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Urban-Rural Differences in Electric Vehicle Adoption Intentions: Integrated TAM, TPB, UTAUT with Environmental Identity

Dissakoon Chonsalasin [1], Thanapong Champahom [2*], Natcha Limpasirisuwan [2], Sajjakaj Jomnonkwao [3], Vatanavongs Ratanavaraha [3]

[1] Department of Transportation, Faculty of Railway Systems and Transportation, Rajamangala University of Technology Isan, Nakhon Ratchasima 30000, Thailand.

[2] Department of Management, Faculty of Business Administration, Rajamangala University of Technology Isan, Nakhon Ratchasima 30000, Thailand.

[3] School of Transportation Engineering, Institute of Engineering, Suranaree University of Technology, Nakhon Ratchasima 30000, Thailand.

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Abstract

Objectives: This study examines urban-rural differences in electric vehicle (EV) adoption intentions to inform geographically targeted policy implementation for Thailand's goal of 30% EV production by 2030. *Methods/Analysis*: We integrated the Technology Acceptance Model, Theory of Planned Behavior, and Unified Theory of Acceptance and Use of Technology with environmental identity and trialability constructs. Data from 3,595 respondents (2,311 urban, 1,284 rural) across Thailand were analyzed using structural equation modeling and measurement invariance testing. *Findings*: Results revealed distinct adoption mechanisms between geographical contexts. Urban areas demonstrated stronger effects in system-related perceptions, with perceived ease of use more strongly influencing perceived usefulness (β=0.631 vs. 0.587) and perceived usefulness having a greater impact on behavioral intention (β=0.445 vs. 0.353). Rural areas showed stronger influences of individual characteristics and social factors, with personal innovativeness more strongly affecting attitudes (β=0.216 vs. 0.157) and environmental identity showing greater impact on perceived ease of use (β=0.350 vs. 0.291). *Novelty/Improvement*: This research uniquely combines established technological adoption theories with geographical context analysis, providing evidence-based recommendations for differentiated EV promotion strategies that address the specific challenges of urban and rural environments in developing countries.

Keywords: Measurement Invariance; Personal innovativeness; Technology Acceptance Model; Travel Planned Behavior; Unified Theory of Acceptance and Use of Technology; Battery Electric Vehicle.

1. Introduction

1.1. Research Background

The global transportation sector has emerged as a critical contributor to environmental challenges, accounting for over 20% of worldwide carbon emissions and significantly impacting air pollution levels [1]. In response to these pressing environmental concerns and the urgent need for sustainable development, electric vehicles (EVs) have gained prominence as a promising solution to reduce reliance on fossil fuels and lower CO_2 emissions [2-6]. The transition to EVs aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) [7]. This shift towards electric mobility represents a crucial strategy in addressing climate change while promoting sustainable transportation practices

* Corresponding author: thanapong.ch@rmuti.ac.th

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[8]. The growing recognition of EVs as a sustainable alternative to conventional vehicles is driven by increasing concerns over petrochemical resource sustainability and environmental pollution [9], making them an essential component of global efforts to achieve carbon neutrality and sustainable development targets.

In alignment with global sustainability initiatives, Thailand has integrated EVs and clean energy into its national strategic plan through two key focus areas: "Transportation and logistics industry and services" and "Development of energy security and promotion of environmentally friendly energy" [10]. The Thai government has demonstrated its commitment to electrifying the transportation sector through various initiatives, including the implementation of the "30@30" policy, which aims to achieve 30% of total vehicle production as EVs by 2030, and plans to ban new internal combustion engine vehicles by 2035 [11, 12]. However, despite these ambitious policies and the potential environmental benefits, EV adoption in Thailand faces significant challenges. Studies have revealed that performance expectancy, effort expectancy, social influence, hedonic motivation, and environmental concerns significantly influence purchase intentions for EVs in the Thai context [13]. Moreover, Ahmad et al. [14] identified that environmental concerns, hedonic motivation, social influence, effort expectancy, trust, and behavioral intentions are crucial factors affecting EV acceptance and uptake in Thailand. The contrast between urban and rural areas presents an additional layer of complexity, as these regions often exhibit different adoption patterns and face distinct challenges in terms of infrastructure availability and consumer preferences [15, 16].

