



The role of perceived values, habits, and social influence in shaping electric vehicle adoption intentions in Indonesia

Kelly Callista¹

Vanesa Alvineta²

Margaretha Pink
Berlianto^{3*}

^{1,2,3}Department of Magister Management, Faculty of Economics and Business,
Universitas Pelita Harapan, Banten, Indonesia.

¹Email: 01619240054@student.uph.edu

²Email: 01619240008@student.uph.edu

³Email: margaretha.berlianto@uph.edu



(+ Corresponding author)

ABSTRACT

Article History

Received: 1 July 2026

Revised: 12 August 2026

Accepted: 4 September 2026

Published: 8 October 2026

Keywords

Electric vehicles

Habits

Perceived values

Social influence

Sustainable mobility

UTAUT2.

The research gaps addressed in this study include the use of a partial theoretical framework, the lack of implementation in emerging market countries, and the inclusion of more comprehensive key coefficients. This study aims to investigate the role of perceived values, habits, and social influences in shaping electric vehicle adoption intentions in Indonesia. A cross-sectional design with a survey method was employed in this study, involving 220 electric vehicle users in Indonesia. Several instruments used were scales measuring hedonic motivation (HM), habits (HB), perceived physical risk (PPR), attitude (ATT), subjective norm (SBN), perceived behavioral control (PBC), and intention to use (ITU) electric vehicles (EVs) in Indonesia. Partial least squares structural equation modeling (PLS-SEM) data analysis was used to evaluate the data. The study findings indicate that monetary value is a value-based construct that significantly increases attitude (ATT), while hedonic motivation (HM) and habits (HB) significantly decrease attitude. Furthermore, the attitude construct does not significantly influence intention to use (ITU) electric vehicles (EVs). Conversely, subjective norm emerged as the strongest predictor of intention. Furthermore, the Importance-Performance Map Analysis (IPMA) also shows that social influence and monetary value are key strategic factors in accelerating EV adoption among the public. This research suggests that policymakers and industry stakeholders should focus not only on increasing awareness but also on strengthening financial incentives, expanding infrastructure, promoting trial-based experiences, and leveraging social proof to accelerate EV adoption.

Contribution/Originality: This research contributes to a comprehensive understanding of the key factors driving electric vehicle purchase intentions, particularly in Indonesia, which can be used as a consideration in policymaking. Its originality lies in the use of a more comprehensive theoretical framework and key coefficient factors.

1. INTRODUCTION

Sustainable transportation development is currently a very important global priority, including in Indonesia to reduce greenhouse gas emissions, air pollution, and dependence on fossil fuels. Electric vehicles (EVs) are widely considered as a key driver in the transition to a low-carbon transportation system (Budnitz, Meelen, & Schwanen, 2026; Senyapar, Akil, & Dokur, 2023). The urgency of this transition has been heightened by geopolitical disruptions to the global oil supply chain, which have driven the need to accelerate the shift to alternative energy-based mobility.

Governments have responded by introducing fiscal incentives, charging infrastructure programs, and industrial policies to promote the adoption of electric vehicles as part of their net-zero emissions strategies (Ajao, Prio, & Sadeeq, 2025; Wu, Salgado, & González, 2025). Indonesia has positioned EVs as a central element of its transportation decarbonization agenda, targeting 2 million electric cars and 13 million electric motorcycles in active use by 2030. However, EV market penetration remains very low, with EVs accounting for approximately 4.98% of total national vehicle sales in 2024 (Farhan, Rana, & Baig, 2025; Mustafa, Shi, Adan, Luo, & Al Humdan, 2026).

To support this target, in recent years, the Indonesian government has taken significant steps to support the transition to electric cars as part of its global commitment to reducing carbon emissions and preserving the environment. Through a series of policies, ranging from subsidies and fiscal incentives to regulations supporting the development of charging infrastructure, the government seeks to accelerate the adoption of electric cars across all levels of society. The subsidy policy is a reduction in the price of electric cars by around 20-25% from the original price. Fiscal incentive policies include a reduction in Value Added Tax (VAT) and the elimination of import duties for electrical components. Finally, the infrastructure development policy is the development of charging infrastructure (Nazari & Mohammadian, 2026; Salim, Syafri, & Nasrullah, 2024). The gap between policy ambitions and market realities suggests that adoption is shaped not only by technological and infrastructure readiness, but also by consumer behavioral factors. Range anxiety stemming from concerns about insufficient battery capacity remains a persistent psychological barrier, although this can be mitigated through improved user experience and consumer education (Davies & Hart, 2025; Ramadoss, Lee, Davis, Hardman, & Tal, 2025).

This study integrates the Theory of Planned Behavior (TPB) with the Value-Based Adoption Model (VAM), Habit Theory, and several constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT2) to examine how perceived values, habits, and social influence shape electric vehicle adoption intentions in Indonesia. Previous research on the TPB has validated the role of attitudes, subjective norms, and perceived behavioral control. Furthermore, other studies have shown that VAM emphasizes monetary and convenience values, and UTAUT2 research has highlighted hedonic and habitual motivations (Sitinjak, Simanullang, Ober, Kochmańska, & Siburian, 2025; Turk, Schittekatte, Duenas-Martinez, Joskow, & Schmalensee, 2025). However, these studies remain partial or isolated, limiting existing explanations. This is due to the absence of a single framework that adequately captures the cognitive, affective, social, and habitual dimensions that shape adoption behavior. The lack of an integrative model is a significant gap in the literature. Furthermore, most previous studies were conducted in developed countries, such as the United States, Germany, China, and South Korea, with infrastructure, policy environments, and high levels of technological literacy that differ significantly from emerging markets (Wang, Li, Yu, Ruangkanjanases, & Chen, 2025; Yu, Zhang, Teoh, Wang, & Wang, 2023). Therefore, the findings may not be meaningfully applicable to emerging markets like Indonesia. EV marketing in some developing countries remains below 5% of total vehicle sales, infrastructure is still in its infancy, and socioeconomic conditions are significantly different (Amirgholy, Chowdhury, Wang, & Kanigiri, 2026; Derboni & Salani, 2026). The specific institutional, regulatory, and cultural dynamics of the Indonesian market remain underexplored. Range anxiety has received substantial empirical attention as a psychological barrier (Kwon & Silva, 2023; Nazari & Mohammadian, 2026). However, other dimensions of consumer risk perception, particularly concerns about battery safety and long-term technology reliability, remain relatively unexplored (Büttner, 2025; Çelikkilek, Duleba, Moslem, & Esztergár-Kiss, 2026).

The construct of risk plays a strong role in technology adoption decisions. However, the specific construct of perceived physical risk in the context of EVs, particularly in emerging markets, has not been empirically tested. Previous TPB-based studies have confirmed attitude as a direct predictor of behavioral intention (Budnitz et al., 2026; Mustafa et al., 2026). Attitude can mediate the relationship between upstream perceptual antecedents such as perceived value and risk assessment, and adoption intention. However, in the current study, attitude is used as a mediating variable, not just a direct predictor. This will offer a more comprehensive explanation of the psychological pathways driving EV adoption decisions. Previous studies were mostly conducted under relatively stable regulatory

and market conditions, thus failing to account for sudden policy shifts or industry-level disruptions (Higueras-Castillo, Singh, Singh, & Liébana-Cabanillas, 2024; Sonar, Belal, Foropon, Manatkar, & Sonwaney, 2025). This limitation is particularly pronounced in the current Indonesian context. The cessation of fiscal incentives for imported EVs, effective in 2026, and the tightening of domestic content requirements represent significant regulatory discontinuities that are likely to reshape consumers' assessments of the economic value of EVs (Senyapar et al., 2023; Sitingjak et al., 2025). Furthermore, recent geopolitical developments, including resurgent tensions affecting oil transit routes, have increased the perceived economic urgency to shift to alternative energy-based mobility. The extent to which these external shocks strengthen or diminish individual-level adoption motivation remains largely unexplored in the EV consumer behavior literature (Bacci, Gentile, & Pizzari, 2026; Mahani et al., 2026).

To address some of these gaps in previous studies, this study develops an integrated conceptual model combining UTAUT2, VAM, TPB, and Habit Theory. This model examines how monetary value, convenience value, hedonic motivation, habit, and perceived physical risk shape consumers' attitudes toward electric vehicle (EV) adoption, and how attitudes, along with subjective norms and perceived behavioral control, influence adoption intentions. Attitude is further examined as a mediating variable to explain the psychological mechanisms linking perceptual antecedents to behavioral intentions. Theoretically, this study extends the consumer behavior literature through a multidisciplinary lens that integrates the economic, psychological, social, and habitual dimensions of EV adoption. Based on this explanation, this study proposes hypotheses that also serve as research questions. The proposed hypotheses are that monetary value, convenience value, hedonic motivation, habits, and perceived physical risk impact consumer attitudes toward electric vehicles. This study also hypothesizes that attitudes, subjective norms, and perceived behavioral control impact the intention to use an electric vehicle (EV). Furthermore, the next hypothesis is that attitudes can mediate the relationship between consumer perception factors and the intention to adopt an EV. Practically, these findings are expected to inform government agencies and industry stakeholders in designing evidence-based marketing strategies, consumer education programs, and policies to accelerate EV adoption in Indonesia. Based on this explanation, the researchers formulate the following research questions.

