

The Influence of Consumer Trust in Smart Energy Ecosystems on Purchase Intention for New Energy Vehicles: The Mediating Role of Perceived Smart Mobility Benefits and the Moderating Effect of Digital Readiness*



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Abstract

The quick growth of smart energy ecosystems is creating intelligent charging networks, connected vehicles and digital service applications. As a result, consumers are appraising new energy vehicles (NEVs) in a different environment. However, we know little about consumer trust in these ecosystems and purchase decisions. To analyse the effect of consumer trust in smart energy ecosystem on NEV purchase intention, with perceived smart mobility benefits mediating and digital readiness moderating, the present study aims to fill this business research gap. Based on the theories of technology acceptance, trust transfer, perceived value, and stimulus-organism-response, a research model with hypotheses was developed and validated. Survey data were collected from 523 consumers in the Hebei Province of China. Important findings were resulted from the modeling. To begin with, consumer trust in smart energy ecosystems, covering technology, service provider, system reliability, and data security dimensions, has helped in having a positive impact and increase in smart mobility benefits ($\beta = 0.536$, $p < 0.001$). Furthermore, similarly consumer trust in smart energy ecosystems, has also managed to help with the increase in purchase intention ($\beta = 0.187$, $p < 0.01$). Secondly, the trust-intention relationship was partially mediated by perceived benefits of smart mobility, that is, 57.8% of the total impact. The effect of trust and perceived benefit on the intention to purchase is moderated by digital readiness, as it became significantly stronger for those digitally ready. It is important to note that digital readiness does not moderate the effect of trust on benefit perceptions. Rather, it affects whether benefit perceptions lead to purchase. The research results further extend trust research to the emerging realm of smart energy ecosystems. It clarifies that the cognitive pathway from trust to purchase intention and considers digital readiness a meaningful boundary condition. Strategies to boost NEV adoption have been suggested in the course of the research findings. They were termed complementary strategies.

*Received December 22, 2025; Revised February 6, 2026; Accepted February 20, 2026

Keywords: Consumer Trust; Digital Readiness; New Energy Vehicles; Smart Mobility Benefits; Purchase Intention

Introduction

Transportation is responsible for almost a quarter of global CO₂ emissions from fuel combustion, which makes the decarbonization of mobility a major global priority. New energy vehicles include battery electric vehicles, plug-in hybrid electric vehicles, fuel cell vehicles and are widely seen as the most effective technological pathway to reduce transport-related emissions. China is now at the forefront of this shift. According to the China Association of Automobile Manufacturers (2024), in 2023, the sales of China's NEVs (New Energy Vehicles) stood at 9.49 million units which is a 38 per cent year-on-year increase. Moreover, over 60 per cent global NEV sales took place in China. Although the market is rapidly expanding, consumers' true motivation to go for NEVs over conventional vehicles is not fully clear.

Previous research focused primarily on economic incentives and savings in fuel expense, environmental attitude, technological constraints such as driving range and charging availability (Li et al., 2017; Wang et al., 2018). These factors still influence consumer decisions, but the context of decision-making has changed. Consumers of new energy vehicles (NEVs) today are becoming more engaged with a wider smart energy ecosystem, which includes charging infrastructure, digital service platforms, connected vehicles technologies, and energy management systems (Sovacool et al. 2019) In China, the rapid construction of public charging sites and the launch of mobile apps that allow for real-time charging-site finding, reservation, and payment have helped to make vehicles and energy infrastructure functionally dependent on each other.

This integration completely changes how consumers evaluates. Consumers today are expected to put faith not just in the vehicle itself but also in the system around it which has various providers and technologies and is aided and upgraded through data received on a continuous basis. For a long time, trust has been known to reduce perceived risk and uncertainty in technology adoption contexts (Gefen et al., 2003). NEV studies so far, however, rarely investigate the trust at the ecosystem level, where consumers are tasked with evaluating the reliability, safety, and coordination of interconnected systems rather than merely a single product or brand.

The existing literature has three issues requiring further investigation. First, we do not have it all figured when it comes to trust in smart energy ecosystems. Forthcoming studies have addressed the trust on the autonomous vehicles by the people (Rauh et al., 2015) or the online platform (Kim et al, 2008). However, trusting the trust is defined as the multidimensional construct which encompasses the performance of the technology, service providers, reliability of the system and the data security in an integrated energy ecosystem. Moreover, the mechanisms in which trust impacts NEV purchase intention are not specified

enough. Trust cannot be expected to have a purely direct effect; rather, it may influence consumers' perceptions of the benefits of smart mobility, such as convenience, economic efficiency, environmental value, and social status.

