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Hierarchical Behavioral Models: A SOR-TPB Framework for Electric Vehicle Adoption in China

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Abstract

Background and Aim: Despite the rapid expansion of China's electric vehicle (EV) market, fueled by robust policy support and technological innovation, understanding consumer adoption dynamics is crucial for developing effective policies. Previous research often isolates particular drivers, such as subsidies or psychological traits, while neglecting the integrated effects of multidimensional policy frameworks and cognitive constructs. This study reconceptualizes the integration of the Stimulus–Organism–Response (SOR) model and the Theory of Planned Behavior (TPB) by proposing a hierarchical, theory-driven framework that clarifies the indirect pathways connecting policy mix, perceived value, psychological factors, and EV purchasing behavior.

Materials and Methods: This study employs a reconceptualized second-order framework to connect first-order constructs to behavioral outcomes. In total, 658 valid responses were collected from potential electric vehicle (EV) consumers in five strategically selected regions across China. Utilizing a two-stage Partial Least Squares Structural Equation Modeling (PLS-SEM), the study rigorously assesses measurement robustness and structural relationships within a multi-layered SOR–TPB model.

Results: The findings reveal that the policy mix significantly enhances both perceived value ($\beta = 0.686$, $p < 0.001$) and psychological factors ($\beta = 0.398$, $p < 0.001$), with direct implications for purchase behavior ($\beta = 0.318$, $p < 0.001$). Furthermore, perceived value exerts a strong influence on psychological factors ($\beta = 0.536$) and purchase intention ($\beta = 0.433$), whereas psychological factors significantly mediate intention ($\beta = 0.480$), which subsequently affects behavior ($\beta = 0.315$). Importantly, direct effects from the policy mix or perceived value to intention, and from psychological factors to behavior, were insignificant, underscoring the predominance of indirect mediation as the principal behavioral pathway.

Conclusion: This study provides theoretical and methodological contributions by reconceptualizing second-order constructs in EV adoption research. It emphasizes aligning multidimensional policy instruments with consumers' cognitive mechanisms to optimize behavioral outcomes. The proposed hierarchical SOR–TPB model presents a robust analytical framework for future behavioral research and offers actionable insights for policymakers and organizations seeking to expedite the sustainable transition to electric mobility in emerging markets.

Keywords: Hierarchical Behavioral Model; Electric Vehicles; Policy Mix; Perceived Value; Psychological Factors; Purchase Intention; Purchasing Behavior; PLS-SEM; China

Introduction

Electric vehicles (EVs) are increasingly seen as a vital strategy in the global effort to combat climate change and support energy transitions. This is particularly true in China, the world's largest market for electric vehicles, where comprehensive policy measures — such as subsidies, tax exemptions, and infrastructure development—are implemented to stimulate consumer adoption (Tian et al., 2021; Zhang et al., 2013). Despite these efforts, a persistent intention–behavior gap remains, particularly among first-time EV adopters, wherein consumers express a strong intention to adopt EVs but fail to follow through with actual purchase behavior (Gupta et al., 2024; Zhao et al., 2024).

Existing research primarily examines EV adoption from two independent perspectives: the policy perspective, which emphasizes instrumental factors like subsidies and license plate preferences (Liu et al.,

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2017), and the psychological perspective, which focuses on cognitive factors including attitudes and risk perception (Wei et al., 2024). However, these streams of research largely overlook how the policy environment and consumer psychology interact, creating a fragmented understanding of the adoption process. Chen et al. (2023) emphasize the absence of theoretical integration in current research, while Gondoiswanto and Wijaya (2023) further confirm this limitation, suggesting that without a comprehensive framework, understanding the complexities of EV adoption remains elusive.

This study proposes a novel approach that integrates the stimulus-organism-response (SOR) model with the Theory of Planned Behavior (TPB) to establish a hierarchical framework capable of elucidating the intricate relationships between policy interventions, psychological factors, and consumer behavior. This integration is realized in two steps: first, transforming standardized first-order latent variables into measurement indicators, then constructing second-order constructs such as policy mix (PM) and perceived value (PV). This method preserves multidimensional characteristics while enhancing model interpretability (Su & Wan, 2024), aligning with the optimization direction proposed by Wang et al. (2017).

We empirically validate this model by analyzing data from 658 respondents across five Chinese regions, employing a two-stage Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This rigorous methodology not only assesses measurement robustness but also uncovers the indirect behavioral mechanisms through which policy interventions shape psychological readiness and influence both purchase intention (PI) and purchase behavior (PB).

By bridging policy design with consumer psychology through a reconceptualized hierarchical model, this study significantly contributes to the literature on EV adoption and behavioral modeling, offering valuable insights that can aid policymakers, marketers, and EV manufacturers in emerging economies striving for a sustainable mobility transition.

Objectives and Contributions

To investigate the mechanisms by which policy mix directly influences purchase behavior, while not directly influencing purchase intention

Theory and Literature Review

1. Electric Vehicle Adoption: An Overview

Through decisive policy intervention, technological progress, and changes in consumer preferences, China has now become a global leader in the production and consumption of electric vehicles (Broadbent et al., 2017; Wang, 2024). Measures such as the government-led "dual credit" policy, state subsidies, and infrastructure investment have driven the exponential growth of the market (Gomes et al., 2022; Zhou & Yang, 2021). Despite the remarkable effectiveness of market feedback, there is still a considerable gap between consumers' purchasing intention and the adoption rate of electric vehicles. (Bai & Tan, 2021). This gap may stem from consumer skepticism about policy sustainability—for instance, rural charging subsidies (Xue et al., 2023) may be perceived as temporary, delaying adoption decisions. Many existing studies have isolated the technical, financial, or psychological dimensions without integrating them into a comprehensive behavioral framework. In order to assist the government and enterprises in formulating effective promotion strategies for electric vehicles, it is necessary to have a more unified understanding of consumer behavior influenced by policy and cognitive drivers (Yang & Jianyi, 2023; Zhang & Qin, 2018).

