*, 13, 2007.

Sheng, L. J., & Xie, T. (2019). Research on the influencing factors of consumers' purchasing intention of new energy vehicles. *China Business Review*, 21, 84–87.

Wang, L. L., Wei, L. P., Zhou, X. L., & Xiao, W. W. (2024). The impact of consumer perceptions on the purchase intention of mid-to-high-end new energy vehicles: Based on the moderating role of individual innovation. *Business and Management*, 8, 92–101.

Wang, M. H., & Xiong, B. C. (2023). Analysis of the impact of consumer promotion policies for new energy vehicles on potential consumer purchase intention in Jilin Province. *Journal of Hunan University of Finance and Economics*, 6, 18–25.

Wang, R. H., Yan, C. Y., Zhu, J. Y., Yang, Z. Q., Zhou, Z. Y., & Li, R. R. (2023). Research on the influencing mechanism of consumers' green purchase intention of new energy vehicles under the background of low-carbon economy: An empirical analysis based on six provinces and one city in East China. *Modern Industrial Economy and Informatization*, 9, 56–62.

Wang, Y. L., & Xu, K. (2021). The impact of policy support on consumers' purchase intention of new energy vehicles under the COVID-19 pandemic. *Journal of Shanghai University of Electric Power*, 1, 47–52, 56.

Wang, Y., & Li, Y. (2013a). Empirical research on consumer purchase intention of new energy vehicles based on perceived risk and involvement. *Mathematical Statistics and Management*, 5, 863–872.

Wu, Z., He, Q., Li, J., Bi, G., & Antwi-Afari, M. F. (2023). Public attitudes and sentiments towards new energy vehicles in China: A text mining approach. *Renewable and Sustainable Energy Reviews*, 178, 113242.

Xiao, X., & Qi, Y. D. (2024). Research on the ideas and paths for reconstructing the foundation of China's new energy vehicle industry. *Journal of Beijing Normal University (Social Sciences Edition)*, 3, 148–156.

Xie, R. Y. (2023). The influence of innovation characteristics on diffusion effects: Based on the study of risk amplification factors [Doctoral dissertation, Northwest University].

Xu, G., Wang, S., Li, J., & Zhao, D. (2020). Moving towards sustainable purchase behavior: Examining the determinants of consumers' intentions to adopt electric vehicles. *Environmental Science and Pollution Research*, 27(18), 22535–22546.

Yin, J. L., Zhang, Z. Q., Liao, G. L., & Ge, X. Q. (2019). Research on consumers' new energy vehicle purchase intention based on the technology acceptance model and perceived risk theory. *Forecasting*, 6, 83–89.

Zhang, D. H. (2024). Research on the impact of priority rights and preferential policies on the initial purchase intention of new energy vehicles [Master's thesis, Tianjin University of Finance and Economics].

Zhang, G. F., Wang, Q., & Jing, L. (2023). The impact of new energy vehicle technology characteristics on consumer purchase intention. *Journal of Wuhan University of Technology*, 9, 103–109.

Zhao, C. Z. (2023). Exploring the application prospects of user ecosystems and the "new four modernizations" in cars based on SWOT. *Vibrance*, 24, 196–198.

Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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