The mediation of this pathway has few empirical tests. Consumers differ greatly in how well they know and feel at ease with technology. Differences in digital readiness may condition whether trust and perceived benefits translate into actual purchase intentions. However, this heterogeneity has received low empirical attention.

Objectives of the Research

1. To examine the effect of consumer trust in a smart energy ecosystem on purchase intention toward new energy vehicles (NEVs).
2. To investigate the mediating role of perceived smart mobility benefits in the relationship between consumer trust and NEV purchase intention.
3. To analyze the moderating role of digital readiness in influencing the strength of trust-based effects on perceived smart mobility benefits and NEV purchase intention.
4. To develop and empirically test a moderated mediation model integrating the Technology Acceptance Model, trust transfer theory, perceived value theory, and the Stimulus–Organism–Response framework using survey data from consumers in Hebei Province, China.

Research Methodology

The 1st Step: Research Design and Context

The proposed hypothesis was tested empirically in this study that adopted a cross-sectional survey design. Because they allow for the investigation of relationships involving multiple latent constructs simultaneously while still maintaining data collection efficiency from large samples, consumer behaviour researchers frequently choose survey-based designs (Hair et al., 2019). In this study, smart energy ecosystems are defined as integrated socio-technical systems in which digital technologies, energy infrastructure, transportation systems, policy mechanisms, and consumer participation interact to enable efficient, sustainable, and intelligent energy use. Within the scope of this research, smart energy ecosystems specifically refer to the interaction between NEVs, charging infrastructure, digital platforms (e.g., mobile applications, intelligent payment systems), supportive public policies, and consumer trust in technology-enabled energy services. This definition emphasizes the consumer-facing dimension of smart energy ecosystems rather than their engineering or grid-level characteristics, aligning the concept with behavioral and marketing research objectives. The empirical context of this study was Hebei Province, China, which provides a suitable setting for examining NEV purchase intention within smart energy ecosystems for several reasons. First, smart transportation development and clean energy transitions are key policy priorities

within the Beijing–Tianjin–Hebei coordinated development strategy, positioning the region as a national pilot area for ecosystem-based energy innovation. Second, Hebei hosts major NEV manufacturers, such as Great Wall Motors, increasing consumer exposure to NEV products, related technologies, and promotional activities. Third, the province exhibits substantial variation in urbanization levels, economic development, and charging infrastructure maturity across different areas, allowing for the examination of consumer perceptions under diverse ecosystem conditions. Finally, provincial-level subsidies, infrastructural investments, and regulatory incentives actively promote NEV adoption, making Hebei an appropriate context for investigating consumer behavior within an evolving smart energy ecosystem.

H1: Consumer trust in smart energy ecosystems positively influences perceived smart mobility benefits.

H2: Consumer trust in smart energy ecosystems positively influences NEV purchase intention.

H3: Perceived smart mobility benefits positively influence NEV purchase intention.

H4: Perceived smart mobility benefits mediate the relationship between consumer trust and NEV purchase intention.

H5: Digital readiness positively moderates the relationship between consumer trust and NEV purchase intention.

H6: Digital readiness positively moderates the relationship between consumer trust and perceived smart mobility benefits.

H7: Digital readiness positively moderates the relationship between perceived smart mobility benefits and NEV purchase intention.