2. Behavioral Theories: SOR and TPB Frameworks

The stimulus-organism-response model (SOR) is derived from the classical stimulus-response theory, and its core view is that external environmental stimuli will change the individual's cognitive and emotional states and eventually trigger specific behaviors (Mehrabian & Russell, 1974)Research focusing on emotion assessment (EV) finds that policy signals and market incentives significantly affect consumers' perceived emotions, thus affecting their purchase intention and behavior.

The Theory of Planned Behavior (TPB) was proposed by Ajzen (1991). The influence mechanism of attitude, subjective norm, and perceived control on behavioral intention is emphasized. Although this theory

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has been fully verified in environmental behavior studies (such as EV purchase decisions of electric vehicles) (Liu et al., 2017), existing applications often ignore the systematic role of external environmental stimuli.

This study innovatively combines the SOR model with TPB theory to establish a hierarchical analysis framework. Policy mix and perceived value act as external stimuli in the framework, psychological factors form internal response mechanisms, and purchase intention and behavior are the outcomes. This cross-theoretical integration connects the macro policy and micro decision-making process and provides a new perspective for comprehensively explaining the electric vehicle (EV) consumption behavior.

3. Perceived Value

Consumers' comprehensive evaluation of product utility and cost constitutes the core of perceived value (Zeithaml, 1988). The concept contains three key dimensions: functional value, emotional value, and social value.

Functional value (FUN): Refers to consumers' rational evaluation of the actual attributes of a product, including objective indicators such as vehicle performance and battery life, as well as the responsiveness of policy incentives (Han et al., 2017).

Emotional Value (EMO) comes from the emotional connection between users and brands. Actual cases show that high-quality test driving experience, timely after-sales service, and innovative designs such as NIO's battery swapping system can effectively enhance consumer trust (Zhang et al., 2024).

Social Value (SOC): Reflects the identity differences that vehicle use brings. Urban consumers tend to regard EVs as a symbol of an environmentally friendly lifestyle (Wang et al., 2023). While rural users pay more attention to vehicle utility functions, a difference that is particularly evident in cross-regional comparisons (Pamidimukkala et al., 2024).

Analyzing the differences in perceived value of different user groups is crucial for formulating accurate EV marketing strategies and policy schemes.

4. Psychological Factors

Multiple psychological mechanisms affect consumers' decision-making process when they choose electric vehicles. These mechanisms include perception judgment, attitude tendency, social pressure perception, and other elements, which together act on the formation and realization of purchase intention.

Social and subjective norms (SSN) mainly reflect the influence of social groups on car purchase decisions. For example, the purchasing behaviors of relatives and friends around them, as well as regional cultural concepts, will significantly change consumers' choice intentions, which is particularly obvious in a society that emphasizes collective consciousness (Peng & Bai, 2024).

Perception and attitude (PA): derived from consumers' awareness of environmental protection and depth of technical understanding. Studies have shown that consumers who are familiar with electric vehicle technology are more likely to have a positive attitude, which directly affects the purchase decision (Morton et al., 2015).

Perceived Behavioral Control (PBC): involves consumer evaluation of the convenience of using a car. The more fully the information about charging facilities coverage and car purchase cost is obtained, the easier it is for consumers to transform their purchase intention into actual actions (Zhang et al., 2022).

Trust (TRU): Accepting new technology products highly depends on trust building. In particular, the confidence in battery technology and the after-sales support system directly affects whether consumers are willing to try electric vehicles (Aditiya et al., 2024).

These psychological elements play a bridging role between the policy environment and consumer behavior, and are an important basis for predicting the market reaction of electric vehicles.

5. Purchase Intention and Behavior

Purchase intention refers to the motivation of consumers to purchase electric vehicles (EVs), which reflects the cognitive commitment to subsequent behaviors (Ajzen, 1991; Li et al., 2020). Purchase behavior is the actual completion of the purchase action under realistic conditions. Purchase intention is influenced by psychological factors, including external factors such as attitude, subjective norm, behavioral control,

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policy incentives, and value perception, while actual purchase behavior is influenced by environmental factors such as vehicle price, performance, and charging facilities (Chandon et al., 2005; Lee & Lee, 2011).

Policy ambiguity, inadequate infrastructure, and immature markets often hinder the transformation of intentions into behavior. Research shows that policy stability, information transparency, and accurate value perception can significantly improve the probability of purchase behavior (Chang, 2023; Lin & Shen, 2022). Exploring the gap between intention and behavior is important for developing effective strategies for translating consumption intention into actual EV use.

6. Modeling Higher-Order Constructs: Repeated Indicator, Two-Stage, and Theoretical Approaches

Higher-order constructs (HOCs) present abstract concepts with multiple sub-dimensions. The repeated index method assigns all indicators of LOCs to the HOC. Although this method is intuitive and easy to use, it is easy to cause multicollinearity, inflate the R-squared value, and often limit the inclusion of exogenous predictor variables due to shared measurement variance (Sarstedt et al., 2019).

The two-stage rule estimates LOCs in the first stage and then uses construct scores as HOC indicators in the second stage. This can reduce measurement redundancy and improve parameter accuracy, especially when HOC is an endogenous variable. However, when there are multiple HOCs, the model design becomes complicated because all LOCs need to be connected in the first stage according to the HOC structure, which may cause the path model inflation and reduce the interpretability (Cheah et al., 2024).

To address these limitations, this study adopts a **theoretical approach** that departs from the strict modeling of HOC structures in the first stage. Instead, each LOC is modeled based on its theoretical relevance (e.g., as guided by SOR and TPB), independent of hierarchical structure. In the second stage, **standardized construct scores of the LOCs are used directly as reflective indicators of the HOC**, reducing complexity while preserving theoretical clarity. This approach, illustrated in Figures 1 and 2, ensures model parsimony and allows the inclusion of multiple second-order constructs without overloading the path model.