1. How do monetary value, convenience value, hedonic motivation, habit, and perceived physical risk impact consumer attitudes toward EVs?
2. How do attitudes, subjective norms, and perceived behavioral control impact the intention to use electric vehicles (EV)?
3. Does attitude mediate the relationship between consumer perception factors and EV adoption intentions?
4. What factors most significantly influence Indonesians' intention to adopt EVs?

2. LITERATURE REVIEW

2.1. UTAUT2 (*Unified Theory of Acceptance and Use of Technology*)

This study uses the UTAUT2 theoretical model, which integrates several components and comprehensive theories about people's acceptance behavior towards the use of technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) model is a model of technology acceptance and use proposed by Venkatesh, Thong, and Xu (2012). UTAUT integrates the best features of eight other theories and consists of fundamental theories about technology acceptance and use behaviour. The model was created by reviewing and combining earlier models. The following eight prominent theories are integrated into UTAUT, namely the Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivation Model (MM), Theory of Planned Behavior (TPB), Combination of TAM and TPB (C-TAM-TPB), PC Utilization Model (MPCU), Diffusion of Innovations Theory (IDT), and Social Cognitive Theory (SCT) (Çelikbilek et al., 2026; Martin, Powell, & Rajagopal, 2025). The four direct drivers of UTAUT- performance expectancy, effort expectancy, social variables, and facilitating conditions have a substantial impact on the desire to use and exploit information technologies (Matsuda-Dunn, Hale, Estreich, Lavin, & Konar-Steenberg, 2026; Turk et al., 2025). Compared to the other eight hypotheses, UTAUT has been demonstrated to be

up to 70% more successful in explaining variance in technology adoption intentions. The UTAUT2 model is an extension of the UTAUT model, which examines how consumers accept and utilize technology (Abbasi, Mamdoohi, Ciari, & Sierpiński, 2024; Chen, Liu, Lyu, Wang, & Wen, 2025). The UTAUT2 model aims to modify some of the relationships already present in the UTAUT model, add new relationships, and identify three key constructs from technology acceptance and use research for both consumers and the general public (Ajao et al., 2025; Lyu, 2026). UTAUT is extended to UTAUT2 with the addition of three constructs: price value, habit, and hedonic motivation.

2.2. Theory of Planned Behavior (TPB)

One of the most basic conceptual frameworks for understanding human behavior is the Theory of Planned Behavior (TPB), which is an expansion of the Theory of Reasoned Action (TRA). The TPB holds that a person's purpose to carry out a specific activity determines their conduct (Vafaei-Zadeh, Tsetsegtuya, Hanifah, Ramayah, & Choo, 2025; Yu et al., 2023). Their attitude toward the behavior and subjective norms are the two factors that determine this aim. Subjective norms are described as an individual's impression of what most significant others believe they should or shouldn't do in relation to the planned activity, whereas attitude toward a behavior relates to an individual's positive or negative feelings (evaluative affect) regarding the target action (Kwon & Silva, 2023; Senyapar et al., 2023). This hypothesis states that people are more likely to act in a certain way when they are feeling good. According to the TPB, only intentions, attitudes, and subjective norms have an impact on conduct. According to the Theory of Planned Behavior (TPB), attitudes affect three aspects of behavior: behavior is influenced by both general and more specific attitudes toward an object; behavior is influenced by both attitudes and subjective norms; and finally, attitudes toward the behavior, along with subjective norms, form the intention to behave (Lazuardy, Nurcahyo, Farizal, & Oktavina, 2025; Lee, Shim, & Hardman, 2026). The three objectives of the TPB are to predict and comprehend how motivation affects conduct, to find methods for altering behavior, and to explain almost all human activity, including the reasons behind word-of-mouth. The three objectives of the Theory of Planned conduct are to predict and comprehend how motivation affects conduct, to find methods for altering behavior, and to explain almost all human activity, including the reasons behind word-of-mouth (Bursan & Berto, 2023; Vafaei-Zadeh et al., 2025). The measurement of subjective standards, attitudes, and behavioral control, or the formative aspects in TPB, must be understood in order to fully comprehend the TPB. Figure 1 provides an explanation of the elements of the TPB. A person's attitude toward a behavior is based on their views about the repercussions of that activity. It can also be referred to as behavioral beliefs, which are beliefs about the person's subjective perception of the environment. A person's subjective view of the expectations of significant others in his life regarding the performance or non-performance of a particular action or behavior is known as a subjective norm (Bursan & Berto, 2023; Pamidimukkala, Kermanshachi, Rosenberger, & Hladik, 2024). An individual's views about the availability of resources—such as opportunities, compatibility, expertise, and equipment—that both support and impede expected behavior, as well as the extent to which these resources play a role, impact perceived behavioral control.

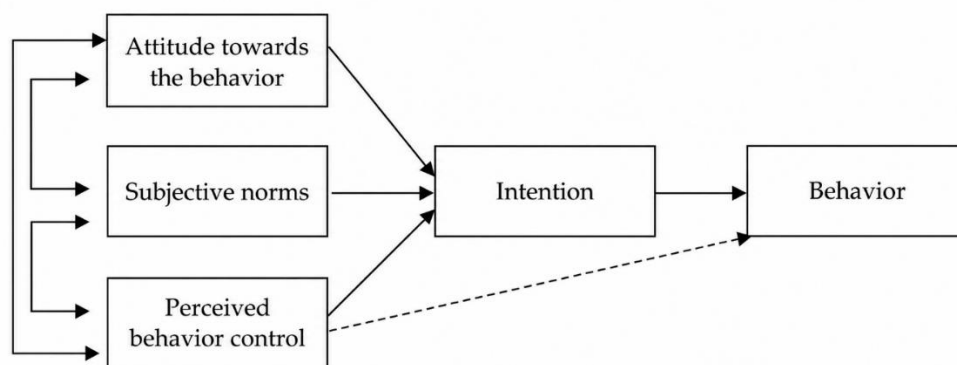


Figure 1. Model Theory of Planned Behavior (TPB).

2.3. Value-Based Acceptance Model (VAM)

The Value-Based Acceptance Model (VAM), in contrast to TAM and other cognitive models, emphasizes the balance between perceived advantages and perceived sacrifices by focusing on people's perceptions of the value of embracing new technology. Because of this, the VAM has been found to be a better framework for studying the adoption of electric vehicles (EVs), especially in situations where emotional factors are important. Based on its successful application in earlier research by Bursan and Berto (2023) and Higuera-Castillo et al. (2024), this study employs the VAM to identify the factors driving EV adoption in Malaysia. A key component of the Value-Based Acceptance Model (VAM) is perceived value, which represents the ratio of perceived advantages to perceived costs when embracing new technology. It is crucial to specifically examine how emotions, especially pride and guilt, interact with PV to influence behavioral choices, even though PV has been shown to be a significant predictor of adoption intention (Dean & Kockelman, 2024; Senyapar et al., 2023). The theoretical framework and the emotional dynamics that underlie EV adoption are strengthened by this debate.

Operational economic advantages, perceived enjoyment, and perceived utility are examples of perceived benefits. Operational economic benefits are observable cost savings that raise an EV's perceived worth, such as lower fuel and maintenance expenses. Perceived delight includes the pleasure that comes from operating an electric vehicle (EV), whether it is from driving cutting-edge technology or making meaningful contributions to sustainability (Goudis, Victoriano-Habit, Carvalho, & El-Geneidy, 2025; Kwon & Silva, 2023). The practical benefits of EVs in effectively fulfilling transportation needs are reflected in perceived usefulness. EV adoption intentions are raised by these perceived advantages, which have a positive impact on perceived value. On the other hand, EV adoption may be hampered by perceived tradeoffs like perceived risk, charging risk, and technical performance risk (Han, Mo, Liu, Lei, & Ye, 2024; Nazari & Mohammadian, 2026). While charging risk represents lifestyle modifications necessary to suit an EV's charging schedule, technology performance risk is related to worries about dependability or safety. Perceived risk includes more general concerns about EV use, like possible malfunctions or the accessibility of infrastructure for charging (Higuera-Castillo et al., 2024; Şimşek, Gür, & Ünal, 2025). These compromises have a detrimental effect on perceived value, which prevents ongoing adoption intentions. The correlation between variables based on the VAM model is presented in Figure 2.

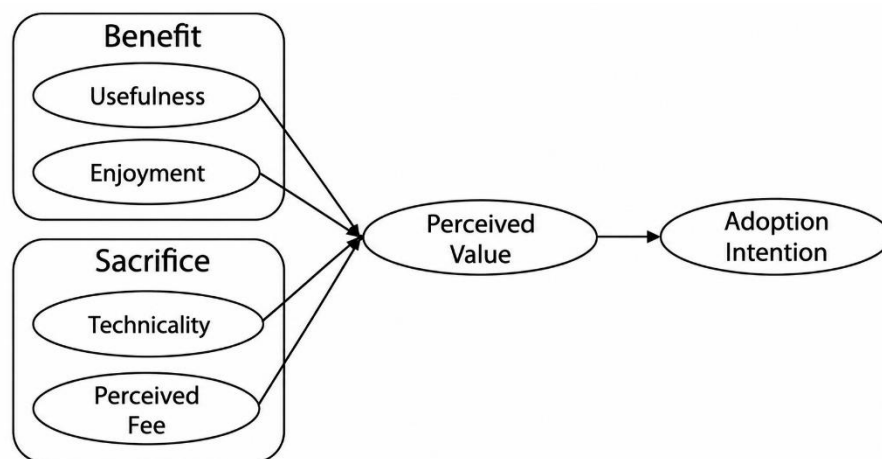


Figure 2. Value-Based Acceptance Model (VAM).