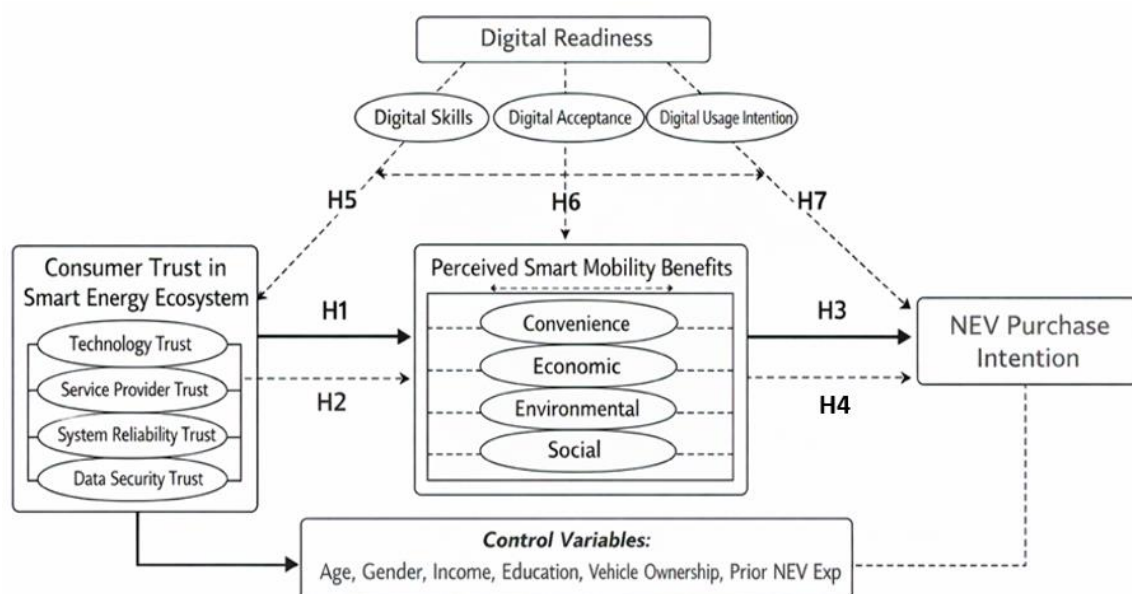


Figure 1: Conceptual Framework

The 2nd Step: Sample and Data Collection

The data were collected between March to May 2024, using a mixed-mode online-offline survey technique. The online data collection took place via Wenjuanxing, a popular Chinese survey platform. Distribution of the survey links was done using social media platforms, automobile-related websites, and local driving schools. Research assistants trained by the researcher moved to NEV dealerships and shopping malls and public charging stations in four cities to conduct the offline data collection of this research (Shijiazhuang, Baoding, Tangshan, and Langfang) This mixed-mode approach mitigated the coverage bias of online-only sampling.

Population and Sampling

The population size is based on Yamane (1973) formula with a margin of error of 0.05 to population 1,040 individuals, a sample size of 650 corresponds. The respondents had to meet three screening criteria; being at least 18 years, possessing a valid driver's license, and having an elementary knowledge of NEVs. The study included those who own a vehicle and non-vehicle owners. In line with the Structural Equation Modeling (SEM) guidelines of adequate sample size and ensuring stable estimation as suggested by Hair et al. (2019), the targeted sample for this study was set at approximately 500 valid responses.

A total of 650 questionnaires were distributed to the target population using the specified sampling procedure. Of these, 598 questionnaires were returned, yielding a response rate of 92.00%. After data screening, 75 responses were excluded due to incompleteness and patterned answering, including questionnaires completed in less than 10 seconds. Consequently, a total of 523 valid questionnaires were retained for data analysis, representing 80.46% of the distributed questionnaires and 87.46% of the returned questionnaires. The last sample showed a balanced gender representation, concentration around the 26–45 age group, moderate to high levels of education, diverse income brackets, as well as varied vehicle ownership and NEV experience. The sample broadly represents potential consumers of NEV in the province of Hebei.

The 3rd Step: Measurement Instruments

All constructs were measured with multi-item scales taken from literature. The survey items were translated and back translated from English to Chinese to gain semantic equivalence. A Pilot test on 50 respondents was conducted to confirm the clarity of the items and its reliability. All the items were measured using a 7-point Likert scale (1= strongly disagree; 7 = strongly agree). Consumer trust in smart energy ecosystems can be considered as a second-order reflective construct that embodies four first-order dimensions, viz., trust in technology (McKnight et al., 2002), trust in service provider (Sirdeshmukh et al., 2002), trust in system reliability (Lee and See, 2004) and trust in data security (Dinev & Hart, 2006). The researchers specified perceived smart mobility benefits as a second-order reflective construct consisting of convenience (Kim et al., 2007), economic benefits (Helveston et al., 2015), environmental

benefits (Jansson et al., 2017), and social benefits (White et al., 2019). Digital readiness functions as a second-order variable it consists of digital skills (Hargittai and Hsieh, 2012), digital acceptance (Parasuraman, 2000), and digital usage intention (Venkatesh et al., 2012). The intention to purchase NEVs was measured by means of existing items concerning purchase likelihood, consideration, preference and recommendation (Degirmenci and Breitner, 2017; Wang et al., 2018). To control for the effect of demographic and experiential factors on mode choice, we added gender, age, education, income, current vehicle ownership, residential location, and NEV experience to our controls.

The 4th Step: Step of Data Collection

Data collection was conducted between March and May 2024 using a mixed-mode survey approach that combined both online and offline methods to enhance sample coverage and reduce potential sampling bias. Online data were collected through Wenjuanxing, a widely used survey platform in China. The survey link was distributed via social media platforms, automobile-related websites, and networks associated with local driving schools. Offline data collection was carried out by trained research assistants at new energy vehicle (NEV) dealerships, shopping malls, and public charging stations located in four major cities of Hebei Province: Shijiazhuang, Baoding, Tangshan, and Langfang. The integration of online and offline approaches helped mitigate the limitations of relying solely on online sampling and ensured access to a broader group of potential NEV consumers.

