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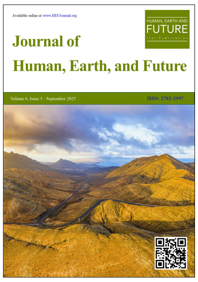

Unveiling Multi-Dimensional Factors of Consumer Switching Intention Towards Electric Vehicles

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Abstract

Objectives: This study explores consumers' intentions to switch from traditional fuel vehicles to electric vehicles (EVs) by employing the Push-Pull-Mooring (PPM) model as an analytical framework. It seeks to gain a deep understanding of how push factors (such as financial, infrastructure, privacy, and environmental risks), pull factors (such as product innovativeness, instrumental attributes, and policy support), and mooring factors (such as inertia and switching costs) influence consumers' switching decisions. *Methods/Analysis:* Employing a purposive sampling method, the research targets consumers in Taiwan with EV purchase experience, acknowledging the rapid growth of the EV market in Taiwan and the unique characteristics of EV consumers. The survey was conducted using a dual approach, both online and offline, distributing questionnaires through EV community platforms, owner forums, and dealership locations to ensure the diversity and representativeness of respondents. *Findings:* The results indicate that push factors, including financial risk, infrastructure risk, privacy risk, and environmental risk, all have a significant negative impact on switching intentions, with environmental and financial risks being the most prominent. In contrast, pull factors such as product innovativeness, instrumental attributes, and policy support show a positive influence, with product innovativeness having the most substantial effect. Regarding mooring factors, switching costs significantly negatively affect switching intentions, while inertia does not show a significant effect. This suggests that consumers are more concerned with tangible benefits and risk considerations when adopting electric vehicles rather than being constrained by existing habits. *Novelty/Improvement:* The originality of this study lies in its first comprehensive application of the PPM model to the context of electric vehicle adoption, providing a multidimensional and integrated analytical framework that overcomes the limitations of previous single-theory perspectives.

Keywords: Environmental Risk; Financial Risk; Inertia; Infrastructure Risk; Instrumental Attributes; Policy Support; Privacy Risk; Product Innovativeness; Push-Pull-Mooring; Switching Costs.

1. Introduction

The electric vehicle (EV) market has seen continuous growth in recent years, driven by increasing consumer demand for environmentally friendly and energy-efficient options and government policies aimed at reducing carbon

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emissions [1]. With the public's growing awareness of environmental protection and continuous improvements in EV performance, more consumers are beginning to accept and choose electric vehicles as their primary mode of transportation for daily commuting. However, the widespread adoption of EVs depends not only on technological advancements and infrastructure development but also closely relates to consumer adoption intentions and purchasing behaviors. In recent years, governments worldwide have promoted the development of the EV market through policy incentives such as subsidies and tax reductions. However, as these policies gradually phase out, the EV industry is transitioning from policy-driven to market-driven. This transition presents new challenges and opportunities for consumer purchasing intentions and market adoption of electric vehicles.

Taking China as an example, the Chinese government ended its 13-year EV subsidy policy in 2023. From 2010 to 2020, China's subsidies for electric vehicles exceeded 152.1 billion RMB, supporting the sale of at least 3.17 million EVs [2]. Terminating such subsidy policies will lead the EV industry into a new phase of market competition, shifting away from reliance on policy support. This transition not only imposes higher demands on automakers, compelling them to achieve sustainable profitability without relying on subsidies, but also profoundly impacts consumers' purchasing decisions [3]. Therefore, despite the rapid growth trend in the electric vehicle market, consumers still face numerous considerations when adopting EVs. These considerations include practical issues such as the convenience of charging facilities, limitations on driving range, and higher purchase costs [4, 5]. Additionally, consumers' adoption intentions are influenced by psychological factors such as personal environmental attitudes, acceptance of innovation, and social influence [6, 7]. Therefore, a deep understanding of the key factors affecting consumers' intentions to adopt electric vehicles is crucial for promoting the development of the EV market. Moreover, from a sustainable development perspective, electric vehicles represent a revolution in transportation tools and a significant milestone in society's progress toward a low-carbon economy. According to a report by the International Energy Agency, the transportation sector accounts for approximately 24% of global carbon emissions, with private vehicles contributing the largest share. The widespread adoption of electric vehicles will aid in achieving the carbon neutrality goals of various countries [2].

Current research on electric vehicle (EV) adoption often focuses on single-dimensional factors, such as economic benefits [4] or policy incentives [5]. However, the decision-making process for consumers adopting EVs is a multi-layered and multifaceted evaluation. Therefore, this study uses the Push-Pull-Mooring (PPM) model as the core theoretical framework to explore consumer behavior in EV adoption. Firstly, the EV market is undergoing a critical transition period, and the decision-making process for consumers shifting from traditional fuel vehicles to EVs involves complex trade-offs. The PPM model, originating from migration theory, provides an integrative perspective particularly suited to explaining such transition behaviors. Its three-dimensional structure captures the negative factors driving consumers away from traditional options, the positive incentives attracting them to new technologies, and the personal and situational characteristics influencing the transition process. Secondly, the PPM model offers a more comprehensive analytical perspective compared to traditional technology acceptance theories such as the Technology Acceptance Model (TAM) or the Theory of Planned Behavior (TPB). It not only focuses on the attractiveness of new products but also considers the repulsive forces of existing products and the barriers encountered during the transition process. This multidimensional consideration is crucial for understanding the EV market, as consumer decisions are often influenced by multiple factors such as environmental consciousness, economic benefits, and charging convenience.

Furthermore, the PPM model has a unique advantage in explaining consumers' internal conflicts and external constraints when encountering innovative products. It effectively reveals the key barriers and facilitating factors in EV adoption. Expanding the PPM model, this study aims to establish a more comprehensive framework for understanding EV adoption behavior, providing empirical evidence for industry development and policy formulation.

The PPM model, originating from migration studies [8], has been widely applied to the analysis of consumer switching behavior, providing a theoretical foundation for understanding the transition from traditional fuel vehicles to electric vehicles (EVs). The model comprises three core dimensions:

- ***Push factors*** are the negative aspects that drive consumers away from existing products or services. In the context of EVs, these may include environmental concerns about reliance on fossil fuels, rising fuel prices, and increasing maintenance costs.
- ***Pull factors*** are the positive attributes that attract consumers to adopt new products. In the EV scenario, these can include product innovativeness, service innovativeness, instrumental attributes, and policy support.
- ***Mooring factors*** encompass the personal traits and situational factors influencing the switching decision. Examples include inertia, switching costs, and perceived herd behavior.

PPM model provides a comprehensive framework for analyzing the multifaceted decision-making process involved in consumer transitions to electric vehicles.

Previous research on consumer switching behavior has primarily relied on single theoretical frameworks, such as the Technology Acceptance Model (TAM) [9], the Theory of Planned Behavior (TPB) [10], or the Innovation Diffusion Theory [11]. While these theories provide valuable insights, they fail to capture the complexity of switching behavior, which involves evaluating the negative aspects of current products, the attractive features of alternatives, and personal constraints that may facilitate or hinder the transition. The urgency to understand consumer switching behavior is heightened by the imperative of sustainability, as the pace of electric vehicle (EV) adoption directly impacts global climate goals and the timeline for achieving net-zero emissions targets [5]. Furthermore, the limited integration of risk perceptions in existing literature represents a significant gap, as few studies have comprehensively analyzed how multiple risk dimensions simultaneously influence adoption decisions. The emergence of smart, connected EVs has introduced new risk categories, particularly privacy and data security concerns, which remain underexplored in adoption literature.