2.4. Acceptance of Electric Vehicle (EV) Technology (Perceived Values, Habits, and Social Influence)

The theory of planned behavior states that behavioral intention, purchasing intention, attitude, subjective norm, and perceived behavioral control all have an impact on how consumers adopt new technologies. There are a number of other elements that may affect how users feel about new technology, according to recent research (Farhan et al., 2025; Nisyrios, Matthaiou, Chau, & Gkiotsalitis, 2025). Notable instances include compatibility, perceived utility,

perceived simplicity of use, and individual inventiveness. Regarding EV technology, an individual's attitude toward technological acceptance is influenced by variables pertaining to perceived compatibility and personal inventiveness (Bo, Di, MinYi, Nong, & Lin, 2019; Dean & Kockelman, 2024). Additionally, the public's acceptance of EV has been found to be significantly influenced by maintenance costs, indicating the importance of financial benefits for EV adoption (Turk et al., 2025; Wang et al., 2025). In addition to these expenses, the survey identified basic infrastructure and an EV range on a single charge as the most important contributing factors. Adoption of EV is a complex process including social, economic, environmental, and infrastructure components (Davies & Hart, 2025; Nisyrios et al., 2025). The intention to adopt EVs is significantly influenced by a number of factors, including the availability of charging infrastructure, government incentives, environmental concerns, perceived benefits, performance-related issues, and EV awareness (Cervini, Burra, Jung, & Gkritza, 2026; Yu et al., 2023). Widespread EV adoption intention is also hampered by customer perceptions of EVs, worries about range anxiety, problems with battery technology, and total cost of ownership. Building a sustainable transportation future thus requires examining factors impacting adoption intention and lowering barriers to EV adoption intention (Ramadoss et al., 2025; Seger, Brand, Clement, Dixon, & Wilson, 2025). The factors that shape EV adoption intention investigated in the current study are Hedonic Motivation (HM), Habit (HB), Perceived Physical Risk (PPR), Attitude (ATT), Subjective Norm (SBN), Perceived Behavioral Control (PBC), and Intention To Use (ITU).

The purpose of this study is to look at the main determinants of EV adoption intention. By examining the elements impacting EV adoption intention, this study aims to give stakeholders supporting electric car marketing in emerging nations a thorough understanding of current EV adoption intention. Even while earlier research has offered insightful information about EV adoption intention, there are still a number of important gaps that need to be filled (Sitinjak et al., 2025; Turk et al., 2025). Although basic assessments of earlier research have summarized EV-related consumer behavior, their coverage is constrained in a number of ways. Comprehensive evaluations of EV adoption intention are also offered by other research, which emphasize other categories of variables while ignoring a methodical analysis of the mediators and moderators that affect these correlations (Amirgholy et al., 2026; Zhang, Li, & Cham, 2026). Although research on EV adoption intention is growing, previous assessments have been limited by fragmented methodologies and a lack of attention to mediating and moderating variables. By integrating UTAUT2, VAM, TPB, and Habit Theory to methodically arrange theory, context, variables, and procedures in research on EV adoption intention, this work closes this gap. This approach not only makes previous research more understandable, but it also reveals previously undiscovered connections and understudied areas for further study.

2.5. Hypothesis Formulation

Based on a theoretical study of several components influencing the adoption of electric vehicles, this study formulates several hypotheses to be tested. The hypothesis (H) proposed in this study is H1: Monetary Value (MV) has a positive impact on Attitude (ATT), H2: Attitude (ATT) is a positive intermediary media between Monetary Value (MV) and Intention to Use (ITU), H3 Convenience Value (CV) has a positive impact on Attitude (ATT), H4: Attitude (ATT) is able to mediate the positive contribution of Convenience Value (CV) to Intention to Use (ITU) electric vehicles, H5: Hedonic Motivation (HM) has a positive impact on Attitude (ATT), H6: Attitude (ATT) is able to mediate the positive contribution of Hedonic Motivation (HM) to Intention to Use (ITU) electric vehicles, H7: Habit (HB) has a positive impact on Attitude (ATT), H8: Attitude (ATT) is able to mediate the positive impact of Habit (HB) to Intention to Use (ITU) electric vehicles. H9: Perceived Physical Risk (PPR) has a negative impact on Attitude (ATT). H10: Attitude (ATT) is able to mediate the negative impact of Perceived Physical Risk (PPR) on Intention to Use (ITU) of electric vehicles, H11: Attitude (ATT) has a positive impact on Intention to Use (ITU) of electric vehicles, H12: Subjective Norm (SBN) has a positive impact on Intention to Use (ITU), H13: Perceived Behavioral Control (PBC) has a positive impact on Intention to Use (ITU) of electric vehicles.

3. METHODOLOGY

3.1. Design and Participants

This study used a cross-sectional design with a survey method to investigate the role of Hedonic Motivation (HM), Habit (HB), Perceived Physical Risk (PPR), Attitude (ATT), Subjective Norm (SBN), and Perceived Behavioral Control (PBC) in shaping Intention to Use (ITU) of electric vehicles (EV). This study used non-probability sampling with a purposive sampling method, with the criteria of Indonesian citizens domiciled in the Jakarta area, aged 17 years and above, and who have never purchased an EV before. The minimum sample size was determined using the inverse square root method proposed by Noll, Schmidt, and Egli (2026), which recommends a minimum of 160 respondents to detect a path coefficient of 0.20 or greater at a 5% significance level with 80% statistical power. This threshold was further strengthened by the 10-fold rule (29), resulting in a minimum of 50 respondents based on the largest indicator block. Therefore, this study involved 220 respondents determined to ensure adequacy considering the complexity of the model, which consists of 43 indicators across nine constructs. Data collection was conducted from January to April 2026. The sample size met the minimum threshold required for Partial Least Squares Structural Equation Modeling (PLS-SEM), which involves multiple latent constructs and structural paths, thus ensuring sufficient statistical power for hypothesis testing (28,29). Data were collected through an online survey distributed via social media platforms such as WhatsApp, email broadcasts through universities, and Instagram. The participant recruitment procedure involved several stages, including determining sample characteristics: age 18 or older, never having purchased an electric vehicle, middle- to upper-class economic status, and residing in the Jakarta area. Next, the questionnaire distribution media were determined via WhatsApp, email broadcasts through universities, and Instagram. The next stage involved explaining the purpose of data collection, distributing the questionnaire, and analyzing the data. Ethical standards were upheld through voluntary participation, respondent anonymity, and informed consent. This research has been approved by the Ethics Committee of Pelita Harapan University, Indonesia, on January 18, 2026 (Ref. No. 206a/FEB-UPH/V/2026).

3.2. Research Instruments

Several instruments used were scales measuring hedonic motivation, habit, perceived physical risk, attitude, subjective norm, perceived behavioral control, and intention to use. All constructs within the measurement scales were operationalized using previously validated items adapted from Budnitz et al. (2026) and Mustafa et al. (2026). A five-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree") was used throughout the study. Monetary Value was assessed using five indicators; Convenience Value consisted of four indicators; and Hedonic Motivation, Habit, Perceived Physical Risk, Attitude, Subjective Norm, Perceived Behavioral Control, and Intention to Use were each measured with five indicators. To reduce common method variance, survey items were systematically randomized before administration. Translation and adoption of the instrument were conducted using back translation reviewed by specialists in the field. Harman's Single Factor Test was used to address possible data bias in the study findings. According to the results of the Harman's Single Factor Test, there was no evidence of common method bias because the single factor explained 21.45% of the variance (standardized <50%).

3.3. Data Analysis

Partial least squares structural equation modeling (PLS-SEM) data analysis was used to evaluate the data. PLS-SEM, run through SmartPLS 4.0, was selected as the analysis technique based on several methodological justifications: (1) its suitability for prediction-oriented research on behavioral intentions; (2) its ability to handle complex structural models with multiple latent variables and mediating paths; (3) its robustness to non-normal data distributions common in survey research; and (4) its suitability for exploratory extensions of integrated theoretical models, such as the TPB-VAM-Habit framework used in this study. The measurement model evaluation followed established PLS-SEM criteria. Indicator reliability was assessed using outer loadings, with a minimum threshold of

Description	Total	Percentage
Depok	3	1.4%
Tangerang	7	3.2%
Bekasi	3	1.4%
Occupation		
Not working	5	2.3%
Student	118	54.4%
Private sector employees	56	25.8%
Civil Servant	5	2.3%
Entrepreneur	33	15.2%
Highest level of education		
< Bachelor's degree	120	55.3%
Bachelor's degree	94	43.3%
Master's degree	3	1.4%
PhD	0	0.0%

Table 1 presents the participant profiles in detail. Respondents in this quantitative study were predominantly male (75.6%), while females accounted for 24.4%. Most respondents were from the young, productive age group, with the 18–27 age group dominating at 67.7%, followed by the 28–43 age group at 29%. Geographically, the sample was highly concentrated in urban areas, with Jakarta accounting for 88.5% of respondents, with the remainder spread across. Professionally, the majority of respondents were students (54.4%) and private sector employees (25.8%), indicating a socially active population with a potential interest in new technologies. Respondents' educational attainment was also relatively high, with over 43.3% holding a bachelor's degree, while 55.3% had lower levels of education. Overall, these characteristics indicate that this study successfully reached a young, educated, and urban-oriented population, a highly relevant profile for evaluating factors influencing the adoption of new technologies such as BYD electric vehicles.