Respondents were required to meet three screening criteria: (1) being at least 18 years old, (2) holding a valid driver's license, and (3) possessing basic knowledge of NEVs. Both vehicle owners and non-vehicle owners were included to capture a comprehensive view of potential consumers. Following SEM guidelines for adequate sample size and stable parameter estimation (Hair et al., 2019), the target sample size was set at approximately 500 valid responses. A total of 650 questionnaires were distributed, of which 598 were returned. After excluding incomplete questionnaires and patterned responses with completion times of less than 10 seconds, 523 valid responses were retained for analysis. The final sample demonstrated balanced gender representation, a concentration in the 26–45 age group, moderate to high education levels, diverse income ranges, and varying degrees of vehicle ownership and NEV experience. Overall, the sample reasonably represents potential NEV consumers in Hebei Province.

The 5th Step: Data Analysis Strategy

The data analysis adhered to the SEM procedures (Anderson & Gerbing, 1988), which was performed via SPSS 26.0 and AMOS 26.0. We assessed missing data, normality, and data quality in the preliminary analyses. The expectation–maximization imputation method was applied to the missing values, which was minimal. The distribution of the items met the recommended skewness and kurtosis levels for employing a maximum likelihood estimation (Kline, 2016). Harman's single-factor test and a common latent factor approach (Podsakoff et

al., 2003) were used to check common method bias. The findings showed that common method variance would not be a serious problem. A confirmatory factor analysis investigated the measurement model. The multiple indices such as χ^2/df , CFI, TLI, RMSEA, and SRMR were used to test the model fit. The reliability and validity of the study were evaluated through the use of the Cronbach's alpha, composite reliability, average variance extracted, factor loadings, the Fornell–Larcker criterion, and HTMT ratios tools. The structural model was then estimated to test direct effects. Mediation impacts were evaluated utilizing bootstrapping with 5,000 resamples and bias-corrected confidence intervals. The study utilized latent variable interaction modeling to test moderation hypotheses with mean-centered indicators, and significant interactions were interpreted through simple slope analyses (Ping, 1995).

The 6th Step: Summary and Presentation of Results

The data analysis followed a two-step SEM procedure consisting of measurement model evaluation and structural model testing. First, confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the measurement model. The results indicated that all constructs exhibited satisfactory internal consistency, with Cronbach's alpha and composite reliability values exceeding the recommended thresholds. Convergent validity was confirmed through significant factor loadings and acceptable average variance extracted (AVE) values, while discriminant validity was supported by the Fornell–Larcker criterion and HTMT ratios.

Model fit indices demonstrated an acceptable to good fit between the measurement model and the observed data, as indicated by χ^2/df , CFI, TLI, RMSEA, and SRMR values within recommended ranges. These findings confirm that the measurement instruments were appropriate for subsequent structural analysis.

The structural model results revealed that consumer trust in the smart energy ecosystem had a significant positive effect on NEV purchase intention. Furthermore, perceived smart mobility benefits significantly mediated the relationship between consumer trust and purchase intention, indicating that trust influences purchase intention through consumers' cognitive evaluation of smart mobility benefits. Bootstrapping analysis with 5,000 resamples confirmed the significance of the indirect effects.

In addition, digital readiness was found to play a significant moderating role, strengthening the effects of consumer trust on perceived smart mobility benefits and NEV purchase intention. Simple slope analyses further illustrated that the trust-based effects were stronger among consumers with higher levels of digital readiness.

Overall, the results support the proposed moderated mediation model and provide empirical evidence for the theoretical framework integrating technology acceptance, trust transfer, perceived value, and the stimulus–organism–response perspective. The findings offer both theoretical contributions and practical insights for stakeholders seeking to promote NEV adoption and sustainable mobility.

Research Results

Sample Overview and Preliminary Tests

There were 523 respondents from Hebei Province, China in the final sample. The sample slightly favored men (53.7%) and was concentrated in the 26–45 age group, which is the main segment of automobile consumers in China. The majority of the respondents were urban residents and with a moderate to high level of education and income. About half the sample had previous involvement with NEVs, through having test driven, rented, or owned one of them. Due to the use of self-reported, cross-sectional data, common method variance was checked. According to the single factor test (Harman) carried out in our study, first factor accounts for 31.47% of total variance which is not significant (Podsakoff et al., 2003). Also, there were only little improvements in the model fit when using the unmeasured method factor, and this did not explain as much variance as the substantive construct did. Overall, these results suggest that the common method bias is unlikely to drive the findings.