To address these theoretical gaps, this study employs the PPM framework, which offers several advantages over traditional technology adoption theories. Unlike single-dimensional models, PPM simultaneously considers negative factors driving consumers away from current options (push), positive attributes attracting them to alternatives (pull), and personal/situational factors influencing the transition process (mooring). The framework is specifically designed to explain transition behaviors rather than general adoption, making it particularly suitable for understanding the shift from conventional to electric vehicles. The model's migration theory origins make it uniquely suited to understanding switching behavior, as it recognizes that consumers must overcome attachment to existing solutions while simultaneously evaluating new alternatives under conditions of uncertainty and incomplete information. This research represents the first comprehensive application of the PPM model to EV adoption, extending the theory by incorporating contemporary risk dimensions relevant to smart, connected vehicles, particularly privacy and environmental risks that have received limited attention in switching behavior research. The study's focus on experienced EV consumers provides insights into post-adoption perspectives that can inform the understanding of market development in mature EV markets. By addressing these research questions through the PPM framework, this study aims to provide actionable insights for multiple stakeholders: for manufacturers, identifying specific risk mitigation strategies and product features that can enhance market appeal; for policymakers, revealing the relative effectiveness of different support mechanisms and highlighting infrastructure development priorities; and for marketers, suggesting targeted communication strategies that address specific consumer concerns while highlighting attractive product attributes.

2. Theoretical Background and Foundation of the Research Model

2.1. Push-Pull-Mooring

The PPM model originally emerged from migration literature and has recently been widely applied in studies explaining consumer switching behavior [8]. It expanded upon the original push-pull model to develop a more comprehensive PPM model. This model provides a holistic framework for analyzing the factors influencing consumers to switch from one product or service to another. The PPM model categorizes influencing factors into three types: Push factors refer to the negative aspects of the current product or service that drive consumers to consider switching; Pull factors denote the attractiveness of alternative products or services; and Mooring factors encompass personal, social, and psychological elements that may hinder or facilitate the switching process [12].

Previous research utilizing the PPM model explored the switching behavior of mobile instant messaging application users, identifying dissatisfaction and the attractiveness of alternative products as key push and pull factors influencing users' switching intentions. Additionally, switching costs and subjective norms were significant mooring factors that moderated the effects of push and pull factors on switching intentions [13]. Lai et al. [14] applied the PPM model to the mobile shopping domain, revealing that consumer dissatisfaction with traditional shopping methods (push), the convenience of mobile shopping (pull), and personal innovativeness and switching costs (mooring) collectively influenced consumers' intentions and behaviors towards mobile shopping. These studies demonstrate the robust explanatory power of the PPM model in elucidating switching behavior across various consumer contexts.

In recent years, the PPM model has been applied to multiple consumer domains and integrated with other theoretical frameworks to enhance its explanatory capacity. For instance, Kordi Ghasrodashti [15] combined the PPM model with the Theory of Reasoned Action to investigate antecedents of brand-switching behavior. The study results indicated that brand image and perceived value served as pull factors, dissatisfaction as a push factor, and switching costs and social influence as mooring factors, collectively impacting consumers' switching intentions. This theoretical integration provides a more comprehensive perspective for understanding consumer decision-making processes.

In the study of smartphone brand switching, Guo et al. [16] integrated the PPM framework to analyze the switching intentions of Chinese consumers. They found that issues with product quality and price dissatisfaction were the main push factors, while the innovative features and reputation of alternative brands were key pull factors. Additionally, consumer brand loyalty and switching costs significantly influenced the final switching decision. Similarly, in research on the adoption of mobile payments in physical stores, Handarkho & Harjoseputro [17] developed a model based on PPM theory, identifying convenience of use (pull), perceived security risks (push), and personal innovativeness (mooring) as critical factors affecting consumer adoption intentions.

As digital transformation accelerates, the PPM model demonstrates new applicability in explaining cross-channel consumer behavior. Haridasan et al. [18] applied the PPM framework to study consumers' cross-channel switching intentions, particularly from offline to online information search behavior. The results indicated that the inconvenience of offline channels (push), the convenience and variety of online channels (pull), and consumers' online self-efficacy (mooring) collectively influenced cross-channel switching intentions. This research provides new insights into consumer behavior in omnichannel retail environments. Marx [19] conducted a meta-analysis reviewing the application of the PPM model in consumer service-switching research, finding that the model has stable predictive power in explaining service-switching intentions and behaviors. The study results showed that push factors (such as dissatisfaction) and pull factors (such as perceived advantages of alternative services) directly affect switching intentions, while mooring factors (such as switching costs and social relationships) primarily play a moderating role.

In the field of electric vehicles (EV), Hu et al. [20] integrated the Theory of Planned Behavior (TPB) with the Technology Acceptance Model (TAM) to propose key dimensions within the PPM framework: push factors (such as rising fuel costs and environmental anxiety), pull factors (such as government subsidies and the convenience of charging facilities), and mooring factors (such as brand loyalty and switching costs), which collectively influence switching intentions. This model was validated in a study on EV adoption among motorcycle riders in Vietnam, revealing that subjective norms significantly moderate the effect of pull factors [21]. The PPM model provides a robust and flexible theoretical framework for understanding consumer switching behavior. As the digital consumer environment continues to evolve, the PPM model demonstrates sustained value in explaining switching behavior in emerging and innovative consumption contexts.

2.2. Antecedents of Push

With the increasing global awareness of environmental protection and the advancement of sustainable development goals, electric vehicles (EVs) are a key solution for achieving low-carbon transportation. However, consumers face various perceived risks when adopting this emerging technology, directly affecting their purchase intentions and the pace of market expansion [22]. This literature review focuses on four significant dimensions of perceived risk in the EV adoption process: financial risk, infrastructure risk, privacy risk, and environmental risk. The aim is to gain a deeper understanding of the psychological barriers consumers face when adopting EVs, thereby providing a theoretical foundation and practical guidance for promoting the expansion of the EV market.

2.2.1. Financial Risk

Financial risk is one of the most significant concerns for consumers considering the adoption of electric vehicles, encompassing aspects such as purchase cost, maintenance expenses, residual value depreciation, and energy costs [22]. Although the long-term ownership cost of electric vehicles may be lower than that of traditional gasoline vehicles, the higher initial purchase price remains a significant barrier to adoption [23]. Through empirical research, Liao et al. [23] found that consumers often overestimate the total cost of ownership of electric vehicles and have insufficient awareness of their long-term economic benefits. This cognitive bias significantly affects purchase intentions. Hardman et al. [24] further elucidated this phenomenon, noting that when evaluating the financial risks of electric vehicles, consumers tend to focus excessively on short-term investment costs while overlooking the advantages of lower long-term operating costs, leading to a "cost perception asymmetry" phenomenon.

Additionally, battery replacement cost, as a specific financial risk factor, can also significantly influence consumer decision-making. Despite continuous advancements in battery technology, consumers remain concerned about battery durability and future replacement costs, reinforcing the perception of financial risk. Palmer et al. [25] found that transparent battery warranty policies and residual value guarantee programs can reduce consumers' perceived financial risk and increase purchase intentions. Based on the discussion above, this study derives the first research hypothesis as follows:

H1a: *Financial risk has a negative impact on switching intention towards EVs.*

2.2.2. Infrastructural Risk

Infrastructure risk primarily manifests in aspects such as the accessibility of charging networks, charging efficiency, and standardization. The study by Neubauer & Wood [26] revealed that range anxiety is a key barrier to adopting electric vehicles. This refers to consumers' concerns that battery capacity may be insufficient to meet daily driving needs, especially in areas lacking widespread charging facilities.

The uncertainty of charging infrastructure and range anxiety create a mutually reinforcing effect. Through longitudinal studies, Berkeley et al. [27] found that even when the actual range of electric vehicles is sufficient to meet most daily needs, consumers still experience significant range anxiety, which is negatively correlated with the density of charging station distribution. Zhang et al. [4] further pointed out that the charging infrastructure planning should consider geographical coverage and focus on charging efficiency and peak service capacity to mitigate consumers' time cost risks.