7. Research Gap and Theoretical Contribution

Despite the prevalence of numerous studies concerning electric vehicle (EV) adoption, the existing literature fails to present a cohesive model that integrates multidimensional policy constructs alongside consumer cognition within a hierarchical framework. Most prior models have treated variables as first-order elements, neglecting the layered complexity inherent in behavioral decision-making. Additionally, conventional methodological approaches frequently depend on repeated indicators or simplistic two-stage methods, constraining theoretical interpretability.

This study addresses these gaps by:

- Reconceptualizing second-order constructs using latent score transformation.
- Integrating SOR and TPB frameworks in a unified hierarchical model.
- Introducing a theoretical approach to modeling HOCs that emphasizes parsimony and interpretability.
- Highlighting indirect pathways from policy stimuli to behavioral outcomes.

This approach contributes to theory and practice by offering a more robust framework for analyzing and promoting EV adoption behavior in emerging markets like China.

Conceptual Framework and Hypothesis Development

Based on the stimulus-organism-response (SOR) and Theory of Planned Behavior (TPB) frameworks, this study established a hierarchical structure model to analyze the impact of policy and psychological mechanisms on electric vehicle (EV) purchase behavior. The model covers three second-order constructs, policy mix (PM), perceived value (PV), and psychological factors (PF), which are all constituted by the corresponding first-order dimensions.

The policy mix (PM) contains policy consistency (CON), coherence (COH), credibility (CRE), local adaptation (LOC), and communication effectiveness (POL) to reflect the design quality of policies related

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to electric vehicles. Perceived value (PV) contains functional value (FUN), emotional value (EMO), and social value (SOC), and these value dimensions will affect the evaluation of consumers. Psychological factors (PF) include perception and attitude (PA), social norm (SSN), perceived behavioral control (PBC), and trust (TRU), which represent internal cognitive mediating factors.

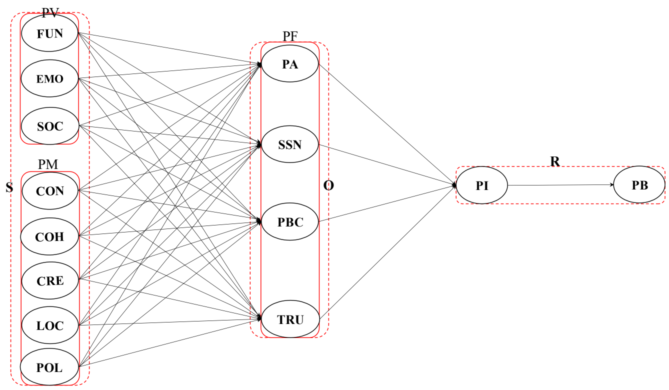

Figure 1 First-order model

Figures 1 and 2 present the model's first-order and second-order structure. These constructs follow the SOR logic (stimulus → organism → response) and can be used to examine both direct and indirect effects. The study used a theoretical two-stage PLS-SEM approach with standardized first-order scores as a reflection indicator of higher-order constructs. This helps to enhance the simplicity, clarity, and theoretical precision of complex behavior modeling.

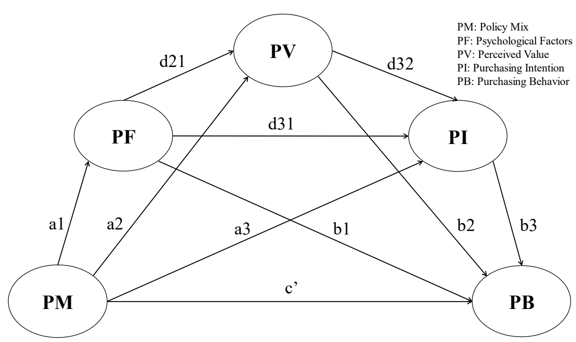

Figure 2 Second-order model

a1. Policy Mix → Psychological Factors (H1)

A policy mix integrating fiscal incentives, regulatory tools, and infrastructure support is key in shaping consumer psychology. Based on the theory of Planned Behavior (TPB) framework (Ajzen, 1991). External policies affect behavioral decision-making through four core dimensions: attitude, subjective norm, perceived behavioral control, and trust. Local adaptive policies (such as special subsidies for rural charging) can enhance the perceived relevance of policies and strengthen the social identity of electric vehicles (Xue et al., 2023). The transparency and credibility of policy implementation can dispel public doubts and enhance the driving force of behavioral change through the establishment of institutional trust

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(Li et al., 2023). Scientifically designed policy combinations can effectively guide consumer psychological tendencies.

H1: Policy mix (PM) positively affects psychological factors (PF).

a2. Policy Mix → Perceived Value (H2)

Policy intervention can shape consumers' value perception of electric vehicles by reducing decision-making uncertainty and increasing expected returns. Scientifically configured policy combinations can effectively control economic costs, eliminate battery life concerns, and improve supporting facilities, thus strengthening the functional attributes, emotional identity, and social value of products (Han et al., 2017; Zeithaml, 1988). Studies have confirmed that continuous subsidy policies and charging infrastructure investment can significantly improve consumers' positive evaluation of vehicle economy and practicality (Li et al., 2020). As an external driving force, the policy mix optimizes the consumer's value perception through a multidimensional path.

H2: Policy mix (PM) positively affects perceived value (PV).

a3. Policy Mix → Purchase Intention (H3)

Integrating SOR theory and TPB framework, the policy mix directly affects purchase decisions by improving value perception and behavioral feasibility. Infrastructure investment has boosted confidence in use, and long-term incentive policies have sent government support signals, effectively reducing consumption concerns. Policy credibility and local adaptability further promote the adoption of electric vehicles by enhancing consumption motivation (Han et al., 2017; Li et al., 2020). A sound policy system has a significant role in promoting consumers' purchase intention.