Measurement Model Assessment

Analysis using descriptive statistics revealed that for all constructs considered, participants provided fairly high evaluations, with item means lying above the midpoint of the 7-point scale and an acceptable level of item variability. The maximum likelihood estimation was valid to use (Kline, 2016) as skewness and kurtosis fell between ranges. Confirmatory factor analysis demonstrated very strong measurement properties. All the constructs had high internal consistency with Cronbach's alpha and composite reliability values exceeding threshold value. The standardized factor loadings for all variables were significant and the average variance extracted (AVE) values were greater than 0.50 (Fornell and Larcker, 1981), confirming convergent validity. Both the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio help confirm discriminant validity (all HTMT values were below 0.85 (Henseler et al., 2015)). The latent constructs showed good fit for the data as the measurement overall model showed good fit for the data.

Table 1: Measurement and Structural Model Fit Indices

Effect	β	95% CI
Total effect (Trust $\rightarrow$ PI)	0.443	[0.352, 0.541]
Direct effect	0.187	[0.076, 0.302]
Indirect effect (via benefits)	0.256	[0.184, 0.337]

Structural Model and Hypothesis Testing

After establishing satisfactory measurement properties, the structural model was estimated. The smart energy ecosystem is presented as a model. Consumer trust in smart energy ecosystems, smart mobility benefit perceived and digital readiness have been

modelled as second-order construct respectively. The model fit well in terms of structure (Table 1).

According to the findings displayed in Table 2, consumer trust exerted a substantial positive influence on the perceived benefits of smart mobility ($\beta = 0.536$, $p < 0.001$), thereby offering support for H1.

The effect of trust on NEV purchase intention was positive and direct ($\beta = 0.187$, $p < 0.01$), hence H2 was supported. The hypothesis (H3) was accepted because the perceived smart mobility benefits significantly predict purchase intention. ($\beta = 0.478$, $p < 0.001$)

The model accounted for 42.3% variance in perceived smart mobility benefits and 53.7% NEV purchase intention, reflecting a considerable explanatory capacity for consumer behaviour in the NEV context.

Table 2: Structural Path Results

H.	Structural Path	β	SE	t	p	Result
H1	Trust $\rightarrow$ Perceived Smart Mobility Benefits	0.536	0.052	10.31	< 0.001	Supported
H2	Trust $\rightarrow$ NEV Purchase Intention	0.187	0.058	3.22	0.001	Supported
H3	Perceived Smart Mobility Benefits $\rightarrow$ NEV Purchase Intention	0.478	0.054	8.85	< 0.001	Supported
H4	Trust $\rightarrow$ Perceived Benefits $\rightarrow$ Purchase Intention (Mediation)	0.256	0.039	—	95% CI [0.184, 0.337]	Supported (Partial mediation)
H5	Trust $\times$ Digital Readiness $\rightarrow$ NEV Purchase Intention	0.118	0.043	2.74	0.006	Supported
H6	Trust $\times$ Digital Readiness $\rightarrow$ Perceived Benefits	0.062	0.047	1.32	0.187	Not supported
H7	Perceived Benefits $\times$ Digital Readiness $\rightarrow$ NEV Purchase Intention	0.096	0.041	2.34	0.019	Supported

Mediation Analysis

Using bootstrapping with 5,000 resamples (Hayes, 2018), the study examined the role of perceived smart mobility benefits as a mediator. Consumer trust has a significant positive effect on purchase intention. The direct effect of trust remained significant when including perceived benefits but was diminished. The indirect effect through perceived benefits was also significant. The total effect of trust on purchase intention is 1.487. Among that total effect, the indirect effect accounted for 0.861 which is 57.8%. Trust has more pattern influence on

purchase intention through perceived smart mobility benefits. The results partially mediate and support H4.

Table 3: Mediation Results (Bootstrap)

Effect	β	95% CI
Total effect (Trust $\rightarrow$ PI)	0.443	[0.352, 0.541]
Direct effect	0.187	[0.076, 0.302]
Indirect effect (via benefits)	0.256	[0.184, 0.337]

Moderation Analysis

The examination of moderation hypotheses utilized the methods of latent variable interaction modeling (Ping, 1995). The association between consumer trust and purchase intention was significantly moderated by digital readiness ($\beta=0.118$, $p<0.01$) supporting H5. The relationship between perceived smart mobility benefits and purchase intention ($\beta = 0.096$, $p < 0.05$) was also moderated by it. H7 was supported. Nonetheless, the effect of digital readiness on the connection between trust and perceived benefits was not statistically significant, and H6 was not backed. Through simple slope analyses, it was observed that trust becomes a driver for purchase intention especially for those with high digital preparedness. It was similarly found that perceived benefits had a significantly stronger effect on purchase intention for digitally ready consumers, thus marking digital readiness as an important boundary condition.