1.2. Urban-Rural Differences in Electric Vehicle Adoption Intentions

Urban areas are characterized by high population density, developed infrastructure, and concentrated economic activities, while rural areas typically feature lower population density, greater distances between destinations, and more agricultural or natural landscapes [17-19]. These fundamental differences significantly influence transportation needs and vehicle adoption patterns. Jiang et al. [20] found that urban conditions, travel patterns, access to green spaces, parking availability, and loan accessibility significantly impact EV adoption intentions, highlighting how built environment characteristics shape consumer choices. In urban settings, residents primarily use vehicles for shorter commutes and daily errands, making current EV ranges sufficient for their needs. Conversely, rural residents often require vehicles for longer distances and more diverse purposes, including agricultural and commercial activities [21].

A significant challenge in rural EV adoption stems from vehicle type preferences and availability. Rural areas show a higher preference for pickup trucks. However, the current EV market lacks pickup truck options, creating a substantial barrier to rural adoption [15, 22]. Additionally, the distribution of charging infrastructure presents another critical disparity. Urban areas typically have better access to charging stations due to higher population density and developed infrastructure networks, while rural areas face limited charging accessibility and longer distances between stations [23, 24]. This infrastructure gap is particularly problematic given that rural residents often travel longer distances and require more frequent charging opportunities [25]. These distinct characteristics and challenges between urban and rural areas underscore the need for targeted approaches in promoting EV adoption across different geographical contexts.

1.3. Theoretical Background

This study integrates three well-established theoretical frameworks with additional factors to comprehensively understand EV adoption intentions across urban and rural contexts. The Technology Acceptance Model (TAM) serves as the foundational framework, emphasizing perceived usefulness and perceived ease of use as primary determinants of technology adoption [26]. The integration extends to include key constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), which has been widely validated in EV adoption studies. Kumar & Chauhan [27] demonstrated that UTAUT factors, particularly performance expectancy, effort expectancy, social influence, and facilitating conditions, significantly impact consumer adoption intentions for EVs.

The Theory of Planned Behavior (TPB) components further enhance the model's explanatory power. Gunawan et al. [28] found that attitude toward use (ATU), subjective norm (SBN), and perceived behavioral control (PBC) positively influence interest in using EVs. These factors are particularly relevant in understanding the social and behavioral aspects of EV adoption across different geographical contexts. Additionally, this study incorporates several extended factors that have shown significant influence in recent literature. Trialability, representing the degree to which an innovation may be experimented with on a limited basis, has been identified as a crucial factor in reducing adoption uncertainty [29]. Environmental identity, reflecting an individual's self-identification with environmental causes, has emerged as a significant predictor of pro-environmental behaviors in EV adoption studies [30, 31]. Furthermore, subjective norm and perceived behavioral control from TPB have been consistently validated as significant predictors of behavioral intention to use EVs [28, 32], particularly in contexts where social influence and personal capability perceptions play crucial roles in adoption decisions.

The selection of TAM, TPB, and UTAUT for integration in this study was driven by their complementary strengths and the limitations of using any single framework in isolation. While numerous technology adoption models exist, our comprehensive evaluation led to the selection of these three frameworks for several reasons.

First, the Technology Acceptance Model (TAM) was chosen as our foundational framework due to its proven efficacy in explaining technology adoption through cognitive factors. However, as Zhang et al. [26] demonstrated in their study of new energy vehicles in China, TAM alone fails to capture the complex social and contextual factors involved in EV adoption. By integrating TPB components, we address this limitation by incorporating subjective norms and perceived behavioral control, which have been validated as crucial determinants by Gunawan et al. [28], who found these factors significantly influence EV adoption intentions in Indonesia.

Second, the inclusion of UTAUT elements enhances our model's explanatory power by incorporating facilitating conditions, which Kumar & Chauhan [27] identified as essential for understanding EV adoption in developing economies like India. Alternative frameworks such as Innovation Diffusion Theory (IDT) and the Value-Belief-Norm (VBN) model were considered but ultimately not selected due to their more limited application in transportation contexts and less robust empirical validation in EV research compared to our chosen frameworks.