H3: Policy mix (PM) positively affects purchase intention (PI).

b1. Psychological Factors → Purchase Intention (H4)

The theory of Planned Behavior (TPB) points out that psychological factors such as attitude, subjective norm, perceived behavioral control, and trust directly affect purchase intention (Ajzen, 1991). Consumers' positive attitudes towards environmental protection, their perception of social identity, and their confidence in the feasibility of the technology all contribute to the formation of clear purchase intentions. Battery safety trust and policy stability expectation can reduce consumption risk expectation, thus strengthening purchase motivation (Hasan & Simsekoglu, 2020; Morton et al., 2015). These psychological factors are key mediators of converting external stimuli into purchase intentions.

H4: Psychological factors (PF) positively affect purchase intention (PI).

b2. Purchase Intention → Purchase Behavior (H5)

Behavioral intention is the most proximal antecedent of actual behavior. According to implementation intention theory, individuals who form specific purchase plans and are supported by enabling conditions (e.g., subsidies, infrastructure) are more likely to follow through with action (Sheeran, 2002; Webb & Sheeran, 2006). In the EV context, firm intention translates into vehicle acquisition behavior when combined with reduced barriers. Thus, it is hypothesized that consumers' intention will significantly influence their actual purchase decisions.

H5: Purchase intention (PI) positively affects purchase behavior (PB).

b3. Psychological Factors → Purchase Behavior (H6)

Psychological readiness influences intention and behavior, particularly when external conditions align with internal motivation. Consumers with strong perceived control and environmental attitudes are more likely to overcome cost and infrastructural barriers to actualize purchase decisions (Rahahleh et al., 2020). Social norms, such as community EV adoption rates, also exert direct behavioral pressure by encouraging conformity. These factors enable the leap from cognitive endorsement to concrete action.

H6: Psychological factors (PF) positively affect purchase behavior (PB).

c′. Policy Mix → Purchase Behavior (H7)

The policy mix acts on the psychological level and directly affects consumption behavior through economic regulation and administrative supervision. According to the signaling theory (Spence, 1973), positive incentives, such as purchase tax reduction, can reduce the cost of behavior implementation, while restrictive

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policies, such as fuel vehicle restrictions, increase the cost of maintaining the status quo. Such policy signals directly affect consumption decisions by adjusting the cost-benefit balance of consumers, bypassing the intermediary role of attitude and intention (Chandon et al., 2005; Li et al., 2021).

H7: Policy mix (PM) positively affects purchase behavior (PB).

d21. Perceived Value → Psychological Factors (H8)

Perceived value, comprising functional efficiency, emotional satisfaction, and social identity, directly enhances trust, attitudes, and behavioral control. Drawing on the cognitive–affective model, positive evaluations of EV benefits reduce internal conflict and promote emotional alignment with green behavior (Bagozzi, 1992; Kim et al., 2018). When consumers believe they are gaining worthwhile utility, they are more inclined to adopt favorable psychological stances toward EVs.

H8: Perceived value (PV) positively affects psychological factors (PF).

d31. Perceived Value → Purchase Intention (H9)

The value–intention relationship suggests that when consumers perceive high net utility—economically and symbolically—they become committed to adopting the product (Sweeney & Soutar, 2001). Functional aspects, such as low maintenance cost, appeal to logic, while emotional and social dimensions fulfill psychological needs. They generate a strong motivation toward purchase intention (Ying-Hueih et al., 2010).

H9: Perceived value (PV) positively affects purchase intention (PI).

d32. Perceived Value → Purchase Behavior (H10)

High perceived value fosters behavioral conversion by reducing hesitation and increasing perceived urgency. Consumers who view EVs as valuable are more likely to test-drive, compare prices, and proceed to an actual purchase. Chandon et al. (2005) found that high-value perception significantly increases intention–to–behavior conversion rates. Thus, perceived value is a direct enabler of EV adoption.

H10: Perceived value (PV) positively affects purchase behavior (PB).

Methodology

1. Research Design

This study uses a structured questionnaire to explore the mechanism of Chinese consumers' electric vehicle (EV) consumption behavior. The theoretical framework integrates the stimulus-organism-response (SOR) model and the Theory of Planned Behavior (TPB), in which the policy mix and perceived value are used as external stimuli, and psychological variables such as attitude, subjective norm, and perceived behavioral control are used as mediating variables. The TPB theory focuses on explaining the behavioral transformation process from psychological cognition to purchase decision.

2. Population and Sample

The research sample covers potential EV consumers over the age of 18 in five regions of China, including first-tier cities such as Beijing, Shanghai, and Guangzhou, second-tier cities such as Chongqing and Tianjin, as well as third-tier and fourth-tier emerging consumer markets. The non-probability sampling method is used to ensure the diversity of samples in terms of geographical distribution, age structure, and consumption power.

3. Questionnaire Development

The questionnaire was designed based on the existing maturity scale, and the content validity was optimized after three rounds of expert review and consumer focus group discussion. In the pre-survey stage, the clarity of the statement of the items, the reliability of the scale (Cronbach's α>0.85), and the construct validity were verified. The final scale includes the policy mix (10 items), psychological factors (12 items), and other dimensions, and adopts the 7-point Likert scale (1= strongly disagree, 7= strongly agree). Rhodes et al. (2010) proved that compared with the 5-level scale, the 7-level scale can improve the discriminant validity of attitude measurement. The data were collected through the WPS smart form platform, and the effective recovery rate was 92.3%.

4. PLS-SEM Analysis

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This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0 to assess the measurement and structural models. PLS-SEM is appropriate for theory extension, complex hierarchical models, and predictive-oriented research, mainly when constructs include first- and second-order components.