The compatibility risks arising from the lack of standardized charging standards are also significant. Berkeley et al. [27] found that differences in charging standards adopted by different manufacturers lead to consumer concerns that their purchased electric vehicles may not be compatible with certain charging stations, thereby increasing perceived infrastructure risk. Additionally, with the rapid iteration of electric vehicle technology, consumers worry that their current investment in charging equipment may face the risk of technological obsolescence [28]. Based on the above discussion, we derive the second hypothesis of this study as follows:

H1b: *Infrastructural risk has a negative impact on switching intention towards EVs.*

2.2.3. Privacy Risk

As electric vehicles become increasingly intelligent and networked, privacy and data security risks have emerged as new concerns. Empirical studies on social media have revealed users' worries about privacy breaches [29]. Taeihagh & Lim [30] analyzed the privacy challenges faced in adopting autonomous driving technology, finding that consumers are concerned about the ownership, usage scope, and sharing mechanisms of driving data. These concerns are particularly pronounced in the absence of transparent privacy policies, forming a barrier to adoption.

Cybersecurity threats represent another critical dimension of privacy risk, exacerbating consumers' perceived risks associated with electric vehicles. The study by Cichy et al. [31] further confirmed that concerns about cyberattacks have become a significant factor for specific consumer groups in delaying the adoption of electric vehicles, especially in cultural contexts where privacy is highly valued. Based on the above discussion, we derive the third hypothesis of this study as follows:

H1c: *Privacy risk has a negative impact on switching intention towards EVs.*

2.2.4. Environmental Risk

Electric vehicles are generally viewed as environmentally friendly options but also have perceived environmental risks. Hawkins et al. [32], through life cycle assessment (LCA) studies, found that the environmental benefits of electric vehicles are highly dependent on the structure of the electricity sources. In regions where coal is the primary source of electricity, the carbon emission advantages of electric vehicles may be significantly diminished, leading consumers to question the authenticity of environmental claims.

The environmental risks associated with battery manufacturing and disposal have also drawn attention. Noel et al., [33] highlighted that the production of lithium-ion batteries is resource-intensive and contains potentially harmful substances, which, without effective recycling mechanisms, could pose significant environmental burdens. This perception contradicts the eco-friendly image of electric vehicles, increasing consumers' psychological costs. Egbue & Long [34] found in consumer surveys that environmentally conscious consumers might harbor more doubts about the environmental benefits of electric vehicles, leading to a phenomenon of "environmental skepticism." These consumers focus more on the environmental impact of electric vehicles' full life cycle rather than just the zero emissions during use. Diao et al. [35] further confirmed that consumers' perceptions of the environmental risks of electric vehicles could adjust with changes in energy structure, media reports, and individual environmental knowledge levels, reflecting environmental risk perception's dynamic and complex nature. Based on the above discussion, we derive the fourth hypothesis of this study as follows:

H1d: *Environmental risk has a negative impact on switching intention towards EVs.*

2.3. Antecedents of Pull

2.3.1. Product Innovativeness

Product innovativeness refers to the degree to which consumers perceive a product as novel, unique, and revolutionary, and it is a key factor influencing consumer adoption decisions. In the electric vehicle market context, product innovativeness is reflected in various dimensions, such as technological innovation, functional design, and user experience. Rogers [36] diffusion of innovations theory points out that innovation characteristics, such as relative advantage, compatibility, and complexity, directly affect consumers' willingness to adopt, providing a foundational framework for understanding electric vehicle adoption behavior. Cherubini et al. [37] analyzed the electric vehicle market and highlighted that the convenience of charging services, mobile application integration, and maintenance system innovations significantly influence consumers' willingness to switch, especially in effectively alleviating range anxiety.

Jansson et al. [38] conducted a study on Swedish consumers and found that the perceived innovativeness of electric vehicles is positively correlated with the innovative personality traits of early adopters, significantly influencing their willingness to adopt. Consumers' perceptions of innovative elements such as the electric vehicle platform, battery technology, and intelligent features form a unique product value cognition. Through a systematic literature review, Franke & Krems [39] further confirmed that consumers' perception of innovation plays a crucial role in electric vehicle adoption decisions, particularly impacting consumer groups willing to take risks and try new things.

In addition, the diversity of service innovations in electric vehicles provides new growth points for their market acceptance. Kley et al. [40] identified various service innovation models within the electric vehicle ecosystem, including battery leasing, battery swapping stations, and smart charging. These service innovations alleviate consumers' concerns about initial investment, battery lifespan, and charging inconvenience.

H2a: *Product innovativeness has a positive impact on switching intention towards EVs.*

2.3.2. Instrumental Attribute

Instrumental attributes refer to electric vehicles' functional and practical characteristics, including core features that directly impact the user experience, such as driving range, charging time, and performance parameters.

As the most prominent instrumental attribute, the impact of the driving range has been widely validated. Franke & Krems [39] pointed out that consumers' psychological threshold for range requirements often exceeds their actual needs, a phenomenon known as "*range anxiety*". This psychological barrier significantly affects their willingness to adopt electric vehicles. A study by Jensen et al. [41] on Danish consumers found that after actually test-driving electric vehicles, consumers' estimates of range requirements became more rational, and their willingness to adopt increased. This underscores the importance of real-world experience in consumer education.

As a unique utilitarian attribute, the convenience of charging is increasingly gaining attention. The study by Berkeley et al. [27] found that the accessibility of charging infrastructure and the charging speed are significant predictors of consumers' adoption intentions. This factor is particularly important for consumers living in densely populated urban areas. The direct experiential attributes of electric vehicles, such as power performance and handling feel, also influence purchasing decisions. Skippon & Garwood [42] found that even after controlling for environmental factors, utilitarian attributes like acceleration performance and driving smoothness of electric vehicles still independently explain adoption intentions, confirming the fundamental role of functional experience.

H2b: *Instrumental attributes have a positive impact on switching intention towards EVs.*

2.3.3. Policy Support

Policy support, as a crucial catalyst for the electric vehicle market development, directly influences consumer decisions by reducing adoption costs and enhancing usage convenience. The study by Mersky et al. [43] on the Norwegian market indicates that the combined application of financial incentives (such as purchase subsidies and tax reductions) and non-financial measures (such as dedicated lanes and free parking) effectively stimulates the growth of electric vehicle adoption rates, outperforming single policy tools. Non-financial policy measures play a unique role in consumer switching intentions. Research by Holtsmark & Skonhoft [44] found that convenience measures like lane usage rights and toll exemptions in Norway are highly attractive to consumers. Further, Langbroek et al. [45] in their study of Swedish consumers confirmed that everyday convenience measures, such as free parking, have a more sustained impact on adoption intentions compared to one-time purchase incentives, highlighting the importance of policies during the usage phase.

Policy stability and predictability also affect consumer confidence.

H2c: *Policy support has a positive impact on switching intention towards EVs.*

2.4. Antecedents of Mooring

2.4.1. Inertia

In consumer behavior research, inertia is defined as the tendency of consumers to continue using existing products or services, even when better alternatives are available. This behavior pattern stems from consumers' resistance to change and reliance on familiar things. Studies have shown that habit can serve as a significant antecedent of the retention factor in the PPM model, influencing whether consumers switch from one service or product to another [46]. Previous research also indicates that inertia refers to consumers' tendency to persist with current products or services despite superior options [47]. Consumer inertia arises from a preference for the status quo, risk aversion, and the automation of existing behavior patterns, which manifests in the decision-making process as insufficient evaluation of alternatives and a lack of motivation to switch. In consumer behavior research, inertia can be expressed as both passive behavior and active choice.

H3a: *Inertia has a negative impact on switching intention towards EVs.*

2.4.2. Switching Cost

Switching costs refer to the various barriers and sacrifices consumers perceive when transitioning from one product or service to an alternative, serving as a core mooring factor in the PPM model that influences consumer decisions [9]. While closely related to consumer loyalty, switching costs are conceptually distinct. The study by Egbue & Long [34] identified various switching costs, including the purchase cost of electric vehicles, investment in charging infrastructure, charging time costs, and changes in driving habits. Rezvani et al. [48] pointed out that consumers face higher learning costs and usage uncertainties due to the fundamental differences between electric vehicle technology and traditional fuel vehicles. Multiple studies have confirmed the central role of switching costs within the PPM framework. Bansal et al. [49] found that perceived switching costs significantly enhance the retention rate of existing service providers.