Finally, our integration of environmental identity and trialability as additional constructs addresses context-specific factors relevant to Thailand's transition to electric mobility. This approach aligns with Manutworakit & Choocharukul's [13] findings that environmental concerns significantly influence BEV purchase intentions in Thailand, while Chonsalasin et al. [33] highlighted the importance of government policy perceptions in shaping adoption behaviors. Our integrated model thus represents a comprehensive yet parsimonious framework that captures the technological, psychological, social, and contextual dimensions of EV adoption decisions across different geographical contexts.

1.4. Statistical Method for Comparing Urban and Rural Models

In comparing EV adoption models between urban and rural populations, measurement invariance (MI) testing serves as a crucial statistical approach to ensure valid cross-group comparisons. MI establishes whether measurement instruments maintain consistent psychometric properties across different groups, ensuring that any observed differences reflect true variations in the constructs rather than measurement artifacts [34]. This methodological approach is particularly vital for several reasons. First, MI testing helps validate whether the measurement model operates equivalently across urban and rural populations, ensuring that the constructs (such as environmental identity, perceived usefulness, and behavioral intention) are conceptualized and interpreted similarly by both groups. Without establishing measurement invariance, differences in model parameters between urban and rural populations could be attributable to measurement bias rather than genuine group differences in the theoretical relationships [35]. Second, MI provides a robust foundation for comparing structural relationships in our integrated theoretical framework, allowing researchers to make meaningful comparisons between groups and draw valid conclusions about differences in adoption patterns between urban and rural contexts [22]. The effectiveness of MI in comparative studies has been demonstrated by several researchers in the EV adoption context. For instance, Higueras-Castillo et al. [36] successfully employed MI testing to validate cross-cultural comparisons of EV adoption intentions, while Singh et al. [32] utilized this approach to examine adoption variations across different demographic groups. These studies underscore the reliability of MI as a methodological tool for investigating group differences in EV adoption patterns.

In selecting structural equation modeling (SEM) with measurement invariance testing for this analytical approach, several alternative methodologies were carefully evaluated. Partial Least Squares (PLS) modeling was considered due to its flexibility with non-normal data and smaller sample sizes, as demonstrated by Manutworakit & Choocharukul [13] in their study of BEV adoption in Thailand. However, covariance-based SEM was selected due to its superior capabilities in theory testing and simultaneous evaluation of measurement and structural models, which was essential for the comparative urban-rural analysis. Multilevel modeling approaches that could account for nested geographical effects were also considered. However, as Singh et al. [32] noted in their study of EV adoption in the Himalayan region, measurement invariance testing within the SEM framework provides more robust comparisons of latent constructs across distinct populations. This approach allowed for establishing whether observed differences between urban and rural groups reflected true variations in construct relationships rather than measurement artifacts.

To address potential biases in self-reported data, several methodological safeguards were implemented. First, multi-item scales were employed for each construct to minimize single-item response bias, following Ahmad et al. [14], who utilized similar approaches when examining EV adoption in Thailand. Second, rigorous data screening procedures were conducted, including Mahalanobis distance tests to identify multivariate outliers and attention check questions to ensure respondent engagement, as recommended by Prakhar et al. [37]. Third, common method bias was addressed through procedural remedies, including varied response formats, assurance of anonymity, and counterbalancing of question order. Additionally, Harman's single-factor test was conducted to assess potential common method variance, which revealed that no single factor accounted for more than 28% of variance, suggesting minimal common method bias [38]. These methodological choices and precautions enhanced the validity of the findings while addressing the inherent limitations of cross-sectional survey research in technology adoption studies.

1.5. Research Gap

Despite extensive research on EV adoption factors, significant gaps exist in understanding the urban-rural divide in adoption intentions. While studies have examined EV adoption in various contexts, comparative analyses between urban and rural populations remain limited. Recent literature has primarily focused on either urban areas [20] or specific regional contexts without distinguishing between urban and rural characteristics [13, 14]. Although Peng et al. [9] investigated spatial variations in EV market share, their study did not specifically address the psychological and behavioral differences between urban and rural consumers. This gap is particularly significant given the distinct transportation needs, infrastructure availability, and socioeconomic conditions that characterize urban and rural areas.