Control Variables and Hypothesis Summary

Among the control variables, prior NEV experience and income showed significant positive effects on purchase intention, while age, gender, residential location, and current vehicle ownership were not significant. Overall, six of the seven hypotheses were supported. The only unsupported hypothesis concerned the moderating effect of digital readiness on the trust–perceived benefits relationship.

The New Body of Knowledge

This study contributes new knowledge to the literature on sustainable mobility, consumer behavior, and digitalized energy systems by empirically validating an integrated trust-based framework for new energy vehicle (NEV) adoption within a smart energy ecosystem context. Drawing on the Technology Acceptance Model, trust transfer theory, perceived value theory, and the Stimulus–Organism–Response (S–O–R) framework, the findings advance understanding of how trust, perceived benefits, and digital readiness jointly shape NEV purchase intention.

First, this research enriches trust theory by conceptualizing consumer trust in smart energy ecosystems as a multidimensional, second-order construct and empirically

demonstrating its central role in shaping sustainable consumption behavior. The results show that trust exerts both a direct and indirect influence on NEV purchase intention, confirming trust as a critical psychological stimulus in digitally mediated mobility systems. This extends prior trust research beyond isolated technologies or service providers and positions trust as an ecosystem-level construct encompassing technology reliability, service providers, system performance, and data security.

Second, the study generates new cognitive insight by identifying perceived smart mobility benefits as a key mediating mechanism through which trust is translated into behavioral intention. The mediation analysis reveals that more than half of the total effect of trust on NEV purchase intention is transmitted through perceived benefits, indicating that trust primarily operates by enhancing consumers' evaluations of functional, economic, environmental, and social value. This finding advances perceived value theory by demonstrating how trust activates benefit-based cognition in the adoption of complex, technology-intensive mobility solutions.

Third, the study contributes to digital readiness literature by establishing digital readiness as a critical boundary condition in trust-based decision-making. The moderation results indicate that digital readiness significantly strengthens the effects of both consumer trust and perceived smart mobility benefits on purchase intention. These findings suggest that digitally capable consumers are better positioned to transform trust and perceived value into concrete behavioral intentions. However, the non-significant moderation of digital readiness on the trust-benefit relationship reveals that trust formation itself may be less dependent on digital competence, whereas intention formation is highly sensitive to it. This nuanced insight refines the role of digital readiness in technology adoption models.

Fourth, by empirically validating a moderated mediation model, this study advances methodological and theoretical integration within sustainable mobility research. The model explains a substantial proportion of variance in both perceived smart mobility benefits and NEV purchase intention, highlighting its strong explanatory power. The results confirm that consumer behavior in smart mobility ecosystems cannot be adequately explained by linear models but requires consideration of both psychological mechanisms and contextual digital capabilities.

Finally, the findings contribute context-specific knowledge by providing empirical evidence from Hebei Province, China, a rapidly developing NEV market. The results demonstrate that prior NEV experience and income significantly influence purchase intention, while demographic factors such as age and gender play a limited role. This reinforces the argument that experiential and cognitive factors outweigh demographic characteristics in shaping sustainable mobility adoption.

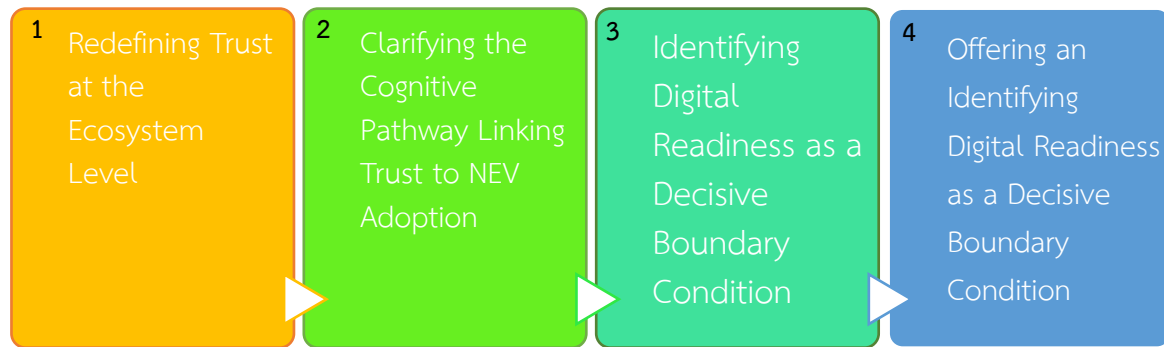


Figure 2: The Body of Knowledge Contribute Context-Specific Knowledge by Providing Empirical Evidence from Hebei Province