The preliminary phase in PLS-SEM (Partial Least Squares–Structural Equation Modeling) analysis is the assessment of the Measurement Model, referred to as the Outer Model. This stage aims to confirm that each latent construct has sufficient validity and reliability by evaluating the suitability of its indicators in reflecting the construct. The evaluation process was carried out using SmartPLS 4.0 software by assessing several key statistical criteria: Average Variance Extracted (AVE) to evaluate convergent validity, Composite Reliability to measure internal consistency, and Discriminant Validity to confirm the distinctiveness of each construct. Meeting all these criteria is an important prerequisite for proceeding to the next phase, specifically the Structural Model testing, to ensure the integrity of the research instrument and the accuracy of the relationships between variables in the model. Three indicators were removed, namely PPR2, SBN4, and ITU3, because their outer loading values were below 0.4. After these indicators were removed and recalculated, the results can be seen in Table 2.

Table 2. Validity and Reliability Testing.

Items and Constructs		Outer Loadings
Monetary Value (CR= 0.891, AVE= 0.621)		
MON1	The present cost of electric automobiles is relatively economical and justifiable	0.878
MON2	The present cost of electric automobiles represents the most advantageous deal available	0.755
MON3	It makes sense that electric cars are rather expensive, given their current quality.	0.809
MON4	The sum paid may be suitable for the electric vehicle I will obtain	0.759
MON5	In my opinion, buying an electric car can save money.	0.729
Convenience Value (CR = 0.874, AVE = 0.634)		
CON1	Operating an electric car resembles the operation of a conventional vehicle	0.742
CON2	Exemption from odd-even number plate regulations is a convenient benefit	0.776

Items and Constructs		Outer Loadings
CON3	The Indonesian government is actively promoting the use of electric vehicles by providing tax conv	0.768
CON4	The Indonesian government is actively providing public electric car charging stations.	0.891
Hedonic Motivation (CR=0.919, AVE=0.696)		
HM1	Using an electric vehicle will increase my comfort	0.867
HM2	If electric vehicles provide sufficient comfort, I would consider purchasing one, even if it is expensive	0.821
HM3	Using an electric vehicle could improve my social status.	0.851
HM4	Driving an electric vehicle reflects my interest in sharing technological knowledge.	0.818
HM5	I would be proud to be an early adopter of electric vehicle technology	0.813
Habit (CR = 0.908, AVE = 0.677)		
HB1	Using conventional petrol-powered vehicles is an old habit of mine.	0.910
HB2	I anticipate some difficulties in transitioning to electric vehicles.	0.884
HB3	I am so accustomed to using conventional petrol-powered vehicles that switching to electric vehicles is a challenge for me.	0.902
HB4	I find it difficult to switch to electric vehicles because of my dependence on conventional petrol-powered vehicles.	0.891
HB5	I find it difficult to learn how electric vehicles work again.	0.410
Perceived Physical Risk (CR= 0.785, AVE= 0.550)		
PPR1	The near-silent operation of electric vehicles may increase the risk of pedestrian accidents	0.784
PPR3	Finding available charging stations for electric vehicles can be challenging	0.650
PPR4	Electric vehicle batteries carry the potential risk of thermal runaway during charging	0.783
Attitude (CR = 0.852, AVE = 0.536)		
ATT1	I have an interest in electric automobiles	0.768
ATT2	I believe that using electric vehicles is important	0.767
ATT3	I wish to evaluate electric automobiles as a potential purchase option	0.748
ATT4	Electric vehicles are positive/beneficial.	0.729
ATT5	If, in the end, the electric car I buy can lessen pollution, I will be happy.	0.641
Subjective Norm (CR=0.810, AVE=0.518)		
SBN1	If my family and relatives use electric vehicles, I might consider it too	0.700
SBN2	Recommendations from close friends would increase my interest in electric vehicles.	0.727
SBN3	Advertisements on various media platforms could encourage me to purchase and use electric vehicles	0.616
SBN5	If my workplace adopts electric vehicles, I would be more likely to use them	0.821
Perceived Behavioral Control (CR=0.873, AVE=0.585)		
PBC1	I possess the autonomy to determine the acquisition of an electric automobile	0.541
PBC2	In the future, I hope to have the money to purchase an electric car.	0.849
PBC3	I can buy and drive an electric car with confidence if I want to.	0.675
PBC4	I possess the requisite knowledge to operate an electric vehicle	0.841
PBC5	I do not doubt that I will eventually own an electric car.	0.865
Intention to Use (CR=0.814, AVE=0.526)		
ITU1	I am considering purchasing a BYD electric car	0.782
ITU2	I plan to purchase a BYD electric car	0.748
ITU4	I anticipate the emergence of diverse electric vehicle brands on the market.	0.769
ITU5	I anticipate purchasing and utilizing a BYD electric vehicle in the future	0.584

Note: CR = Composite Reliability; AVE = average variance extracted.

Although one indicator in the Habits construct (HB5) had a loading of 0.410, it was retained because it did not reduce the construct's overall reliability. Indicators with loadings above 0.40 can still be retained if the construct reliability (CR) and convergent validity (AVE) remain within acceptable limits. In this study, both the CR and AVE for the Habits construct still met the minimum criteria, so the indicator was not removed to maintain the completeness of the construct. Table 2 shows that all constructs showed Composite Reliability (CR) values exceeding 0.7 and

Average Variance Extracted (AVE) values exceeding 0.5, in accordance with recommendations Lazuardy et al. (2025). This indicates that all constructs in the model have met the standards of internal consistency and convergent validity. Consequently, each construct has strong measurement consistency and effectively captures the factors being assessed. Therefore, the research instrument is considered credible and valid for application in the next phase of the structural model analysis using PLS-SEM.

Table 3. Discriminant Validity HTMT.

Variables	ATT	CV	HB	HM	ITU	MV	PBC	PPR	SBN
ATT									
CV	0.092								
HB	0.675	0.113							
HM	0.243	0.098	0.309						
ITU	0.117	0.113	0.205	0.776					
MV	0.255	0.109	0.343	0.665	0.778				
PBC	0.117	0.799	0.120	0.134	0.149	0.106			
PPR	0.421	0.170	0.634	0.564	0.345	0.185	0.204		
SBN	0.694	0.112	0.701	0.215	0.215	0.452	0.159	0.728	

Note: Hedonic Motivation (HM), Habit (HB), Perceived Physical Risk (PPR), Attitude (ATT), Subjective Norm (SBN), Perceived Behavioral Control (PBC), Intention to Use (ITU), Monetary Value (MV), Convenience Value (CV).

Table 3 displays the findings of the discriminant validity study using the Heterotrait-Monotrait Ratio (HTMT) technique, which evaluates whether each model construct is theoretically non-overlapping and empirically distinct. All of the model's constructs have excellent discriminant validity and can be statistically differentiated from one another because each HTMT score is below the suggested cutoff of 0.90 (29.32). The links between the notions reveal differing levels of conceptual closeness upon closer inspection. The association between Perceived Behavioral Control and Convenience Value has the highest HTMT value (0.799), which is below the critical threshold of 0.90 despite being quite high when compared to other construct pairs. This indicates that these two constructs share conceptual similarities in perceived ease and control when using EVs, yet they are still empirically distinguishable. Similar high HTMT values emerged for the relationship between Intention to Use and Monetary Value (0.778) and between Intention to Use and Habit (0.205), which were relatively lower but still demonstrated a theoretical relationship. This reflects that intention to use an EV is not separate from considerations of economic value and user habits in using conventional vehicles, although conceptually the two remain distinct constructs.

Furthermore, the relationship between habit and subjective norm (0.701) and between subjective norm and perceived physical risk (0.728) showed moderate correlations that can be explained by the social context and risk perception in EV adoption decisions. Nevertheless, all these values remained within acceptable limits, indicating the absence of multicollinearity among the constructs. Overall, these HTMT results strengthen the validity of the measurement model used in this study, as no value exceeded the 0.90 threshold. Thus, each latent variable in this model demonstrated adequate discrimination, allowing subsequent structural analysis to be conducted with a high degree of confidence in the independence of each construct. The next phase in the PLS-SEM analysis is the assessment of the Structural Model (Deep Model). This phase evaluates the causal relationships proposed in the research hypotheses, which are derived from the conceptual framework. Before assessing the significance of the path coefficients, the model is first validated for its predictive ability and explanatory adequacy with respect to the dependent variable. A bootstrapping procedure (10,000 runs) is then used to obtain a P-value for each structural path, which serves as the basis for determining whether the hypothesis is accepted or rejected. The visual results of the Deep Model test, including the estimated path coefficients and their significance values, are shown in Figure 4.