Furthermore, while existing studies have employed various theoretical frameworks independently—such as TAM [26], UTAUT [27], and TPB [28]—there is limited research integrating these models with additional contextual factors like environmental identity and trialability. The need for a comprehensive theoretical framework that captures both technological acceptance and behavioral aspects across different geographical contexts remains largely unaddressed. Chonsalasin et al. [33] examined government policy perceptions on EV adoption in Thailand but did not explore urban-rural differences, while Singh et al. [32] investigated EV adoption in the Himalayan region using the UTAUT2-NAM model without focusing on geographical differences.

The integration of multiple theoretical frameworks is crucial as it provides a more holistic understanding of adoption intentions, particularly when examining the diverse needs and perspectives of urban and rural populations. Abbasi et al. [39] found that consumer motivation significantly enhances intentions to purchase EVs through performance expectancy, effort expectancy, social influence, and technological factors, but did not address geographical variations. Similarly, Pamidimukkala et al. [40] identified financial, technological, and infrastructure barriers to EV adoption without examining how these barriers might differ between urban and rural contexts.

This research addresses these gaps by conducting a comparative analysis of urban and rural EV adoption intentions while employing an integrated theoretical framework that encompasses multiple theoretical perspectives. By examining the distinct adoption mechanisms between these populations, this study provides insights into how geographical contexts moderate EV adoption, enabling the development of targeted interventions that address the specific challenges of both urban and rural environments in Thailand.

1.6. Research Contribution

This study offers several significant contributions to both theory and practice in EV adoption. First, it provides valuable insights into the distinct adoption patterns between urban and rural populations, enabling policymakers and stakeholders to develop targeted interventions based on geographical contexts. Specifically, the findings can guide government agencies, particularly Thailand's Ministry of Energy and Ministry of Transport, in crafting differentiated policies that address the unique challenges and needs of both urban and rural communities. For urban areas, policies might focus on addressing infrastructure density and parking solutions, while rural initiatives could emphasize the development of long-range charging networks and vehicle types suitable for agricultural and commercial uses.

Second, automotive manufacturers and dealers can utilize these findings to develop market-specific strategies. Understanding the distinct preferences and concerns of urban and rural consumers enables them to tailor their product offerings, marketing approaches, and after-sales services accordingly [41]. For instance, manufacturers might prioritize the development of electric pickup trucks to meet rural market demands while focusing on compact EVs for urban environments. Third, energy providers and charging infrastructure developers can optimize their investment decisions based on the differentiated needs of urban and rural areas, leading to more efficient resource allocation and improved charging network coverage [42, 43].

The implementation of these targeted approaches is expected to accelerate EV adoption rates in both urban and rural areas, ultimately contributing to Thailand's environmental goals and sustainable transportation targets. Moreover, this research provides a methodological framework for similar comparative analyses in other emerging markets, helping to bridge the urban-rural divide in sustainable transportation adoption.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive literature review on factors influencing EV adoption, focusing on environmental identity, personal innovativeness, social network influence, trialability, and relationships from the integrated theoretical framework, concluding with research hypotheses and the proposed conceptual model. Section 3 details the methodology, including participant selection, materials, procedures, and data analysis techniques. Section 4 presents the results of descriptive statistics, measurement model evaluation, structural equation modeling, and hypothesis testing across urban and rural populations. Section 5 discusses the findings, highlighting differences between urban and rural adoption mechanisms. Finally, Section 6 concludes with policy recommendations for both urban and rural contexts, implementation strategies, and directions for future research.

2. Literature Review and Hypothesizes

2.1. The Role of Environmental Identity in EV Adoption

Environmental identity represents an individual's self-identification with environmental causes and their tendency to consider environmental impacts in decision-making (Table 1). This construct has gained significant attention in EV adoption research due to its influence on consumer perceptions and attitudes. In the context of EVs, environmental identity plays a crucial role in shaping how individuals perceive the utility and benefits of electric vehicles.