In sum, this study advances the body of knowledge by (1) redefining trust at the ecosystem level, (2) clarifying the cognitive pathway linking trust to NEV adoption, (3) identifying digital readiness as a decisive boundary condition, and (4) offering an integrative framework for understanding consumer behavior in smart energy-driven mobility systems. These insights deepen theoretical understanding and provide a foundation for future research on digitalized sustainability transitions.

Discussion of Research Results

Interpretation of Key Findings

With perceived smart mobility benefit as a mediator condition and digital readiness as a moderating condition, this study looks at how consumer trust in smart energy ecosystem influences new energy vehicle (NEV) purchase intention. The findings provide a number of theoretical and practical implications.

First, the consumer's faith in smart energy ecosystems surfaced as a significant predictor of perceived smart mobility benefits and NEV purchase intention. The present finding serves to reaffirm and extend prior trust research on technology-mediated contexts (e.g., Gefen et al., 2003; Kim et al., 2008; Zheng et al., 2018) showcasing that trust operates not only at the individual product/platform level but also at the ecosystem level. The strong influence of trust on perceived benefits reflects the idea that trust serves as a cognitive filter through which consumers perceive the benefits of smart mobility solutions. When confidence is established in the technology and service providers of the ecosystem, the reliability of the system and security of the data, consumers are more willing to believe that the promised benefits will materialize.

Furthermore, it was also found that perceived smart mobility benefits partially mediated the relationship between trust and purchase intention, with more than half of trust's total impact being captured by the mediation. This conforms to the Stimulus–Organism–Response model (Mehrabian & Russell, 1974) whereby trust is an external stimulus that creates

internal evaluation leading to behavioral responses. Notably, a substantial direct effect of trust continues to exist, illustrating that trust impacts beyond benefit cognition, possibly through a reduction in risk and psychological uncertainty. This study extends earlier studies that trust directly affects intention by explaining how trust is transformed into behaviour. It identifies perceived benefits as the main transmission channel (Kim et al., 2012; Chong, 2013).

Additionally, the level of digital readiness served as a relevant boundary condition. The influences of trust and the perceived benefit on purchase intention were strengthened by digital readiness. However, digital readiness failed to moderate the relationship between trust and benefit perceptions. The asymmetric pattern suggests that digital readiness matters for transforming evaluations into action rather than for forming evaluations. Despite trusting the ecosystem and seeing the benefits, people with low digital readiness do not buy. This is because they are unsure about their ability to effectively engage with the digital interface/system. Findings extend the technology readiness (Parasuraman, 2000; Blut & Wang, 2020) literature by showing that digital readiness is a strong antecedent of behavioral readiness, not perceptual readiness.

Thus, what findings suggest is that, trust is necessary but not sufficient for adopting a NEV. Favorable evaluations result due to trust, perceived benefit motivates intention and digital readiness determines if it leads to action.

Theoretical Implications

There are several ways in which this study adds to the literature. To begin with, it advances scientific research trust as it extends the context of smart energy ecosystems, where consumers need to assess connected technologies, services, and institutions. By viewing trust as multidimensional the study goes beyond one-object trust model thus providing a framework to explain complex social technical systems.

The second result clarifies the cognitive mechanism connecting trust with NEV purchase intention. Unlike previous NEV studies that focused on economic and technological features, this study focuses on perceived smart mobility benefits which serve as the key psychological bridge between trust and behavior. This leads to greater focus on processes in sustainable technology adoption.

The identification of digital readiness as a boundary condition integrates technology readiness theory with trust and perceived value perspectives. According to the findings, individual variations in users' digital capabilities affect the effectiveness of trust-based mechanisms in enhancing platform adoption. Hence, adoption models should incorporate the diversity of users' technological capabilities.

In conclusion, the study enhances the nascent literature on sustainable mobility adoption in emerging economies by focusing on the largest NEV market of China. Findings may have a broader relevance to regions going through rapid digital and energy transitions.

Practical Implications

The results have many useful implications. In the determination of NEV manufacturers in establishing user trust, the role of not only vehicle performance but also ecosystem reliability and data security must be considered. The desire to purchase can increase if companies convey tangible benefits made possible by trustworthy ecosystems.