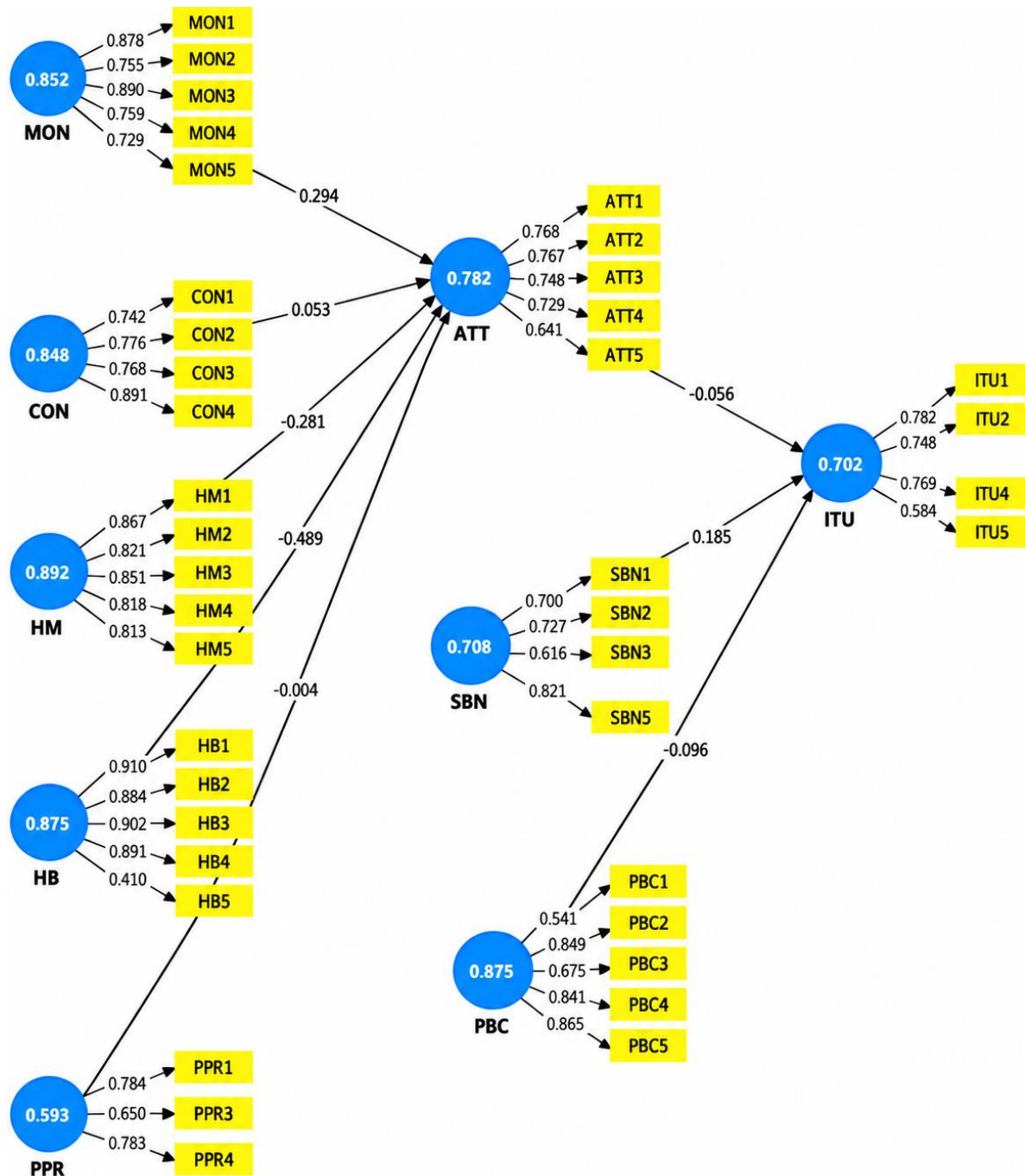


Figure 4. Inner Model Test Results: Path coefficients and structural model fit using R² values.

Note: Monetary Value (MON) and Convenience Value (CON), Hedonic Motivation (HM), Habit (HB), Perceived Physical Risk (PPR), Attitude (ATT), Subjective Norm (SBN), Perceived Behavioral Control (PBC), Intention to Use (ITU).

Before hypothesis testing, the multicollinearity of the Structural Model was evaluated to guarantee the stability and dependability of the path coefficients. This assumption was evaluated by looking at the Variance Inflation Factor (VIF) values for each predictor variable. Table 4 demonstrates that all VIF values, which ranged from 1.011 for Perceived Behavioral Control to 2.078 for Hedonic Motivation, were well below the 5.0 threshold. These findings show that the predictor variables in the model do not exhibit multicollinearity. As a result, it was determined that the model's structural elements satisfied the required statistical presumptions, enabling the study to move on to the hypothesis testing stage.

Table 4. Multicollinearity Testing (VIF).

Variables	Attitude	Intention To Use
Attitude		1.377
Convenience Value	1.031	
Habit	1.400	
Hedonic Motivation	2.078	1.487
Intention To Use		
Monetary Value	1.857	
Perceived Behavioral Control		1.011
Perceived Physical Risk	1.411	
Subjective Norm		1.389

Each independent variable's multicollinearity was assessed using the Variance Inflation Factor (VIF). VIF values were far below the suggested cutoff of 3.3 for PLS-SEM analysis, ranging from 1.011 to 2.078. These results show that each construct makes a distinct contribution to the structural model and that the predictor variables do not show problematic levels of collinearity. Redundancy among the independent variables guarantees that the calculated path coefficients are unbiased and stable when multicollinearity is absent. As a result, the structural model satisfies the statistical requirement of acceptable collinearity, bolstering the validity of further hypothesis testing.

Table 5. R-Square Test Results.

Variables	R-Square	Criteria
Attitude	0.043	Very weak
Intention To Use	0.039	Very weak

Table 5 displays the coefficient of determination (R^2) results, which show how well the model accounts for the variance in the dependent variable. Value-based and risk-related factors can only account for around 4.3% of the diversity in attitudes toward EVs, according to the R^2 value for attitude of 0.043. On the other hand, only around 3.9% of the variance in ITU can be explained by Attitude, Subjective Norms, and Perceived Behavioral Control, according to the R^2 value for Intention to Use of 0.039. Both values fall into the "very weak" category in terms of classification, suggesting that the model has little explanatory ability. However, this low R^2 value does not necessarily indicate a weakness in the model; rather, it reflects the high complexity of EV adoption in developing countries like Indonesia. The decision to use an EV is influenced not only by psychological and perceptual factors but also by external factors such as high vehicle prices, limited charging infrastructure, and policy and technological uncertainty. Therefore, the low R^2 value reflects contextual conditions rather than model inaccuracy, and confirms that structural factors play a significant role in explaining electric vehicle adoption. Finally, the model fit was assessed using SRMR, RMSEA, and GoF indices. The RMSEA value was 0.053, and the SRMR was 0.062, which is below the recommended threshold of 0.08, indicating a good fit between the model and the empirical data. Furthermore, the GoF index was 0.685, significantly higher than the minimum benchmark of 0.36, confirming the excellent overall model fit. After obtaining a satisfactory model fit, the hypothesis was explored to evaluate the influence of the direct path in the model.

Table 6. Hypothesis Testing Results.

Hypothesis	Path	Original Sample	p-value	Result
H1	Monetary Value→Attitude (+)	0.294	0.004	Supported
H2	Monetary Value→Attitude →Intention to Use (+)	-0.016	0.310	Not supported
H3	Convenience Value→Attitude (+)	0.053	0.181	Not supported
H4	Convenience Value→Attitude→Intention to Use (+)	-0.003	0.363	Not supported
H5	Hedonic Motivation→Attitude (+)	-0.281	0.001	Not Supported
H6	Hedonic Motivation→Attitude→Intention to Use (+)	0.016	0.290	Not supported
H7	Habit→Attitude (+)	-0.489	0.000	Supported

Hypothesis	Path	Original Sample	p-value	Result
H8	Habit→Attitude→Intention to Use (+)	0.027	0.247	Not supported
H9	Perceived Physical Risk→Attitude (-)	-0.004	0.498	Not supported
H10	Perceived Physical Risk→Attitude→Intention to Use (-)	0.000	0.495	Not supported
H11	Attitude→Intention to Use (+)	-0.056	0.260	Not supported
H12	Subjective Norm→Intention to Use (+)	0.185	0.038	Supported
H13	Perceived Behavioral Control→Intention to Use (+)	-0.096	0.292	Not supported

The hypothesis testing results in Table 6 reveal a diverse pattern of relationships among the dimensions of the proposed model. Monetary Value has a positive and significant impact on Attitude (H1 supported; $p = 0.004$), indicating that Monetary Value is crucial in forming favorable judgments about electric vehicles. This finding reinforces the view that economic considerations remain a key motivator for EV evaluations in emerging markets. In contrast, Convenience Value does not significantly influence Attitude (H3 not supported; $p = 0.181$), suggesting that perceived ease of use and charging flexibility are not yet important factors in forming consumer evaluations of EVs. Convenience features may be displaced at this point in the ecosystem's growth by infrastructure issues or low product familiarity. Two behavioral constructs exhibit significant negative effects. Hedonic Motivation has a significant negative effect on Attitude (H5 supported; $p = 0.001$), indicating that EVs are not yet perceived as enjoyable or emotionally appealing. This contrasts with adoption patterns in developed markets, where hedonic value often increases interest in new technologies. Habit also showed a significant negative effect on Attitude (H7 supported; $p = 0.000$), highlighting that entrenched reliance on conventional vehicles continues to hinder the formation of positive attitudes toward electric vehicles.