H3b: *Inertia has a negative impact on switching intention towards EVs.*

Based on the derivation of the aforementioned research hypotheses, the research framework of this paper is illustrated in Figure 1.

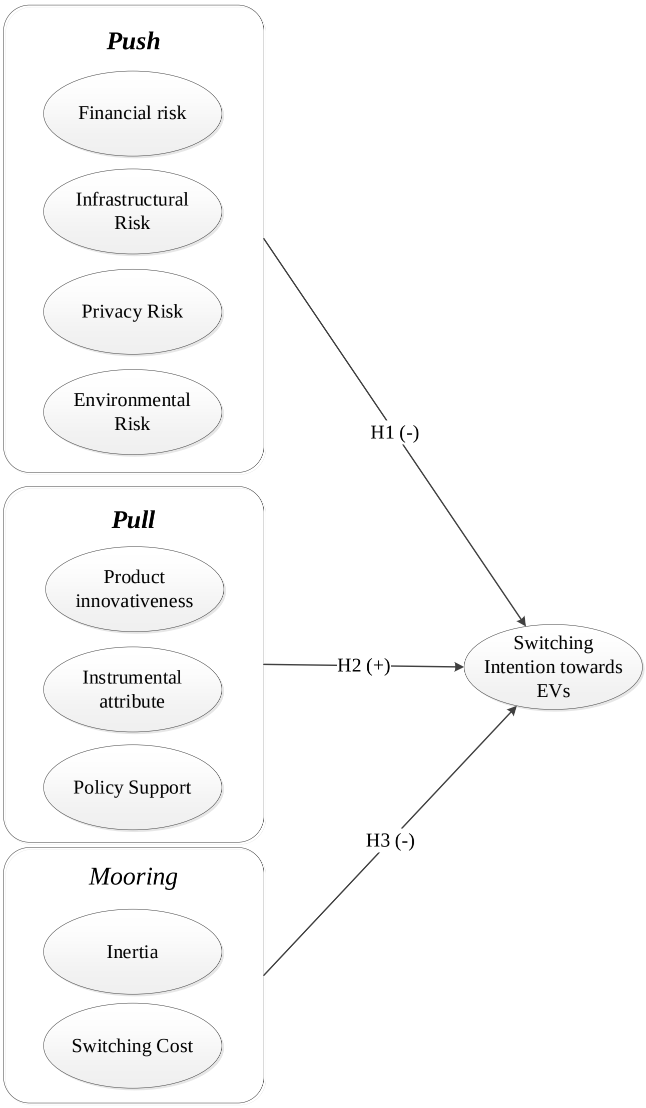


Figure 1. Research framework

3. Research Method

3.1. Operational Definitions and Scales

Before conducting sample collection and statistical analysis, this study establishes operational definitions for all potential variables. The quality of these operational definitions directly affects the reliability and validity of the measurement model. Latent variables must be quantified through observable measurement indicators, which must possess sufficient convergent and discriminant validity to ensure the reliability and validity of the research findings. The push, pull, and mooring factors in the PPM theoretical framework may vary across different market environments. However, through consistent operational definitions and scales, researchers can effectively compare research results across different regions or periods, thereby enhancing the external validity and generalizability of the theory. The operational definitions and scales for each latent variable in this study are presented in Table 1.

Table 1. Operational definition and measurement items

Latent variable	Operational definition and measurement items	Reference
Financial risk	Operational definition: Consumers perceive potential financial loss risks when purchasing electric vehicles, which include the purchase cost, maintenance costs, and possible future financial burdens. Measurement items: FINR1: I am concerned that the total cost of purchasing an electric vehicle (including purchase price and maintenance costs) will exceed my budget. FINR2: Compared to conventional vehicles, I think buying an electric vehicle might cause a greater financial burden. FINR3: I worry about the additional financial risks from battery replacement and repair costs of electric vehicles.	Hu et al. (2023) and Abbasi et al. (2024) [20, 22]
Infrastructural Risk	Operational definition: Consumers' perceptions of the charging infrastructure for electric vehicles, including the availability, convenience, and reliability of charging facilities. The degree of concern regarding the accessibility, convenience, and reliability of charging facilities, including the distribution density of charging stations, the availability of charging equipment, and the uncertainties that may be encountered during the charging process. Measurement items: INFR1: I am worried about not being able to find suitable charging stations when needed. INFR2: I think the current charging infrastructure network is insufficient and may affect my daily use. INFR3: I am concerned about charging station equipment malfunctions or unavailability.	Featherman et al. (2021) [6]
Privacy Risk	Operational definition: The degree of concern consumers have regarding the collection, use, sharing, or misuse of personal data when using smart electric vehicles, including security concerns over personal privacy information such as driving data, location information, and charging habits. Measurement items: PRVR1: I am concerned that the electric vehicle will collect too much personal information. PRVR2: I worry that unauthorized third parties might access or use my driving data. PRVR3: I am concerned that my location information and charging habits might be used for other unknown purposes.	Featherman et al. (2021) and Koester et al. (2022) [6, 50]
Environmental Risk	Operational definition: The extent to which consumers perceive the potential negative environmental impacts of electric vehicles throughout their lifecycle, including the assessment of environmental risks related to battery manufacturing, waste disposal, and energy consumption. Measurement items: ENVR1: I am concerned about the environmental pollution caused by the manufacturing and disposal of electric vehicle batteries. ENVR2: I worry that the electricity sources required for electric vehicles may not be completely environmentally friendly. ENVR3: I am concerned about the negative impact on ecosystems from the recycling and disposal of electric vehicle components.	Mukesh & Narwal (2023) [51]
Product innovativeness	Operational definition: Consumers' level of perception regarding electric vehicles as an innovative product, including their technological advancement, novelty, and innovative characteristics compared to traditional automobiles. Measurement items: PINO1: I am concerned about the environmental pollution caused by the manufacturing and disposal of electric vehicle batteries. PINO2: I worry that the electricity sources required for electric vehicles may not be completely environmentally friendly. PINO3: I am concerned about the negative impact on ecosystems from the recycling and disposal of electric vehicle components.	Shanmugavel & Micheal (2022) [52]
Instrumental attribute	Operational definition: The functional and practical features of electric vehicles, which directly impact the vehicle's actual user experience and utility. These features primarily include technical performance indicators such as range, charging convenience, and performance parameters. Measurement items: INAT1: The driving range of electric vehicles meets my daily travel needs. INAT 2: Electric vehicles' charging time and charging convenience meet my expectations. INAT 3: The overall performance of electric vehicles (e.g., acceleration, handling) is satisfactory.	Schuitema et al. (2013) [53]

Policy Support	Operational definition: Supportive policy measures implemented by the government to promote the adoption of electric vehicles, including purchase subsidies, tax incentives, and support for the development of charging infrastructure. Measurement items: PLSU1: The subsidies (including government subsidies and/or manufacturers' subsidies) for purchasing EVs are helpful to me. PLSU2: The tax policies are important to me when purchasing energy vehicles. PLSU3: The government investment in the construction of the energy vehicles' charging piles is helpful to me.	Chonsalasin et al. (2024) [54]
Inertia	Operational definition: Consumers' psychological tendency to maintain the status quo, which can hinder changes in existing consumption behavior patterns. In the context of electric vehicle adoption, this refers to consumers' attachment to their current traditional gasoline vehicles. Measurement items: INE1: Switching to an electric vehicle requires too much learning and adaptation for me. INE2: Even if electric vehicles might have advantages, I tend to stick with the conventional vehicles I am familiar with.	Hu et al. (2023) and Liu et al. (2020) [20, 55]
Switching cost	Operational definition: The various costs consumers need to bear when transitioning from traditional gasoline vehicles to electric vehicles, such as monetary costs, time costs, and learning costs. Measurement items: SWCO1: The infrastructure required for an electric vehicle (e.g., charging equipment) represents a significant expense for me. SWCO2: Switching to an electric vehicle would result in a loss of significant time and monetary investments. SWCO3: Compared to continuing with a conventional vehicle, switching to an electric vehicle requires significant time investment in learning and adaptation.	Lin et al. (2021) and Chang et al. (2017) [12, 56]
Switching intention	Operational definition: The intensity of consumers' behavioral intention to switch from traditional gasoline vehicles to electric vehicles. Measurement items: SINT1: I am very likely to choose an electric vehicle over a traditional gasoline vehicle for my next car purchase. SINT2: I will continue to use or purchase electric vehicles in the future.	Lin et al. (2021) and Wang et al. (2014) [12, 57]

3.2. Sampling and Data Collection

This study investigates consumers in Taiwan who have experience purchasing electric vehicles (EVs). Employing a purposive sampling method, the research targets consumers with EV purchase experience, acknowledging the rapid growth of the EV market in Taiwan and the unique characteristics of EV consumers. The survey was conducted using a dual approach, both online and offline, distributing questionnaires through EV community platforms, owner forums, and dealership locations to ensure the diversity and representativeness of respondents.