As charging infrastructure operators and smart energy service providers ramp up activity, system reliability and cybersecurity investments will become essential trust-building strategies. When the benefits of ecosystems are made visible and easier to understand, it increases value.

The moderating role of digital readiness for policymakers suggests that enhancing digital literacy could complement infrastructure expansion. Inducing consumers to use digital services more effectively could significantly enhance the impact of trust-creating and incentivization policies on more digitally anxious groups.

Limitations and Future Research

Several limitations should be acknowledged. The cross-sectional design limits causal inference, and future studies could adopt longitudinal or experimental approaches. Reliance on self-reported data may introduce bias, suggesting value in incorporating behavioral or transactional data. In addition, the focus on a single province limits generalizability, and future research should examine cross-regional or cross-national differences. Finally, future studies could disaggregate trust across specific ecosystem actors to examine compensatory or substitutive trust mechanisms.

Conclusion

This study delves into the effect of consumer trust in smart energy ecosystem on their NEV purchase intention. Also, it discusses the mediating role of perceived smart mobility benefit. Further, it discusses the moderating role of digital readiness. Drawing on survey evidence from 523 consumers in Hebei Province, China, we find that trust is a central driver of NEV adoption, operating largely through benefit perceptions tempered by consumers' digital readiness.

According to the findings, trust has a positive impact on perceived benefits and purchase intention. Moreover, it appears that most of trust's impact is transmitted through perceived benefits. Likewise, digital readiness determines whether positive evaluations are translated into behavioral intention. Implications for theory and practice: These insights extend existing technology adoption theories and provides practical guidance suggesting how the transition to smart and sustainable mobility can be accelerated.

In the development of intelligent energy ecosystems, knowing the psychological mechanisms behind consumer responses will be crucial. This research lays the groundwork for such comprehension while indicating advantageous directions for future studies.

Suggestions

Based on the empirical findings and theoretical insights of this study, several suggestions are proposed for practitioners, policymakers, and future research to enhance the adoption of new energy vehicles (NEVs) within smart energy ecosystems.

1. The suggestions for NEV manufacturers and ecosystem stakeholders

First, NEV manufacturers should move beyond emphasizing vehicle-level technological features and place greater strategic focus on building trust at the ecosystem level. Since consumer trust significantly influences both perceived smart mobility benefits and purchase intention, manufacturers should actively communicate the reliability of integrated systems, the credibility of service providers, and the security of data-sharing mechanisms. Transparent information on system performance, data protection standards, and collaboration with reputable energy and digital service partners can strengthen ecosystem-wide trust and reduce perceived risk.

Second, ecosystem actors such as charging infrastructure operators, energy service providers, and digital platform developers should highlight tangible smart mobility benefits in their communication strategies. The results indicate that perceived benefits constitute the primary cognitive pathway through which trust translates into purchase intention. Therefore, marketing and user education should explicitly demonstrate convenience, cost savings, environmental advantages, and social value enabled by smart energy ecosystems. Simplifying benefit narratives and using real-life use cases can enhance consumer understanding and perceived value.

2. The suggestions for policymakers and public institutions

Third, policymakers should recognize digital readiness as a crucial enabling condition for translating positive attitudes into actual adoption behavior. While trust and perceived benefits may be present, consumers with lower digital readiness may still hesitate to adopt NEVs. Thus, policy initiatives aimed at promoting sustainable mobility should be complemented by programs that enhance digital literacy, user confidence in digital systems, and familiarity with smart energy services. Public campaigns, training programs, and user-friendly digital interfaces can help reduce the digital divide and amplify the effectiveness of trust-building policies.

Fourth, policy design should prioritize experience-based exposure to NEVs, such as test-driving programs, pilot projects, and shared mobility initiatives. The findings show that prior NEV experience significantly influences purchase intention, suggesting that experiential learning plays a key role in reducing uncertainty and reinforcing trust. Expanding access to NEV trials in urban areas and integrating them into public transportation or community programs may accelerate consumer acceptance.

3. The suggestions for future research

Finally, future research should extend this study by adopting longitudinal or experimental research designs to better capture causal relationships and dynamic changes in trust, perceived benefits, and digital readiness over time. Comparative studies across regions or countries could further examine how institutional environments and levels of digital infrastructure shape trust-based adoption mechanisms. Additionally, future studies may disaggregate ecosystem trust into specific actors (e.g., government, manufacturers, digital platforms) to explore how different trust sources interact or compensate for one another in influencing NEV adoption.

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