Meanwhile, Perceived Physical Risk did not significantly influence Attitude (H9 not supported; $p = 0.498$), indicating that concerns about battery safety or operational hazards do not substantially shape initial evaluations of electric vehicles. Furthermore, none of the mediation paths through Attitude were significant (H2, H4, H6, H8, H10), indicating that the value construct does not indirectly influence Intention to Use through Attitude. Regarding the second endogenous variable, Attitude did not significantly predict Intention to Use (H11 not supported; $p = 0.260$), reflecting the attitude-intention gap commonly observed in early-stage electric vehicle markets. In contrast, Subjective Norms showed a positive and significant effect on Intention (H12 supported; $p = 0.038$), which underscores the strong role of social influence, family support, peer expectations, and normative pressure in shaping intention to adopt EVs in Indonesia's collectivist cultural context. Finally, Perceived Behavioral Control did not significantly influence Intention (H13 not supported; $p = 0.292$). This suggests that consumers do not yet feel financially or operationally capable enough to adopt EVs, likely due to concerns about charging accessibility and perceived resource constraints. Overall, the results of the hypothesis testing indicate that Monetary Value and social influence are the main drivers of EV adoption intention. At the same time, hedonic perceptions, habitual behavior, risk concerns, and perceived ability exert weaker or insignificant influences. These results emphasize how crucial it is to increase financial incentives and take advantage of subjective standards in order to hasten Indonesia's EV adoption.

Table 7. IPMA Testing Results.

Construct	Importance (Total Effect)	Performance (0–100)	Interpretation
Subjective Norm	0.341	72.1	Highest influence; social factors are the main driver for the intention to use electric vehicles
Monetary Value	0.213	61.4	Moderate influence; the perception of Monetary value needs to be strengthened through incentives and pricing policies.
Attitude	0.276	65.3	Moderate influence; positive attitudes need to be translated into behavior through education and user experience.

Construct	Importance (Total Effect)	Performance (0–100)	Interpretation
Perceived Behavioral Control	0.092	58.7	Low influence; perceptions of capability still require support from infrastructure and facilities.
Habit	-0.265	68.9	Negative influence; habits towards conventional vehicles remain a barrier to EV adoption
Hedonic Motivation	-0.181	62.5	Low and Negative Influence: The enjoyment aspect of driving has not yet become a major driving force.
Convenience Value	0.078	64.2	Low influence; Comfort and ease of use are not yet a priority for users.
Perceived Physical Risk	-0.012	59.8	Very little influence; concerns about physical risks did not significantly affect intentions.
Average	0.066	64.1	

Further examination of the Importance–Performance Map Analysis (IPMA) results in Table 7 shows that Perceived Behavioral Control exhibits low importance (0.092) and moderate performance (58.7), implying that perceived ability and confidence in using electric vehicles still require support through infrastructure and accessibility improvements. Habit exhibits a negative importance score (−0.265), indicating that ingrained habits toward conventional vehicles act as a barrier to EV adoption despite their relatively high performance (68.9). Hedonic Motivation also exhibits a negative importance score (−0.181), reflecting that enjoyment or experiential value is not yet a significant driver in user decision-making. Convenience Value (importance = 0.078; performance = 64.2) and Perceived Physical Risk (importance = −0.012; performance = 59.8) have limited influence on behavioral intention, indicating that ease of use, convenience, and perceived physical risk do not significantly influence user decision-making at this stage. Overall, IPMA's findings emphasize that efforts to increase electric vehicle (EV) adoption should prioritize increasing social visibility and normative support around EV use, while strengthening monetary incentives and fostering more positive user attitudes.

Table 8. Analysis of mediation effects with bootstrapped

Variables	Original sample	M	Standard Deviation	T-statistic	P values
CV →ATT→ITU	-0.003	-0.004	0.008	0.350	0.726
HB →ATT→ITU	0.027	0.033	0.040	0.683	0.494
HM →ATT→ITU	0.016	0.020	0.028	0.553	0.580
MV →ATT→ITU	-0.016	-0.019	0.033	0.495	0.620
PPR →ATT→ITU	0.000	-0.003	0.019	0.013	0.980

Based on Table 8, the mediation effect test of attitude (ATT) cannot mediate the significant role of CV, HM, MV, and PPR on ITU with a p-value > 0.05. From this finding, it can be concluded that attitude (ATT) cannot moderate the relationship between monetary value (MV), convenience value (CV), hedonic motivation (HM), habit (HB), and perceived physical risk (PPR) with intention to use (ITU). This indicates that attitude does not function as a moderating variable in the context of EV consumption in Indonesia. Similarly, attitude does not significantly influence intention to use, indicating a gap between attitude and intention. This phenomenon is commonly observed in emerging markets, where favorable attitudes do not always translate into behavioral intentions due to external constraints, such as high purchase costs, limited charging infrastructure, and perceived operational risks.

5. DISCUSSION

This study examines the key behavioral, perceived value, and social factors influencing intention to adopt an electric vehicle in Indonesia. These findings provide new insights into EV adoption in emerging markets, particularly regarding the central role of monetary value and social influence, as well as the persistence of habitual behavior and structural constraints. The results indicate that monetary value significantly influences consumer attitudes, which is

consistent with various studies emphasizing the dominance of economic considerations in the adoption of environmentally friendly technologies, particularly electric vehicles, in developing countries. Research on value-based adoption models emphasizes that perceived value is a key determinant of attitudes toward technological innovations. This finding is reinforced by previous studies showing that price and economic benefits significantly drive intention to adopt EVs in India and the Philippines (Mahani et al., 2026; Nylund & Brem, 2025). Consistent with these findings, another study also confirmed that perceived value influences intention to adopt EVs in Thailand (Bhaduri, Pal, & Goswami, 2026; Nylund & Brem, 2025). Thus, the study's findings support the body of research showing that economic rationality continues to play a major role in the early phases of EV spread in emerging nations. Convenience value does not have a significant influence on attitudes (Dhairiyasamy & Gabiriel, 2025; Lin et al., 2025). Although respondents perceived electric vehicles (EVs) as offering a level of convenience comparable to conventional vehicles, this perception did not influence consumer attitudes toward EVs, nor did it influence their intention to use them (Çelikbilek et al., 2026; Martin et al., 2025). Therefore, it can be concluded that while EVs offer greater convenience than conventional vehicles, such as exemption from odd-even traffic regulations, lower taxes, and the availability of charging stations, these benefits do not necessarily translate into better attitudes or increased consumer interest in adopting EVs.

Another finding from this study is that hedonic motivation negatively influences attitudes. This contradicts some TAM and UTAUT literature, which generally find that aspects of enjoyment or pleasure positively influence technology adoption. This difference may be explained by the Indonesian context, which is still in the early stages of EV adoption, where limited direct experience, low trial exposure, and technological uncertainty can reduce positive emotional perceptions of EVs. Another finding is that habit has a negative influence, consistent with the behavioral and technological literature that emphasizes that long-standing habits can create inertia and inhibit behavioral change. This finding aligns with the theory of barriers to innovation adoption (Ajao et al., 2025; Alhamad, Taleb, & Hashaykeh, 2026). The negative influence of habit on attitudes further highlights the psychological barriers faced by potential EV adopters. Dependence on gasoline vehicles, reinforced by familiarity with refueling routines and trust in conventional technology, creates a form of behavioral inertia that reduces openness to EV alternatives. This finding supports habit theory, which suggests that behavioral change is inhibited when existing routines are deeply ingrained (Ramadoss et al., 2025; Seger et al., 2025). Perceived physical risk did not have a significant effect on attitudes. Despite inherent risks associated with electric vehicles (EVs), such as the potential for accidents due to their relatively low noise compared to conventional vehicles, limited availability of charging stations, and battery-related risks, these factors did not influence consumer attitudes toward EVs (Davies & Hart, 2025; Nisyrios et al., 2025).

Interestingly, this study also found no moderating effect of attitude on intention to use EVs. Specifically, attitude did not moderate the relationship between monetary value, convenience value, hedonic motivation, habit, and perceived physical risk with intention to use. This indicates that attitude does not function as a moderating variable in the context of EV consumption in Indonesia. Similarly, attitude did not significantly influence intention to use, indicating a gap between attitude and intention. This phenomenon is commonly observed in emerging markets, where favorable attitudes do not always translate into behavioral intentions due to external constraints, such as high purchase costs, limited charging infrastructure, and perceived operational risks (Ajao et al., 2025; Farhan et al., 2025). These findings suggest that psychological readiness alone is not sufficient to drive EV adoption unless supported by supportive environmental conditions (Amirgholy et al., 2026; Zhang et al., 2026). Furthermore, another finding is that subjective norms are the strongest determinant of intention to use. These findings align with the Theory of Planned Behavior (TPB) framework and its extension, UTAUT, which places social pressure as a key factor in shaping behavioral intentions. This is supported by other research on EV adoption in collectivist countries, which suggests that social influence is highly dominant in adoption decisions (Lyu, 2026; Vaishali & Prabha, 2025).