In designing the questionnaire, demographic variables such as gender, age, education level, and driving experience were included as control variables based on characteristics identified in previous studies of EV consumers. Over a two-month data collection period, 257 questionnaires were returned. After data cleaning and screening, 230 valid responses were obtained, resulting in an effective response rate of 89.5%.

The sample comprised 230 valid questionnaires. Regarding gender distribution, male respondents outnumbered females, with 163 males (71%) and 67 females (29%). The age distribution showed that the majority were in the 41-50 age group, accounting for 87 respondents (38%); those over 50 comprised 51 respondents (22%); the 31-40 age group had 48 respondents (21%); and the 21-30 age group had 44 respondents (19%). Regarding educational attainment, the sample exhibited high educational levels, with the most significant proportion holding a bachelor's degree (133 respondents, 58%), followed by master's degrees at 23% (76 respondents), and associate degrees at 9% (21 respondents), indicating a generally high educational level among respondents.

Notably, in terms of driving experience, over 60% (61.2%) of respondents had more than 10 years of driving experience, demonstrating the sample's extensive driving background, which is particularly valuable for assessing the willingness to adopt EVs. The sample structure reflects a middle-class group characterized by stable income, high education levels, and extensive driving experience.

Table 2 provides descriptive statistics for each item in this study. The means of the constructs range from 2.596 to 5.143, with standard deviations between 1.503 and 1.833. The mean scores for Financial Risk (FINR) are between 5.048 and 5.143; Infrastructure Risk (INFR) averages range from 5.052 to 5.122; Privacy Risk (PRVR) means are between 4.826 and 4.917; Environmental Risk (ENVR) averages fall between 5.009 and 5.087. The mean for Product Innovativeness (PINO) is relatively low, ranging from 2.926 to 3.043; Instrumental Attributes (INAT) are similarly low, with means between 2.935 and 2.961; Policy Support (PLSU) averages between 4.757 and 4.770. Inertia (INE) has mean scores ranging from 4.543 to 4.800; Switching Costs (SWCO) means are between 4.991 and 5.026, whereas Switching Intention (SINT) has the lowest mean, only between 2.596 and 2.598.

Table 2. Descriptive statistics and factor loadings for each item

Items	Mean	S.D.	Skewness	Kurtosis	Factor loading	t-value
FINR1	5.048	1.627	-0.395	-0.402	0.939	59.927
FINR2	5.109	1.541	-0.384	-0.316	0.956	82.558
FINR3	5.143	1.552	-0.403	-0.208	0.942	58.523
INFR1	5.104	1.562	-0.333	-0.382	0.954	51.261
INFR2	5.122	1.605	-0.441	-0.307	0.961	94.357
INFR3	5.052	1.609	-0.388	-0.371	0.952	81.193
PRVR1	4.826	1.733	-0.471	-0.297	0.966	106.517
PRVR2	4.917	1.729	-0.578	-0.107	0.960	63.279
PRVR3	4.874	1.698	-0.568	-0.010	0.976	166.265
ENVR1	5.026	1.618	-0.452	-0.113	0.977	164.491
ENVR2	5.009	1.665	-0.480	-0.222	0.961	77.121
ENVR3	5.087	1.602	-0.494	-0.080	0.968	78.011
PINO1	3.043	1.612	0.380	-0.227	0.954	88.668
PINO2	2.926	1.596	0.438	-0.258	0.940	52.621
PINO3	2.978	1.611	0.437	-0.184	0.957	86.527
INAT1	2.935	1.521	0.290	-0.285	0.960	83.240
INAT2	2.957	1.503	0.268	-0.293	0.961	83.361
INAT3	2.961	1.558	0.426	-0.139	0.947	59.308
PLSU1	4.757	1.770	-0.479	-0.275	0.958	72.774
PLSU2	4.770	1.790	-0.483	-0.357	0.964	77.551
PLSU3	4.757	1.792	-0.479	-0.320	0.962	76.417
INE1	4.800	1.760	-0.496	-0.321	0.947	58.717
INE2	4.543	1.833	-0.304	-0.586	0.954	80.214
SWCO1	4.991	1.634	-0.389	-0.353	0.958	89.254
SWCO2	5.022	1.632	-0.428	-0.253	0.952	78.141
SWCO3	5.026	1.655	-0.418	-0.401	0.959	79.801
SINT1	2.596	1.537	0.628	-0.100	0.953	55.799
SINT2	2.598	1.523	0.439	-0.707	0.961	91.199

Note: FINR= financial risk; INFR= infrastructural risk; PRVR= privacy risk; ENVR= environmental risk; PINO= product innovativeness; INAT= instrumental attribute; PLSU= policy support; INE= Inertia; SWCO= switching cost; SINT= switching intention.

Regarding normality testing, this study examined the skewness and kurtosis of each measurement item. The results indicate that all variables have skewness values ranging from -0.578 to 0.628 and kurtosis values between -0.707 and -0.010, none exceeding the critical value of ±2.58 [58]. This suggests that the distribution of all measurement items conforms to the normality assumption.

The standardized factor loadings for all measurement items were above 0.8, with corresponding t-values being significant ($t > 1.96$), indicating good item reliability. PRVR3 (0.976) and ENVR1 (0.977) exhibited exceptionally high factor loadings, demonstrating their effectiveness in measuring their respective latent constructs.

4. Model Evaluation and Path Analysis

4.1. Outer Model Test

This study employed partial least squares (PLS) to assess the reliability and validity of the measurement model. Firstly, we examined the composite reliability indicators Rho_A and Rho_C for reliability. According to Hair et al. [59], these reliability indicators should exceed 0.7 to ensure internal consistency reliability. The analysis showed that Rho_A values ranged from 0.897 to 0.967, and Rho_C values ranged from 0.949 to 0.979, well above the recommended threshold of 0.7 [60].

This study used the Average Variance Extracted (AVE) for evaluation regarding convergent validity. According to Fornell & Larcker [61], AVE values should be greater than 0.5 to confirm that the measurement items reflect the latent constructs effectively. The analysis showed that all constructs had AVE values above 0.89, ranging from 0.894 to 0.939. The Environmental Risk construct had the highest AVE value (0.939), indicating that its measurement items could explain 93.9% of the variance, while the Financial Risk construct, though relatively lower at 0.894, still far exceeds the recommended threshold.

The reliability analysis shows that all constructs have excellent internal consistency, with Cronbach's alpha values falling between 0.893 and 0.967. Every construct meets the 0.8 benchmark for acceptable reliability, and most actually go beyond 0.9, which indicates excellent reliability. Privacy Risk (0.966) and Environmental Risk (0.967) demonstrate the strongest reliability, while inertia shows the weakest but still perfectly acceptable reliability at 0.893. The additional composite reliability (Rho_C) and average variance extracted (AVE) values back up these findings and confirm that the measurement model is solid, with all values comfortably exceeding the recommended thresholds. This gives us strong confidence that the survey instrument is reliable and can be trusted to measure what it's supposed to measure (see Table 3).