Model Fit was evaluated using the standardized root mean square residual (SRMR), d_ULS, and d_G. An SRMR value below 0.08 indicates acceptable fit, while lower values of d_ULS and d_G suggest congruence between empirical and model-implied correlation matrices (Henseler et al., 2015). Additionally, the goodness of fit was confirmed via both saturated and estimated models to ensure robustness across hierarchical layers.

Measurement Model evaluation followed standard procedures to ensure reliability and validity. Indicator reliability was assessed via outer loadings, with values above 0.70 considered acceptable. Internal consistency was verified using Cronbach's alpha (α) and composite reliability (CR), with thresholds of 0.70 or higher. Convergent validity was examined through average variance extracted (AVE), where a value above 0.50 indicates adequate construct-level variance explanation. Discriminant validity was confirmed using the Heterotrait–Monotrait Ratio (HTMT), with values below 0.85 indicating that constructs are empirically distinct (Henseler et al., 2015).

Structural Model evaluation focused on testing path coefficients and predictive relevance. Bootstrapping (5,000 subsamples) was applied to assess the significance of hypothesized relationships. The coefficient of determination (R^2) indicated model explanatory power, with 0.25, 0.50, and 0.75 reflecting weak, moderate, and substantial levels, respectively (Hair et al., 2017). Effect sizes (f^2) were also computed to assess the individual impact of exogenous variables, while Stone-Geisser's Q^2 was used to evaluate predictive relevance. Values above zero indicated adequate predictive performance.

Harman's single-factor test assessed the potential for standard method bias (CMB). The results indicated that no single factor accounted for more than 50% of the total variance, suggesting that standard method variance is not a critical concern in this study.

Results

Demography of the Sample

This study analyzed 658 valid responses from potential EV consumers aged between 18 and 50 across five key regions in China. The sample was predominantly male (59.27%), reflecting current gender patterns in automotive purchasing. Most (38.45%) resided in Southwest China, including Chongqing and Chengdu. Regarding educational background, over 65% held a bachelor's degree or higher. Monthly incomes ranged primarily between 5,000 and 20,000 yuan, indicating a relatively affluent respondent group aligned with the target market for EVs. Regarding vehicle ownership, nearly half of the participants currently owned conventional fuel vehicles, while a smaller segment already owned electric vehicles or both types. These demographics suggest a well-informed and financially capable population, suitable for exploring the psychological and policy-related drivers of EV adoption.

First-Order Model Fit

This study performed a fit test between the saturated and estimated models. The saturation model indexes are SRMR=0.045, d_ULS=1.130, d_G=1.165; the indexes of the estimated model are SRMR=0.089, d_ULS=4.434, d_G=1.363. The SRMR values of the two models are lower than the 0.08 threshold (Hair et al., 2017), indicating that the overall fitness of the models meets the research requirements.

Table 1 First-Order model fit index

	Saturated model	Estimated model
SRMR	0.045	0.089
d_ULS	1.130	4.434
d_G	1.165	1.363

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Measurement Model Reliability and Validity

Reliability and validity are key indicators for evaluating the quality of measurement models. According to Nunnally and Bernstein (1994), a Cronbach's alpha value greater than 0.7 indicates the scale has good reliability. In addition, composite reliability (rho_c) and average variance extracted (AVE) are also important indicators for evaluating validity. According to Fornell and Larcker (1981), the scale demonstrates adequate convergent validity if the rho_c value exceeds 0.7 and the AVE value surpasses a specified threshold of 0.5. The results showed that the Cronbach's alpha and rho_c scores for all parts were above 0.7, and the AVE was over 0.5. This means the measurement model was reliable and had good convergent validity. Loadings show how strongly each item relates to its corresponding concept and are used to assess how well the items measure what they are supposed to. Outer loadings should be at least 0.7. If they are over 0.8, the item explains the concept well. In this study, all of the items had outer loadings over 0.7, which suggests the scale measures what it is supposed to pretty well.

Table 2 First-Order model Reliability and convergent validity

	loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
PB		0.93	0.955	0.877
BEH1	0.935			
BEH2	0.961			
BEH3	0.913			
COH		0.875	0.941	0.888
COH1	0.938			
COH2	0.947			
CON		0.799	0.908	0.832
CON1	0.926			
CON2	0.898			
CRE		0.89	0.948	0.901
CRE1	0.950			
CRE2	0.948			
EMO		0.945	0.973	0.948
EMO1	0.973			
EMO2	0.974			
FUN		0.879	0.943	0.892
FUN1	0.942			
FUN2	0.947			
PI		0.871	0.94	0.886
INT1	0.943			
INT2	0.94			
LOC		0.908	0.956	0.915
LOC1	0.955			
LOC2	0.958			
PA		0.899	0.922	0.665
PA1	0.876			
PA2	0.851			
PA3	0.731			
PA4	0.732			

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	loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
PA5	0.848			
PA6	0.842			
PBC		0.729	0.88	0.786
PBC1	0.874			
PBC2	0.899			
POL		0.927	0.965	0.932
POL1	0.963			
POL2	0.967			
SOC		0.909	0.956	0.916
SOC1	0.957			
SOC2	0.957			
SSN		0.859	0.934	0.876
SSN1	0.932			
SSN2	0.94			
TRU		0.928	0.965	0.933
TRU1	0.966			
TRU2	0.965			

Discriminant validity, the Heterotrait–Monotrait Ratio (HTMT)

This study applied the Heterotrait–Monotrait Ratio (HTMT), a robust indicator commonly used in PLS-SEM to evaluate discriminant validity. The recommended threshold for HTMT is below 0.85 (or 0.90 for more lenient standards) as proposed by. While the HTMT values for most construct pairs met the acceptable criteria, a few exceeded the standard threshold, which may indicate conceptual proximity or partial measurement overlap. Nevertheless, the results were cross-validated with the Fornell–Larcker criterion and theoretical justification, confirming the overall discriminant validity of the measurement model.

Second-order model

Model fit

The SRMR numbers for the second-order model in this study are all under 0.08, and both the d_ULS and d_G values are low, meaning the model fits well overall.