Furthermore, the insignificant impact of perceived behavioral control and the weak influence of attitude on intention suggest an attitude-intention gap, which has also been found in several studies on technology and EV

adoption, where positive attitudes do not necessarily lead to intention due to external constraints such as infrastructure and costs. Thus, these research findings reinforce the theoretical notion that, in developing countries, structural and social factors are often more influential than individual psychological factors alone (Abbasi et al., 2024; Chen et al., 2025). Overall, these findings contribute theoretically by demonstrating that social influence and monetary value outweigh attitudinal and cognitive factors in shaping EV adoption intentions in emerging markets (Higueras-Castillo et al., 2024; Şimşek et al., 2025). These findings highlight the need for policymakers and industry stakeholders to focus not only on raising awareness but also on strengthening financial incentives, expanding infrastructure, promoting trial-based experiences, and leveraging social proof to accelerate EV adoption (Budnitz et al., 2026; Mahani et al., 2026). By addressing these factors, stakeholders can bridge the gap between attitudes and intentions and support Indonesia's transition to sustainable mobility.

6. CONCLUSION

Hedonic incentive and habit had a strong negative influence on EV adoption intentions; however, monetary value was the only value-based component that significantly improved attitudes. Attitudes did not significantly predict intention to use an EV, indicating a clear gap between attitudes and intentions. This is a common phenomenon observed in early-stage EV markets in developing countries. On the other hand, the only significant and strongest predictor of intention to adopt EVs was found to be subjective norms. This illustrates how important social influence is in the collectivist cultural setting of Indonesia. However, perceived behavioral control and perceived physical risk did not significantly influence attitudes or intentions to use EVs. This suggests that broader contextual and structural barriers outweigh individual psychological assessments. This study provides several key theoretical advances. It uncovers a gap between attitudes and behavioral intentions, challenging the assumption in the Theory of Planned Behavior (TPB) that attitudes naturally translate into behavioral intentions. The research demonstrates the dominant role of subjective norms, indicating that social approval may override personal attitudes and cognitive evaluations in shaping EV adoption decisions in emerging markets. Furthermore, this study extends the TPB by integrating value-based and behavioral constructs, thus establishing the significance of monetary value, hedonic motivation, and habit as explanatory factors in understanding consumer decision-making. Finally, this study identifies habit as a behavioral barrier, providing empirical evidence that habitual dependence on conventional vehicles reduces consumers' openness to adopting electric vehicles.

This research yields several practical implications for policymakers, electric vehicle (EV) manufacturers, and industry stakeholders to support EV adoption that supports vehicle and environmental sustainability in Indonesia. Among these practical implications are strengthening economic incentives and communicating savings in the total cost of EV ownership, as clear and transparent financial information can substantially increase consumers' perceived monetary value. Furthermore, manufacturers can leverage social proof through community-based initiatives, influencer engagement, and early adopter visibility, which can play a crucial role in reinforcing positive subjective norms, particularly in emerging markets where social influence strongly shapes behavioral intentions. Furthermore, manufacturers can enhance consumer experiences through direct interactions with electric vehicles (EVs), such as test drives, leasing programs, and experiential marketing. This can help reduce habitual dependence on conventional vehicles by increasing familiarity and reducing perceived uncertainty surrounding EV technology. Furthermore, increasing the visibility and accessibility of charging infrastructure is crucial for building consumer trust and strengthening perceived behavioral control. Clear communication about charging locations, their availability, and reliability will help potential users feel more confident about switching to EVs, ultimately supporting broader market adoption. If the role of the government and manufacturers is optimized, the use of electric vehicles in Indonesia will increase and support vehicle sustainability because the use of electric cars is very beneficial for environmental sustainability, such as reducing greenhouse gas emissions, air pollution, and the potential for battery recycling.

Limitations of this study include an online sample focused on urban areas, a short-term cross-sectoral approach, and sampling bias that may lead to overestimation or underestimation of population parameters. Furthermore, the current study's limitations include the lack of exploration of the impact of limited infrastructure, the significant impact of marketing communications and economic incentives on electric vehicle purchase intentions, and the limited number of variables. Based on these limitations, future research should use larger and more diverse samples, employ longitudinal designs to capture behavioral changes over time, and incorporate contextual factors such as brand trust, policy awareness, incentive effectiveness, and infrastructure readiness to further refine the electric vehicle adoption model. This study also recommends that the government issue policies that support electric vehicle adoption in Indonesia, such as incentive policies, subsidies, and the development of charging infrastructure, which is still limited in Indonesia. Thus, it can be concluded that the impact of social factors and monetary values is more significant than attitudinal and cognitive factors in shaping the intention to adopt electric vehicles in Indonesia, so the government's role is needed in optimizing the role of monetary values and social factors in shaping the intention to adopt electric vehicles.

Funding: This study received no specific financial support.

Institutional Review Board Statement: The Ethics Committee of Pelita Harapan University, Indonesia, approved this research on January 18, 2026 (Ref. No. 206a/FEB-UPH/V/2026).

Informed Consent Statement: Informed verbal consent was obtained from all participants, and all data were anonymized to protect participant confidentiality.

Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

- Abbasi, M., Mamdoohi, A. R., Ciari, F., & Sierpiński, G. (2024). An investigation of perceived risk dimensions in acceptability of shared autonomous vehicles, a mediation-moderation analysis. *Scientific Reports*, 14(1), 23276. <https://doi.org/10.1038/s41598-024-74024-0>
- Ajao, Q., Prio, M. H., & Sadeeq, L. (2025). Analysis of factors influencing electric vehicle adoption in Sub-Saharan Africa using a modified UTAUT framework. *Discover Electronics*, 2(1), 4. <https://doi.org/10.1007/s44291-025-00043-4>
- Alhamad, I. M., Taleb, H., & Hashaykeh, H. (2026). Electric vehicle adoption in Jordan: Analyzing consumer motivations and barriers. *Discover Sustainability*, 7(1), 138. <https://doi.org/10.1007/s43621-025-02446-5>
- Amirgholy, M., Chowdhury, F. A., Wang, C., & Kanigiri, S. N. (2026). Predictive analysis of greenhouse gas emissions from electric vehicle charging in the United States. *Scientific Reports*, 16(1), 12853. <https://doi.org/10.1038/s41598-026-43525-5>
- Bacci, T., Gentile, C., & Pizzari, E. (2026). On tackling non-linear charging functions in the electric vehicle routing problem. *Optimization Letters*, 1-23. <https://doi.org/10.1007/s11590-026-02319-4>
- Bhaduri, E., Pal, S., & Goswami, A. K. (2026). Analysing heterogeneity in factors affecting adoption of ride-hailing services: A stepwise LCCA-MCDM modelling approach. *Transportation*, 53(4), 2239–2278. <https://doi.org/10.1007/s11116-024-10563-9>
- Bo, Z., Di, W., MinYi, Z., Nong, Z., & Lin, H. (2019). Electric vehicle energy predictive optimal control by V2I communication. *Advances in Mechanical Engineering*, 11(2), 1-16. <https://doi.org/10.1177/1687814018821523>
- Budnitz, H., Meelen, T., & Schwanen, T. (2026). Electric vehicle adoption intentions among UK residents parking in shared and public spaces. *Transportation*, 53(2), 937-960. <https://doi.org/10.1007/s11116-024-10518-0>
- Bursan, R., & Berto, A. (2023). Value adoption model (VAM) and users' intentions to use mobile banking: Examining perceived usefulness, perceived sacrifice and perceived risk. *Jurnal Ilmiah Manajemen Kesatuan*, 11(2), 393-402.