Table 3. Reliability and convergent validity

Construct	Cronbach's alpha	Rho_A	Rho_C	AVE
Financial risk	0.941	0.941	0.962	0.894
Infrastructural Risk	0.953	0.956	0.969	0.914
Privacy Risk	0.966	0.966	0.978	0.936
Environmental Risk	0.967	0.967	0.979	0.939
Product innovativeness	0.946	0.948	0.965	0.903
Instrumental attribute	0.953	0.954	0.97	0.914
Policy Support	0.959	0.962	0.973	0.924
Inertia	0.893	0.897	0.949	0.903
Switching cost	0.953	0.957	0.97	0.915
Switching intention	0.908	0.914	0.956	0.916

This study used the bootstrapping method to calculate the 95% confidence intervals of the correlation coefficients between constructs to evaluate discriminant validity. The results showed that none of the confidence intervals for the correlation coefficients between any constructs included 1. The highest correlation was between Infrastructure Risk (INFR) and Switching Intention (SINO), with a 95% confidence interval of [-0.817, -0.597], clearly not including 1. This indicates that there is good discriminant validity between all constructs [62].

This study further employed the Heterotrait-Monotrait Ratio (HTMT) to assess discriminant validity as indicated in Table 4. The analysis results showed that all HTMT values between constructs were below the stringent standard of 0.85, ranging from 0.270 to 0.763. The highest HTMT value was between Infrastructure Risk and Switching Intention (0.763), which is still significantly below the recommended threshold, suggesting clear differentiation between these variables. These results confirm that the measurement model in this study has good discriminant validity [63]. The fact that each construct in the model accounts for distinct variance and doesn't simply replicate the same underlying phenomenon is a reassuring finding. The consistent results across all the relationships between constructs, including the connections between switching intention and various risk factors (such as privacy, infrastructure, financial, and environmental concerns), policy support, product innovation, switching costs, practical attributes, and inertia, lend strong support to the measurement model's structure. The evidence for discriminant validity reinforces the theoretical framework's notion that these factors represent distinct yet interconnected dimensions that influence consumers' decisions to adopt electric vehicles. This indicates that the subsequent structural model analysis will yield meaningful and interpretable relationships between the constructs, as each variable brings unique insights to the table in understanding what drives consumers to switch from conventional to electric vehicles. In essence, these results suggest that the model captures the complexities of consumer behavior in a nuanced and multifaceted way.

Table 4. Discriminant validity

Relationships	Path Coefficient (β)	95% CI Lower Bound	95% CI Upper Bound	HTMT
FINR ↔ ENVR	0.501	0.340	0.667	0.525
INE ↔ ENVR	0.398	0.231	0.568	0.428
INE ↔ FINR	0.371	0.209	0.537	0.405
INFR ↔ ENVR	0.586	0.435	0.734	0.609
INFR ↔ FINR	0.687	0.533	0.839	0.727
INFR ↔ INE	0.336	0.165	0.511	0.364
INAT ↔ ENVR	-0.498	-0.671	-0.331	0.518
INAT ↔ FINR	-0.548	-0.716	-0.378	0.579
INAT ↔ INE	-0.310	-0.497	-0.129	0.336
INAT ↔ INFR	-0.618	-0.772	-0.455	0.648
PLSU ↔ ENVR	0.452	0.290	0.612	0.469
PLSU ↔ FINR	0.504	0.346	0.660	0.530
PLSU ↔ INE	0.288	0.121	0.456	0.310
PLSU ↔ INFR	0.419	0.258	0.581	0.438
PLSU ↔ INAT	-0.479	-0.638	-0.318	0.501
PRVR ↔ ENVR	0.302	0.126	0.488	0.312
PRVR ↔ FINR	0.521	0.353	0.681	0.547
PRVR ↔ INE	0.336	0.156	0.519	0.361
PRVR ↔ INFR	0.435	0.260	0.619	0.451
PRVR ↔ INAT	-0.310	-0.504	-0.128	0.322
PRVR ↔ PLSU	0.278	0.107	0.460	0.288
PINO ↔ ENVR	-0.526	-0.703	-0.354	0.549
PINO ↔ FINR	-0.524	-0.688	-0.363	0.556
PINO ↔ INE	-0.250	-0.437	-0.079	0.270
PINO ↔ INFR	-0.585	-0.741	-0.424	0.616
PINO ↔ INAT	0.580	0.404	0.756	0.610
PINO ↔ PLSU	-0.424	-0.587	-0.261	0.446
PINO ↔ PRVR	-0.389	-0.577	-0.208	0.406
SWCO ↔ ENVR	0.499	0.324	0.675	0.519
SWCO ↔ FINR	0.546	0.390	0.696	0.575
SWCO ↔ INE	0.402	0.231	0.580	0.435
SWCO ↔ INFR	0.535	0.371	0.698	0.560
SWCO ↔ INAT	-0.488	-0.665	-0.308	0.512
SWCO ↔ PLSU	0.432	0.266	0.598	0.451
SWCO ↔ PRVR	0.299	0.128	0.480	0.311
SWCO ↔ PINO	-0.474	-0.648	-0.306	0.497
SINO ↔ ENVR	-0.637	-0.771	-0.495	0.677
SINO ↔ FINR	-0.678	-0.790	-0.560	0.731
SINO ↔ INE	-0.394	-0.545	-0.252	0.437
SINO ↔ INFR	-0.713	-0.817	-0.597	0.763
SINO ↔ INAT	0.616	0.482	0.745	0.660
SINO ↔ PLSU	-0.367	-0.529	-0.211	0.393
SINO ↔ PRVR	-0.508	-0.657	-0.359	0.542
SINO ↔ PINO	0.637	0.503	0.770	0.684
SINO ↔ SWCO	-0.620	-0.750	-0.489	0.663

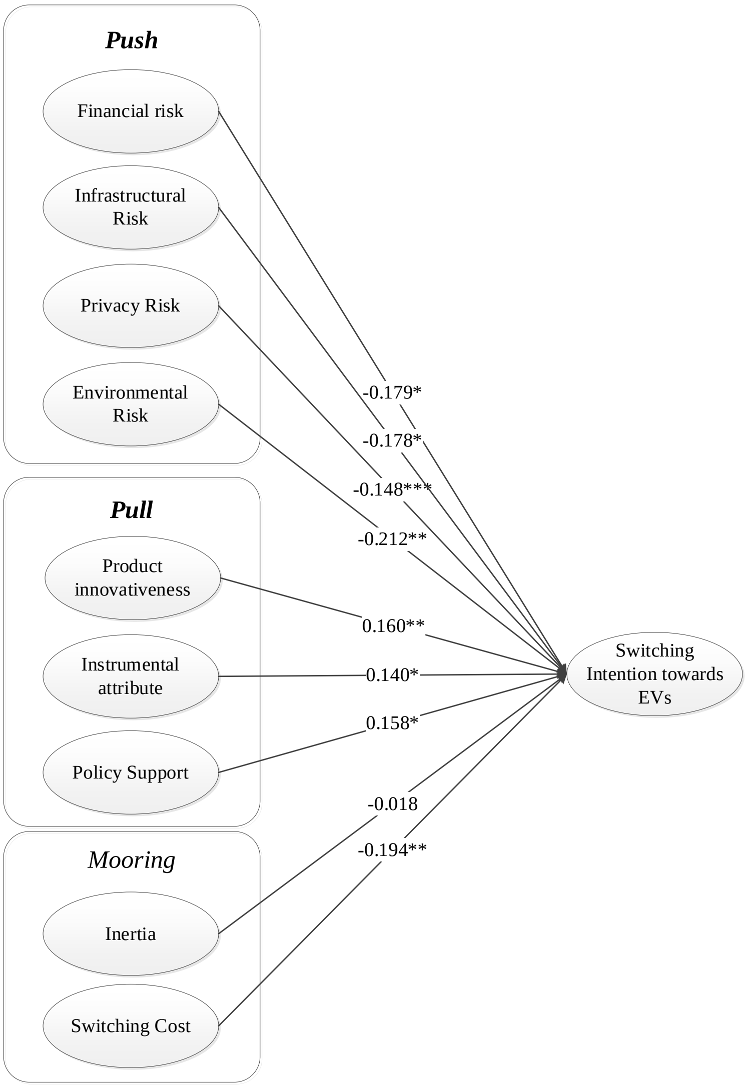
Note: FINR= financial risk; INFR= infrastructural risk; PRVR= privacy risk; ENVR= environmental risk; PINO= product innovativeness; INAT= instrumental attribute; PLSU= policy support; INE= Inertia; SWCO= switching cost; SINT= switching intention; CI= Confidence Interval.