Table 3 Model Fit of Second-Order Model

	Saturated model	Estimated model
SRMR	0.052	0.052
d_ULS	0.420	0.420
d_G	0.326	0.326

The Cronbach's alpha and composite reliability (rho_c) of this study are both greater than 0.7, indicating that the scale has high internal consistency and meets the reliability requirements. The AVE for all constructs is over 0.5, and most are above 0.7. This means the scale is very reliable and meets the standards we need. The factor loadings of most items in this study were more significant than 0.8, indicating that the measurement items of the constructs were of high quality. Only PBC was slightly lower than 0.7, but still within an acceptable range.

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Table 4 Second-Order model Reliability and convergent validity

	Loadings	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
PB		0.930	0.955	0.877
BEH1	0.932			
BEH2	0.961			
BEH3	0.917			
PF		0.865	0.911	0.721
PA	0.938			
PBC	0.651			
SSN	0.881			
TRU	0.898			
PI		0.871	0.940	0.886
INT1	0.942			
INT2	0.941			
PM		0.915	0.936	0.746
COH	0.877			
CON	0.817			
CRE	0.832			
LOC	0.905			
POL	0.887			
PV		0.943	0.963	0.897
EMO	0.954			
FUN	0.948			
SOC	0.939			

Discriminant validity

Homogeneous Factor Ratio (HTMT)

HTMT (heterogeneous-Homogeneous factor Ratio) is the core indicator for testing the discriminative validity of construction in PLS-SEM, and its threshold is usually recommended to be lower than 0.85 or 0.90 (Henseler et al., 2015). The results of this study are all in line with the reference standards.

Table 5 Second-order model discriminant validity (HTMT)

	PB	PF	PI	PM	PV
PB					
PF	0.707				
PI	0.694	0.869			
PM	0.670	0.861	0.647		
PV	0.655	0.887	0.842	0.736	

Structural Model

Direct effects were assessed using standardized path coefficients (β) derived from 5,000 bootstrap subsamples. Statistical significance was determined by 95% bias-corrected confidence intervals (CI) excluding zero and two-tailed *p*-values <0.05. Effect sizes were interpreted using Cohen's Thresholds: β ≥0.10 (small), ≥0.30 (medium), and ≥0.50 (large).

Hypothesis Testing

Citation
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Table 6 Structural model path coefficients and hypothesis testing

Hypothesis	Path	β	Sample Mean (M)	95% CI	T values	p values	Supported
H1	PM → PF	0.398***	0.397	[0.318, 0.479]	9.714	<0.001	Yes
H2	PM → PV	0.686***	0.687	[0.633, 0.738]	25.743	<0.001	Yes
H3	PM → PI	-0.085	-0.088	[-0.188, 0.02]	1.612	0.107	No
H4	PF → PI	0.480***	0.483	[0.339, 0.629]	6.379	<0.001	Yes
H5	PI → PB	0.315***	0.313	[0.189, 0.433]	5.002	<0.001	Yes
H6	PF → PB	0.047	0.049	[-0.084, 0.195]	0.654	0.513	No
H7	PM → PB	0.318***	0.318	[0.209, 0.428]	5.726	<0.001	Yes
H8	PV → PF	0.536***	0.537	[0.457, 0.612]	13.531	<0.001	Yes
H9	PV → PI	0.433***	0.432	[0.322, 0.544]	7.608	<0.001	Yes
H10	PV → PB	0.118	0.116	[-0.017, 0.26]	1.667	0.096	No

Notes: ***p <0.001; β = Standardized coefficients; CI = 95% Bootstrap Confidence Interval (N=5,000).

According to Table 6, hypothesis testing results are: H1 (PM → PF): Policy mix significantly enhances psychological factors (β = 0.398, *p* < 0.001). H2 (PM → PV): Significant positive effect on perceived value (β = 0.686, *p* < 0.001; 95% CI [0.633, 0.738]). H3 (PM → PI): No direct effect on purchase intention (β = -0.085, *p* = 0.107). H4 (PF → PI): Psychological factors strongly influenced purchase intention (β = 0.480, *p* < 0.001). H5 (PI → PB): Strong linkage between intention and behavior (β = 0.315, *p* < 0.001). H6 (PF → PB): No direct effect of psychological factors on purchase behavior (β = 0.047, *p* = 0.513). H7 (PM → PB): Policy mix directly influenced purchase behavior (β = 0.318, *p* < 0.001). H8 (PV → PF): Perceived value significantly affected psychological factors (β = 0.536, *p* < 0.001). H9 (PV → PI): Perceived value validated purchase intention (β = 0.433, *p* < 0.001). H10 (PV → PB): Perceived value's impact on purchase behavior was rejected (β = 0.118, *p* = 0.096).

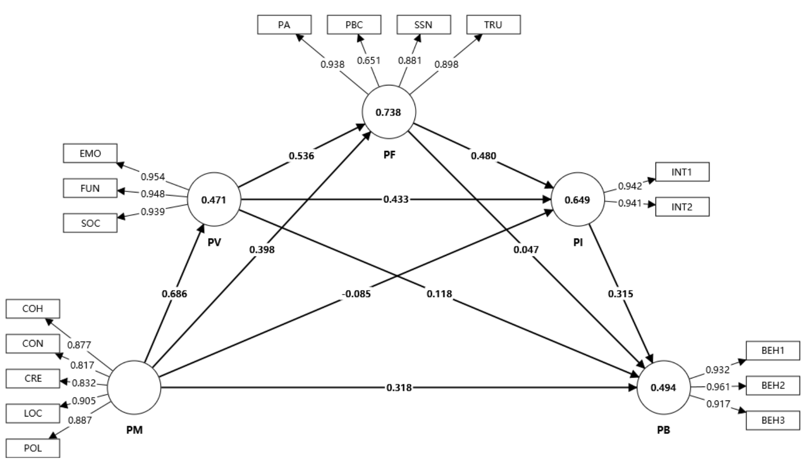

Figure 3 Second-order model, Structural model results

Explanatory power and effect size (R^2 & f^2)

R^2 values (0–1 scale) measure the variance explained in endogenous variables. Thresholds: Weak (<0.25), Moderate (0.25–0.50), Substantial (0.50–0.75), Strong (≥0.75) (Cohen, 1988).