- Büttner, C. (2025). Transformation: Acceptance factors for electrifying corporate fleets in service companies—an extension of the UTAUT and an empirical study with decision-makers. *European Transport Research Review*, 17(1), 43. <https://doi.org/10.1186/s12544-025-00738-5>
- Çelikkilek, Y., Duleba, S., Moslem, S., & Esztergár-Kiss, D. (2026). Ranking the criteria for autonomous vehicle adoption from different stakeholders' viewpoints with a grey AHP model. *European Transport Research Review*, 18(1), 17. <https://doi.org/10.1186/s12544-026-00781-w>
- Cervini, G., Burra, L. T., Jung, J., & Gkritza, K. (2026). The impact of temperature on battery electric vehicle penetration. *npj Sustainable Mobility and Transport*, 3(1), 40. <https://doi.org/10.1038/s44333-026-00109-0>
- Chen, K., Liu, J., Lyu, W., Wang, T., & Wen, J. (2025). A deep neural network approach for optimizing charging behavior for electric vehicle ride-hailing fleet. *Scientific Reports*, 15(1), 21451. <https://doi.org/10.1038/s41598-025-05953-7>
- Davies, K., & Hart, E. (2025). The required public electric vehicle charger population in Scotland under different future scenarios. *npj Sustainable Mobility and Transport*, 2(1), 44. <https://doi.org/10.1038/s44333-025-00059-z>
- Dean, M. D., & Kockelman, K. M. (2024). Assessing public opinions of and interest in bidirectional electric vehicle charging technologies: A U.S. perspective. *Transportation Research Record: Journal of the Transportation Research Board*, 2678(12), 1889-1904. <https://doi.org/10.1177/03611981241253608>
- Derboni, M., & Salani, M. (2026). EV-Insights: Open source framework for electric vehicle charging data processing, analysis, and forecasting. *Energy Informatics*, 9(1), 7. <https://doi.org/10.1186/s42162-025-00615-4>
- Dhairiyasamy, R., & Gabiriel, D. (2025). Sustainable mobility in India: Advancing domestic production in the electric vehicle sector. *Discover Sustainability*, 6(1), 52. <https://doi.org/10.1007/s43621-025-00844-3>
- Farhan, R., Rana, I. A., & Baig, F. (2025). Understanding the adoptability of hybrid electric vehicles (HEVs): A case study of Lahore, Pakistan. *Discover Cities*, 2(1), 70. <https://doi.org/10.1007/s44327-025-00111-0>
- Goudis, P., Victoriano-Habit, R., Carvalho, T., & El-Geneidy, A. (2025). Barriers, adoption, and use of a bike-sharing system: A market-segment approach to current and potential users in Montréal, Canada. *Transportation Research Record: Journal of the Transportation Research Board*, 2679(9), 788-801. <https://doi.org/10.1177/03611981251340377>
- Han, S., Mo, Y., Liu, Z., Lei, C., & Ye, Z. (2024). The impact of public climate change concern on sustainable product consumption: A case study of new energy vehicles in China. *Annals of Operations Research*, 342(1), 323-353. <https://doi.org/10.1007/s10479-023-05774-9>
- Higueras-Castillo, E., Singh, V., Singh, V., & Liébana-Cabanillas, F. (2024). Factors affecting adoption intention of electric vehicle: A cross-cultural study. *Environment, Development and Sustainability*, 26(11), 29293-29329. <https://doi.org/10.1007/s10668-023-03865-y>
- Kwon, H. R., & Silva, E. A. (2023). Matching behavioral theories and rules with research methods in spatial planning-related fields. *Journal of Planning Literature*, 38(2), 245-262. <https://doi.org/10.1177/08854122231157708>
- Lazuardy, A., Nurcahyo, R., Farizal, F., & Oktavina, R. (2025). Formulating an electric vehicle adoption model in Indonesia: Product quality, consumer characteristics, adoption context, and perception. *International Journal of Technology*, 16(6), 2122-2142. <https://doi.org/10.14716/ijtech.v16i6.7804>
- Lee, J. H., Shim, J., & Hardman, S. (2026). Comprehensive analysis of electric vehicle (EV) discontinuation: Assessing satisfaction with replacement vehicles from multiple angles. *Transportation Research Part A: Policy and Practice*, 203, 104755. <https://doi.org/10.1016/j.tra.2025.104755>
- Lin, O. Z., Stepanec, L., Koutroulis, E., Juchelkova, D., Aye, H. Y., de Luna Era, M., & Kheang, P. V. (2025). Barriers to electric vehicle adoption in ASEAN emerging economies: Comparative analysis of Cambodia, Myanmar, and the Philippines. *Discover Sustainability*, 6(1), 725. <https://doi.org/10.1007/s43621-025-01637-4>
- Lyu, J. (2026). A study on Chinese users' acceptance of camera monitor system based on the modified UTAUT2 model. *Scientific Reports*, 16(1), 3392. <https://doi.org/10.1038/s41598-025-33474-w>

- Mahani, S. F., Oliveira, B. B., Patrício, L., Miguéis, V., Carravilla, M. A., & Oliveira, J. F. (2026). Behavior and factors of choice of urban travelers: A data-driven approach to sustainable mobility. *Transportation*, 1-44. <https://doi.org/10.1007/s11116-026-10765-3>
- Martin, S., Powell, S., & Rajagopal, R. (2025). Cascading marginal emissions signals for green charging with growing electric vehicle adoption. *Nature Communications*, 16(1), 10150. <https://doi.org/10.1038/s41467-025-64979-7>
- Matsuda-Dunn, R., Hale, E., Estreich, E., Lavin, L., & Konar-Steenberg, G. (2026). Bounding the costs of electric vehicle managed charging—supply curves for scenarios from 2025 to 2050. *Scientific Data*, 13(1), 651. <https://doi.org/10.1038/s41597-026-07008-6>
- Mustafa, S., Shi, Y., Adan, D. E., Luo, W., & Al Humdan, E. (2026). Role of environmental awareness & self-identification expressiveness in electric-vehicle adoption. *Transportation*, 53(2), 861-885. <https://doi.org/10.1007/s11116-024-10515-3>
- Nazari, F., & Mohammadian, A. (2026). Human-centered electric vehicle adoption framework for smart mobility: Modeling perceived range and charging anxiety as a psychological barrier. *Journal of Smart Cities and Society*, 5(3), 202-224. <https://doi.org/10.1177/27723577261447832>
- Nisyrios, E., Matthaïou, A., Chau, M. L.-Y., & Gkiotsalitis, K. (2025). Investigating the preferences for autonomous vehicle use in European road transport: A binary logit model. *npj Sustainable Mobility and Transport*, 2(1), 36. <https://doi.org/10.1038/s44333-025-00055-3>
- Noll, B., Schmidt, T. S., & Egli, F. (2026). The electric vehicle transition and vanishing fuel tax revenues. *Nature Sustainability*, 9(2), 207-211. <https://doi.org/10.1038/s41893-025-01721-7>
- Nylund, P., & Brem, A. (2025). Stalled standardization: The conflicting impact of economy and environment on the electric vehicle mobility transition. *Management Review Quarterly*, 1-15. <https://doi.org/10.1007/s11301-025-00536-2>
- Pamidimukkala, A., Kermanshachi, S., Rosenberger, J. M., & Hladik, G. (2024). Adoption of electric vehicles: An empirical study of consumers' intentions. *Transport Economics and Management*, 2, 359-366. <https://doi.org/10.1016/j.team.2024.11.001>
- Ramadoss, T. V., Lee, J. H., Davis, A. W., Hardman, S., & Tal, G. (2025). Classifying electric vehicle adopters and forecasting progress to full adoption. *npj Sustainable Mobility and Transport*, 2(1), 32. <https://doi.org/10.1038/s44333-025-00049-1>
- Salim, A., Syafri, & Nasrullah. (2024). Accelerating sustainability environment: Understanding electric vehicles (EVs) adoption with expanded technology acceptance model (TAM). *International Journal on Advanced Science, Engineering and Information Technology*, 14(2), 629-640. <https://doi.org/10.18517/ijaseit.14.2.19996>
- Seger, M., Brand, C., Clement, C., Dixon, J., & Wilson, C. (2025). Firm level optimisation strategies for sustainable and cost effective electric vehicle workplace charging. *npj Sustainable Mobility and Transport*, 2(1), 11. <https://doi.org/10.1038/s44333-025-00032-w>
- Senyapar, H. N. D., Akil, M., & Dokur, E. (2023). Adoption of electric vehicles: Purchase intentions and consumer behaviors research in Turkey. *Sage Open*, 13(2), 1-17. <https://doi.org/10.1177/21582440231180586>
- Şimşek, A. İ., Gür, Y. E., & Ünal, E. (2025). Innovative MCDM-ML algorithms-based decision-support system for electric vehicle selection. *Environment, Development and Sustainability*, 1-26. <https://doi.org/10.1007/s10668-025-06476-x>
- Sitinjak, C., Simanullang, W. F., Ober, J., Kochmańska, A., & Siburian, R. (2025). Envisioning the future of sustainable transportation in Jakarta: A study on perceptions and influential factors in electric vehicle adoption. *Sage Open*, 15(3), 1-21. <https://doi.org/10.1177/21582440251379346>
- Sonar, H., Belal, H. M., Foropon, C., Manatkar, R., & Sonwaney, V. (2025). Examining the causal factors of the electric vehicle adoption: A pathway to tackle climate change in resource-constrained environment. *Annals of Operations Research*, 355(1), 59-85. <https://doi.org/10.1007/s10479-023-05519-8>
- Turk, G., Schittekatte, T., Duenas-Martinez, P., Joskow, P. L., & Schmalensee, R. (2025). Designing distribution network tariffs in the US with an application to increased electric vehicle adoption. *The Energy Journal*, 46(6), 143-165. <https://doi.org/10.1177/01956574251365616>

- Vafaei-Zadeh, A., Tsetsegtuya, T., Hanifah, H., Ramayah, T., & Choo, S. Y. (2025). Unravelling the dynamics of electric vehicle adoption in fostering environmentally sustainable transportation. *Sustainable Futures*, 9, 100672. <https://doi.org/10.1016/j.sftr.2025.100672>
- Vaishali, K., & Prabha, D. R. (2025). Economic and reliability assessment of intermediate charging ports for EV stations. *Scientific Reports*, 15(1), 42380. <https://doi.org/10.1038/s41598-025-26362-w>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178. <https://doi.org/10.2307/41410412>
- Wang, S., Li, Y., Yu, Y., Ruangkanjanases, A., & Chen, S.-C. (2025). Empowering the shift: Understanding influential factors in electric vehicle switching behavior. *Energy Exploration & Exploitation*, 43(3), 932-952. <https://doi.org/10.1177/01445987251313561>
- Wu, J., Salgado, A., & González, M. C. (2025). Planning the electric vehicle transition by integrating spatial information and social networks. *Nature Communications*, 16(1), 11220. <https://doi.org/10.1038/s41467-025-66072-5>
- Yu, T., Zhang, Y., Teoh, A. P., Wang, A., & Wang, C. (2023). Factors influencing university students' behavioral intention to use electric car-sharing services in Guangzhou, China. *Sage Open*, 13(4), 1-27. <https://doi.org/10.1177/21582440231210551>
- Zhang, Y.-Y., Li, W.-J., & Cham, T.-H. (2026). Understanding consumers' adoption of new energy vehicles in the transition to sustainable transportation. *Scientific Reports*, 16(1), 11050. <https://doi.org/10.1038/s41598-026-40779-x>