4.2. Inner Model Test

This study aims to explore the multiple factors influencing consumers' switching intention (SINT) through path analysis using PLS. To ensure the robustness of the results, the study employs 10,000 bootstrapping iterations for hypothesis testing, analyzing the effects of Financial Risk (FINR), Infrastructural Risk (INFR), Privacy Risk (PRVR), Environmental Risk (ENVR), Product Innovativeness (PINO), Instrumental Attribute (INAT), Policy Support (PLSU), Inertia (INE), and Switching Cost (SWCO) on consumers' switching intentions. The detailed synthesis of the analysis results is indicated in Table 5 and Figure 2.

Table 5. Research hypotheses testing and path coefficients

Relationship	Path coefficient	Standard error	t-value	p-value
FINR → SINT	-0.179*	0.085	2.116	0.034
INFR → SINT	-0.178*	0.090	1.980	0.048
PRVR → SINT	-0.148***	0.042	3.488	0.000
ENVR → SINT	-0.212**	0.071	2.969	0.003
PINO → SINT	0.160**	0.061	2.613	0.009
INAT → SINT	0.140*	0.058	2.418	0.016
PLSU → SINT	0.158*	0.062	2.563	0.010
INE → SINT	-0.018	0.047	0.387	0.699
SWCO → SINT	-0.194**	0.070	2.767	0.006



Note: * p-value< 0.05; ** p-value< 0.01; *** p-value< 0.001

Figure 2. Inner Model Results

Firstly, among the push factors in the PPM model, Financial Risk (FINR) has a significant negative impact on switching intention ($\beta = -0.179$, $p < 0.05$). This result indicates that consumers are less likely to switch to new products or services when faced with potential financial losses, particularly in the context of electric vehicle adoption, where high purchase costs or maintenance fees may lead consumers to retain their existing products. Infrastructural Risk (INFR) also shows a significant negative relationship ($\beta = -0.178$, $p < 0.05$), suggesting that concerns about inadequate infrastructure may inhibit switching behavior, such as the lack of electric vehicle charging stations potentially reducing consumers' willingness to adopt electric vehicles.

Privacy Risk (PRVR) has the most significant impact on switching intention ($\beta = -0.148$, $p < 0.001$), demonstrating that consumer concerns about privacy protection play a crucial role in switching decisions, especially in highly digitalized products or services where privacy risk may become a significant barrier. Additionally, Environmental Risk (ENVR) significantly negatively affects switching intention ($\beta = -0.212$, $p < 0.01$), indicating that consumers' sensitivity to environmental risks may inhibit their switching behavior. For example, if consumers believe that a new product or service may have a negative impact on the environment, their intention to switch will significantly decrease.

Secondly, among the pull factors in the PPM model, Product Innovativeness (PINO) has a significant positive impact on switching intention ($\beta = 0.160$, $p < 0.01$). This result indicates that consumers are likelier to switch when a product exhibits higher innovativeness. For example, technological innovations in electric vehicles, such as enhanced range or autonomous driving features, can effectively increase consumers' adoption intentions. Instrumental Attribute (INAT) also significantly positively influences switching intention ($\beta = 0.140$, $p < 0.05$), showing that the functional characteristics of a product or service can facilitate consumer switching behavior, such as the convenience or performance improvements of electric vehicles. Policy Support (PLSU) has a significant positive impact on switching intention as well ($\beta = 0.158$, $p < 0.05$), indicating that supportive policies from governments or companies, such as subsidies or tax incentives, can effectively encourage consumers to switch to new products or services.

Finally, among the mooring factors in the PPM model, Switching Cost (SWCO) significantly negatively impacts switching intention ($\beta = -0.194$, $p < 0.01$), indicating that high switching costs may inhibit consumer switching behavior, including the time and effort required to establish or familiarize oneself with new technologies. However, the relationship between Inertia (INE) and switching intention is insignificant ($\beta = -0.018$, $p = 0.699$), suggesting that consumers' decision-making is driven more by specific risks and benefits than merely existing habits. This implies that consumers may be more inclined to make decisions based on product characteristics and external environments rather than relying on existing usage habits in the context of electric vehicle adoption.

5. Discussion

5.1. Comparison of Results

This study employs the PPM theoretical framework to explore consumers' intentions to switch from traditional vehicles to electric vehicles (EVs). The analysis reveals a diverse and complex mechanism of influence. Regarding push factors, four risk elements—financial risk (FINR), infrastructure risk (INFR), privacy risk (PRVR), and environmental risk (ENVR)—exert a significant negative impact on consumers' switching intentions, with environmental and financial risks being particularly prominent. This highlights consumers' sensitivity to risk factors in their decision-making process. According to the results of the current study, within the push factors group, the prominent impact of environmental risk indicates that concerns about potential environmental issues related to electric vehicles, such as the ecological footprint of battery manufacturing and disposal, significantly inhibit adoption decisions. Financial risk follows closely, reflecting the importance of high initial purchase costs, uncertain maintenance expenses, and potential battery replacement costs in consumers' minds. The significant negative impact of infrastructure risk highlights the persistent issue of inadequate charging facilities as a significant barrier to the widespread adoption of electric vehicles. Although the influence of privacy risk is relatively smaller, it still reflects consumers' ongoing concerns about data collection and usage in smart electric vehicles, especially given the widespread application of IoT and AI technologies in modern EVs. This result can be compared to an earlier study conducted by Lim et al. [64]. Their study tackled the lack of academic focus on how Malaysian consumers behave when considering electric vehicle adoption by looking at the thought process people go through when thinking about switching from regular cars to electric ones. Their research used a PPM theoretical framework, which is strengthened by institutional theory insights, to better understand how consumers made these transition decisions. Their model proposed the significant impacts of their push factors, namely perceived environmental threats and the regulative environment. Their study uses a quantitative survey approach to collect data through online platforms chosen using purposive sampling methods to ensure the respondents had the right characteristics.

In terms of pull factors, product innovativeness (PINO), instrumental attributes (INAT), and policy support (PLSU) exhibit positive influences, suggesting that these factors effectively encourage consumers to adopt electric vehicles. Product innovativeness shows the strongest positive correlation, reflecting the crucial role of technological advancement in facilitating EV adoption. According to the results of the current study, the significant positive effect of product innovativeness aligns with consumers' pursuit of advanced technology, indicating that innovative features such as extended range, fast charging technology, and smart connectivity play crucial roles in attracting consumers. The positive impact of policy support underscores the importance of government subsidies, tax incentives, and other supportive measures in promoting the adoption of electric vehicles. Although the influence of instrumental attributes is relatively lower, it remains significant, suggesting that practical features of electric vehicles, such as acceleration performance and ease of operation, continue to be important considerations for consumers. The present results can be compared to an earlier study by Davis & Chandrasekar [65]. Their study explores the factors that influenced both the initial decision to adopt and the continued use of electric three-wheelers among professional drivers working in India. Their research combined PPM with Extended Expectancy Confirmation Theory. Their study employed non-monetary incentives policy, perceived health outcome, and showroom service quality as pull factors. They analyzed responses from potential electric three-wheeler operators using Structural Equation Modeling methods. Their study found that government incentive schemes, and health benefits are the main factors driving adoption decisions. Surprisingly, the quality of dealership services had almost no impact on whether people chose to adopt these vehicles. The research revealed an interesting behavioral pattern where electric three-wheeler operators value the environmental benefits and better operational comfort that electric alternatives provide, but they still have concerns about infrastructure gaps and how well these vehicles perform compared to their traditional fuel-powered equivalents.