Effect Size (f^2) quantifies an independent variable's influence on an endogenous variable in SEM. Thresholds (Cohen, 1988): Small: ≥0.02, Medium: ≥0.15, Large: ≥0.35.

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Table 7 Effect size (f^2) and Explanatory power of endogenous variables (R^2)

Hypothesis	Path	f^2	Effect size	R^2	Explanatory power
H1	PM → PF	0.321	Large Effect	0.738	Strong
H2	PM → PV	0.890	Large Effect	0.471	Moderate
H3	PM → PI	0.008	No significant effect	0.649	Strong
H4	PF → PI	0.172	Moderate effect	0.649	Strong
H5	PI → PB	0.069	Small effect	0.494	Moderate
H6	PF → PB	0.001	No significant effect	0.494	Moderate
H7	PM → PB	0.08	Small effect	0.494	Strong
H8	PV → PF	0.581	Large Effect	0.738	Strong
H9	PV → PI	0.178	Moderate effect	0.649	Strong
H10	PV → PB	0.008	No significant effect	0.494	Moderate

Discussion

This study elucidates the identified research gap present in the literature by empirically validating a hierarchical behavioral model that integrates policy constructs and psychological mechanisms. Previous research has predominantly neglected the layered pathways through which external stimuli translate into behavioral responses. This study offers a more nuanced understanding of consumer behavior in electric vehicle adoption by applying second-order modeling and confirming the significance of indirect mediation paths.

This study advances the integration of the stimulus–organism–response (SOR) framework and the Theory of Planned Behavior (TPB) by elucidating the behavioral mechanisms through which policy mix (PM), perceived value (PV), and psychological factors (PF) collectively shape Chinese consumers' electric vehicle (EV) adoption behavior. The findings reveal direct and indirect pathways from policy stimuli to purchasing outcomes, affirming the efficacy of employing a hierarchical modeling approach.

The policy mix significantly enhances perceived value (H2: $\beta = 0.686$, $p < 0.001$), confirming that coordinated policy instruments—such as subsidies, infrastructure investment, and communication transparency—stimulate multifaceted consumer value perceptions. This conclusion aligns with prior findings by Wang and Liu (2017) and reinforces the notion that policy co-design enhances EVs' functional and symbolic evaluations. However, the direct effect of the policy mix on purchase intention (H3: $\beta = –0.085$, $p > 0.05$) was not supported, suggesting that policy incentives alone are inadequate to drive intention without the mediation of cognitive processing via perceived value and psychological readiness.

Interestingly, a direct and significant effect of the policy mix on purchase behavior was observed (H7: $\beta = 0.318$, $p < 0.001$), implying that policies may operate through non-cognitive mechanisms such as social conformity or signaling effects Spence, 1973). This finding expands the classical SOR model by incorporating exogenous behavioral triggers that extend beyond value-based decision-making.

Perceived value significantly influenced psychological factors (H8: $\beta = 0.536$, $p < 0.001$) and purchase intention (H9: $\beta = 0.433$, $p < 0.001$), thus emphasizing the centrality of value perception in shaping internal states and subsequent motivation. However, its direct effect on behavior was not statistically significant (H10: $\beta = 0.118$, $p > 0.05$), echoing the work of Chandon et al. (2005) in suggesting that the transition from valuation to behavior is mediated by intention and constrained by external barriers such as infrastructure and affordability.

Psychological factors strongly predicted purchase intention (H4: $\beta = 0.480$, $p < 0.001$), thereby affirming the central thesis of TPB that attitude, perceived behavioral control, and subjective norms are critical antecedents of intention (Ajzen, 1991). Nonetheless, their direct influence on behavior was insignificant (H6: $\beta = 0.047$, $p > 0.05$), again underscoring the mediating role of intention. Lastly, purchase intention moderately influenced actual behavior (H5: $\beta = 0.315$, $p < 0.001$), although the relatively small

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effect size (f^2 = 0.069) suggests that practical constraints continue to inhibit behavioral actualization, consistent with the findings of Lee and Lee (2011).

Conclusion

By integrating the SOR and TPB frameworks into a unified hierarchical model, this study significantly contributes theoretically and methodologically to the existing literature on sustainable mobility. It substantiates that consumer electric vehicle (EV) adoption behavior is influenced by policy architecture and internalized cognitive as well as affective responses. Methodologically, the study employs a robust second-order Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, which is supported by both saturated and estimated model fit indices, and is validated through Average Variance Extracted (AVE), Heterotrait-Monotrait (HTMT) ratio, and R^2/f^2 evaluations. Theoretically, the model elucidates that indirect pathways, particularly those involving perceived value and psychological states, possess greater influence than direct policy effects alone. These findings provide practical guidance for designing electric vehicle promotion strategies more attuned to psychological factors and sensitive to regional contexts.

The proposed hierarchical SOR–TPB model can be extended to study other sustainable behaviors such as renewable energy adoption, circular economy practices, and green consumption across cultural and institutional contexts. For instance, applying it to renewable energy adoption would involve examining similar pathways: external stimuli (e.g., subsidies, infrastructure) influencing perceived value (e.g., cost savings, environmental benefits) and psychological factors (e.g., attitudes, norms, control), while requiring integration of context-specific factors (e.g., technical complexity, community norms) as stimuli or moderators, showcasing its adaptability.