As for mooring factors, switching costs (SWCO) significantly negatively affect switching intentions, whereas inertia (INE) does not show statistical significance. This finding challenges the traditional view of the importance of habitual behavior in consumer decision-making, implying that consumers are more inclined to make choices based on substantive factors rather than inertia when making major purchasing decisions such as EV procurement. As the only variable with a significant impact among the mooring factors, switching costs highlight the inhibitory effect of the time, effort, and financial expenses consumers face when considering a switch. These include barriers such as learning new technologies and installing home charging equipment. The current findings can be somewhat comparable to an earlier study by Ha et al. [21]. Their study aimed to understand better what factors influence motorcyclists' willingness to switch to electric cars in places where two-wheeled vehicles are the dominant form of transportation. They examined survey responses from motorcycle riders in Vietnam. The research framework was built around PPM migration theory to look at how people make transition decisions. Their study used knowledge as a mooring factor. Their analysis showed that knowledge levels didn't directly affect intentions but acted as a moderating factor between attractive features and adoption willingness. People who knew more about electric vehicles were less influenced by attractive features than those who knew less. Their findings lay the groundwork for policy suggestions that could help boost electric vehicle adoption rates.

5.2. Practical Implications

The findings of this study provide crucial practical guidance for stakeholders in the electric vehicle industry. Firstly, for automobile manufacturers, it is essential to reduce perceived consumer risks, particularly by addressing concerns related to environmental and financial risks. Manufacturers should actively enhance battery lifecycle management and strengthen recycling mechanisms while clearly communicating the long-term economic benefits of electric vehicles, such as lower maintenance costs and fuel savings, to alleviate consumers' financial concerns. Simultaneously, product innovation should be a core strategy, with continuous development of breakthrough technologies to extend driving range, shorten charging times, and enhance vehicle smart connectivity features, thereby increasing product attractiveness.

Secondly, for governments and policymakers, the study highlights the significant impact of infrastructure risks, suggesting the acceleration of public charging network construction, especially in intercity roads and residential areas, and the continuous optimization of existing subsidies and tax incentives to enhance the economic appeal of electric vehicles. Considering the inhibiting effect of switching costs, governments could design targeted policies to alleviate consumer transition burdens, such as providing subsidies for installing home charging equipment or simplifying related administrative procedures.

The study recommends optimizing consumer education strategies for electric vehicle retailers and related service providers through experiential activities and practical demonstrations to reduce consumers' unfamiliarity and insecurity with new technologies. Additionally, strengthening data security and transparency, and informing consumers about data collection and usage methods, can alleviate privacy risk concerns. Furthermore, given the finding that inertia does not significantly impact switching intentions, marketing strategies should focus more on highlighting electric vehicles' tangible benefits and innovative features rather than merely challenging existing consumer habits.

In summary, only through coordinated efforts among all parties to specifically address perceived consumer risks, while simultaneously enhancing the innovativeness of electric vehicles and the strength of policy support, can the market penetration and widespread adoption of electric vehicles be effectively promoted, achieving the sustainable development goal of transportation electrification.

6. Conclusion

This study offers a wealth of information about the complex process that consumers go through when deciding to switch from traditional vehicles to electric ones. By closely examining the various factors that push, pull, and moor consumers, the research shows that a delicate balance of motivations, perceived risks, and obstacles influences the decision to adopt electric vehicles. The findings suggest that while concerns about the environment and supportive policies are significant factors that encourage people to adopt electric vehicles, worries about costs, infrastructure, and privacy are substantial barriers. Additionally, the costs and effort required to switch to a new technology and consumers' tendency to stick with what they know play a crucial role in either facilitating or hindering the transition to electric vehicles. The study's measurement model, which was validated through a rigorous analysis, confirms that these factors represent distinct but interconnected aspects of the decision-making process. These results have important implications for both businesses and policymakers who want to increase the adoption of electric vehicles. This research contributes to the growing body of literature on sustainable transportation and provides a foundation for understanding consumer behavior in the rapidly evolving automotive industry.

6.1. Limitations and Future Works

While providing valuable insights into consumers' willingness to adopt electric vehicles, this study has several limitations. This study's use of a cross-sectional design has drawbacks, particularly when understanding how consumer behavior changes over time in the rapidly evolving electric vehicle market. As technology continues to advance at a rapid pace and policies undergo significant changes, it's likely that consumers' perceptions of the benefits and drawbacks of electric vehicles will also shift. A longitudinal approach would be better suited to capture these dynamics and shed light on how the various factors that influence consumer behavior - including the push and pull factors and the mooring factors that keep them tied to their current choices - evolve over time. Researchers can gain a deeper understanding of the complex factors that drive consumer behavior by tracking how technological advancements impact perceived risks, how policy changes affect switching costs, and how market maturity influences consumer inertia. Moreover, longitudinal studies can help identify critical trigger events that significantly impact consumer intentions, providing valuable insights for policymakers and marketers looking to promote sustainable transportation solutions.

Another potential concern with this study is the representativeness of the sample. If the respondents are largely from a specific part of the country or similar socioeconomic backgrounds, it is possible that the findings won't apply to the broader population. The fact that the data was collected exclusively in Taiwan is a case in point. Given the significant differences in electric vehicle adoption patterns from one country to another, the results might not be generalizable to other parts of the world. These differences can be attributed to various factors, including government policies, the state of infrastructure development, cultural attitudes towards technology, and economic conditions. Taiwan's unique policy environment, which includes government incentives and regulatory frameworks, may have had a distinct impact on consumer perceptions and intentions to switch to electric vehicles, potentially setting it apart from other markets. To address this limitation, future studies should strive to collect data from multiple countries and cultural contexts. By doing so, researchers can determine whether the relationships identified in this study hold across different settings. Furthermore, cross-cultural studies could provide valuable insights into how cultural factors, such as attitudes towards uncertainty, environmental awareness, and acceptance of new technology, influence the dynamics between push, pull, and mooring factors, ultimately leading to a more nuanced understanding of electric vehicle adoption patterns worldwide.

The surprising result that inertia didn't significantly impact switching behavior is worth exploring further, and it's possible that the sample may have been skewed toward early adopters or tech-savvy individuals. These individuals tend to be more open to change and eager to try out new technologies, which could be why inertia didn't play a major role in this study. To better understand this phenomenon, future research should consider dividing participants into different groups based on their adoption patterns, using Rogers' diffusion of innovation theory as a framework. By comparing the behaviors of innovators and early adopters to those of the early majority, late majority, and laggards, researchers can better understand how different consumer groups respond to the various factors that influence their switching decisions. Moreover, examining demographic characteristics, such as age and income, technology readiness, and prior experience with alternative technologies, could help identify the key factors distinguishing different adopter segments and their respective switching behaviors.

Furthermore, although the reliance on Partial Least Squares Structural Equation Modeling (PLS-SEM) is suitable for exploratory research, it may not fully reveal the complex relationships and potential interactions between variables. While the research model includes several key variables, it may overlook other important factors influencing consumer decisions, such as brand loyalty, social influence, or technological self-efficacy.

Fourthly, incorporating more moderating variables, such as demographic characteristics, residential environment (urban/rural), or driving habits, could provide a more nuanced understanding.

Lastly, the study does not distinguish between different types of electric vehicles (e.g., fully electric, hybrid), which might obscure unique adoption barriers and drivers specific to each type of electric vehicle. Expanding the scope of research to include other emerging transportation technologies, such as hydrogen fuel cell vehicles or shared mobility services, could help establish a more comprehensive theoretical framework for sustainable transportation adoption. These directions will enhance understanding of the electric vehicle market and provide more effective strategic guidance for promoting the widespread adoption of clean transportation technologies.

7. Declarations

7.1. Author Contributions

Conceptualization, A.R., O.S., A.W., and A.K.; methodology, A.R., O.S., A.W., and A.K.; formal analysis, A.W., A.K., and S.C.; investigation, A.K.; writing—original draft preparation, A.R., O.S., A.W., A.K., and S.C.; writing—review and editing, A.R., O.S., A.W., A.K., and S.C.; validation, A.W. and S.C.; visualization, S.C. and A.K. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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