Limitations and Future Research

This research is subject to several limitations that merit future exploration. Firstly, using cross-sectional data restricts causal inference and precludes the assessment of behavioral dynamics across time. A longitudinal panel design might elucidate how consumer attitudes about policy iteration or market maturation evolve. Secondly, although the sample encompasses five major Chinese regions, the regional environmental, economic, and infrastructural disparities may affect the heterogeneity of behavioral responses. Future studies should consider employing multi-group analysis or moderation modeling to examine regional differences more explicitly. Thirdly, the current study relies exclusively on PLS-SEM, which is optimal for exploratory modeling yet limited in detecting necessary conditions. Future research could incorporate Necessary Condition Analysis (NCA) and Importance-Performance Map Analysis (IPMA) to identify bottlenecks and priority areas for intervention. Furthermore, integrating machine learning classification methods (such as CHAID or decision trees) could enhance predictive accuracy for behavioral segmentation.

Recommendations

Based on empirical findings, the following multi-stakeholder recommendations are proposed:

For Policymakers:

- Prioritize multidimensional policy coordination over single-instrument tools. The synergy of incentives, infrastructure, and clear communication substantially impacts consumer value.
- Implement differentiated regional strategies. For example, environmental identity resonates more in first-tier cities, whereas cost-benefit considerations dominate lower-tier areas.
- Establish dynamic policy evaluation mechanisms, enhance psychological framing in public communication.

For Enterprises:

- Strengthen technological innovation and after-sales service to reinforce functional and emotional value perceptions.

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- Facilitate behavioral transformation through reduced adoption thresholds—e.g., zero-interest installment plans or app-based smart charging integrations.
- Develop tiered experiential marketing strategies and build user communities to activate social norms.

For Industry Institutions:

- Establish a third-party battery health certification system to enhance trust in EV technology.
- Promote data-sharing for cross-brand charging networks, which could alleviate "range anxiety" and reduce psychological resistance to adoption.

These recommendations aim to bridge the intention–behavior gap by aligning structural incentives with consumer psychology, thus facilitating a more inclusive and sustainable EV transition.

Appendix: Constructs, Dimensions, and Sources of Measurement Scales

Constructs	The modified item	References
Policy Mix measures (10 items)		
Consistency (CON) of Policy Mix	CON1: Policies like car subsidies have prompted me to buy an electric car.	(Rogge & Schleich, 2018)
	CON2: Exemption policies, such as the last number and license plate restrictions, have prompted me to buy an electric car.	(Rogge & Schleich, 2018)
Coherence of Policy Mix	COH1: Policy makers will try to eliminate the problems associated with electric vehicles.	(Rogge & Schleich, 2018)
	COH2: The government will constantly adjust its policies to adapt to the development of electric vehicles.	(Rogge & Schleich, 2018)
Credibility (CRE) of Policy Mix	CRE1: The development of electric vehicles mainly benefits from the policy support of the central government.	(Rogge & Schleich, 2018)
	CRE2: The development of electric vehicles mainly benefits from the policy support of provincial and municipal governments.	(Rogge & Schleich, 2018)
Local Adaptation and Coordination	LOC1: The electric vehicle policies in my city consider local specific conditions and needs.	Self-designed
	LOC2: My city and the national EV policy have been well coordinated in their implementation.	Self-designed
Policy Communication and Effectiveness	POL1: The local government in my city effectively communicates electric vehicle-related policies.	Self-designed
	POL2: My city's electric vehicle-specific incentives or restriction policies are attractive compared to those of other cities.	Self-designed
Psychological Factors (12 items):		
Social and Subjective Norm	SSN1: People who are important to me think electric cars should play an important role in our transportation system.	(Haustein et al., 2021)
	SSN2: People whose opinions I value would prefer that I adopt a BEV	(Jaiswal et al., 2022)
Perception and Attitude	PA1: I am interested in Battery Electric Vehicles (BEVs).	(Jaiswal et al., 2022)
	PA2: I think electric vehicles' driving performance would be good.	(Lai et al., 2015)
	PA3: I worry about air pollution.	(Lai et al., 2015)

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Constructs	The modified item	References
	PA4: I care about energy conservation.	(Lai et al., 2015)
	PA5: No matter what others think, I should purchase an EV.	Self-designed
	PA6: Because of my principles, I feel obligated to use EVs to reduce carbon emissions.	Self-designed
Perceived Behavioral Control	PBC1: Whether or not to purchase an EV is entirely my decision.	(Huang & Ge, 2019)
	PBC2: I have enough money to buy an electric car.	Self-designed
Trust	TRU1: I trust the overall quality and performance of EVs.	(Ninh, 2021)
	TRU2: I believe in the safety and environmental protection of electric vehicles.	(Ninh, 2021)
Perceived Value (6 items):		
Functional Experience Value	FUN1: Through the driving experience, I have learned knowledge and skills related to electric vehicles.	(Shen, 2016)
	FUN2: Through the driving experience, I think electric cars are more practical.	(Shen, 2016)
Emotional Experience Value	EMO1: The driving experience is fun.	(Darden & Babin, 1994)
	EMO2: I am delighted with the whole driving experience.	(Rintamäki et al., 2006)
Social Experience Value	SOC1: The driving experience made me realize that electric vehicles can bring social recognition.	(Shen, 2016)
	SOC2: I would like to share my experiences of electric vehicle driving with friends/acquaintances.	(Sweeney & Soutar, 2001)
Purchase Intention (2 items):		
Intention	INT1: My next car will be electric.	(Haustein et al., 2021)
	INT2: If I had an electric car and a gas car, I would mainly use the electric car.	(Haustein et al., 2021)
Purchase Behavior (3 items):		
Behavior	BEH1: I have gathered information about electric vehicles (performance, range, charging facilities, etc.).	Self-designed
	BEH2: I compared the configuration and functions of electric vehicles to make a more suitable choice.	Self-designed
	BEH3: I have already considered the cost of an electric car.	Self-designed

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