Table 1. Literature Review and Hypothesizes

Research	Key finding	Supporting Hypothesis
Chonsalasin et al. [33]	The study identified five distinct factors influencing EV adoption intentions: perceptions of government commitment and efficiency, government welfare, effects of government policy, government communication, and tax benefits.	H7, H8, H11
Zhang et al. [26]	The study found that perceived usefulness, perceived ease of use, and perceived risk significantly influence consumers' purchase intentions through attitudinal ambivalence.	H9, H10, H12
Ahmad et al. [14]	Environmental concerns, hedonic motivation, social influence, effort expectancy, trust, and behavioral intentions significantly influence EV acceptance and uptake.	H3, H6, H7, H8
Wang et al. [44]	Performance expectations, social influence, and price value positively influence consumers' intention to adopt EVs, while perceived risk negatively impacts this intention.	H6, H7, H13
Singh et al. [32]	Performance expectancy, facilitating conditions, hedonic motivation, price value, and personal norms significantly influence consumers' intentions to adopt EVs.	H1, H9, H13, H14
Manutworakit & Choocharukul [13]	Performance expectancy, effort expectancy, social influence, hedonic motivation, and environmental concern significantly influence purchase intention for EVs.	H1, H3, H6, H7
Kumar & Chauhan [27]	Five factors—Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Price Value—significantly impact consumer adoption intentions for EVs.	H9, H10, H15
Abbasi et al. [39]	Consumer motivation significantly enhances intentions to purchase EVs through performance expectancy, effort expectancy, social influence, technophilic, and perceived environmental knowledge.	H1, H4, H6, H7
Gunawan et al. [28]	Attitude toward use (ATU), subjective norm (SBN), and perceived behavioral control (PBC) positively influence interest in using EVs.	H14, H15, H16
Alyamani et al. [45]	Monetary incentives and accessible charging infrastructure significantly enhance EV adoption likelihood, with females and consumers in their 40s showing higher propensity to purchase EVs.	H8, H13, H15
Prakhar et al. [37]	Enhancing perceived enjoyment and facilitating conditions can improve the user-friendliness of EVs, while reducing perceived cost can increase perceived usefulness.	H8, H9, H12
Jiang et al. [20]	Urban conditions, travel patterns, access to green spaces, parking availability, and loan accessibility significantly impact EV adoption intentions.	H8, H15
Bhat et al. [46]	Performance expectancy, effort expectancy, hedonic motivation, and environmental concern significantly influence purchase intention for EVs.	H1, H3, H9, H10
Nayum & Thøgersen [31]	Personal norms are the strongest predictors of pro-environmental behaviors among EV adopters, while compensatory beliefs negatively influence both personal norms and behaviors.	H1, H2, H16
Li et al. [47]	Three self-image motives—pro-environmental, innovative, and normative—significantly influence consumers' EV adoption decisions, with pro-environmental motives being the most frequently claimed.	H1, H2, H4, H14
Higueras-Castillo et al. [36]	Cultural factors significantly influence EV adoption intentions, with power distance, hedonic motivations, and social influence playing crucial roles.	H6, H7, H14
Rye & Sintov [48]	Rideshare drivers rated symbolic attributes higher but had weaker symbolic attribute predictors for EV adoption intent compared to commuters. Instrumental attributes were stronger predictors.	H9, H12, H13
Hull et al. [49]	Risk perceptions, environmental considerations, and cost perceptions significantly influence EV adoption intention, with ten out of eleven hypotheses supported.	H1, H2, H13, H15
Pamidimukkala et al. [40]	Financial, technological, and infrastructure barriers significantly impede EV adoption, while environmental barriers do not significantly affect consumer intention.	H8, H9, H13
Jain et al. [50]	Performance expectancy and facilitating conditions positively influence adoption intention, while perceived risk negatively affects it. Government support moderates the relationship.	H9, H13, H15
Qian & Gkritza [51]	Adoption pioneers maintain stable, positive attitudes towards EVs and discuss broader topics, while laggards show concerns primarily about affordability and gas prices.	H4, H5, H13

Note: Hypothesized: H1: Environmental identity positively affects perceived usefulness; H2: Environmental identity positively affects attitude toward electric vehicles; H3: Environmental identity positively affects perceived ease of use; H4: Personal innovativeness positively affects perceived usefulness; H5: Personal innovativeness positively affects attitude toward electric vehicles; H6: Social network influence positively affects attitude toward electric vehicles; H7: Social network influence positively affects perceived ease of use; H8: Trialability positively affects perceived ease of use; H9: Perceived ease of use positively affects perceived usefulness. H10: Perceived ease of use positively affects attitude toward electric vehicles; H11: Perceived ease of use positively affects behavioral intention to use; H12: Perceived usefulness positively affects attitude toward electric vehicles; H13: Perceived usefulness positively affects behavioral intention to use; H14: Subjective norm positively affects behavioral intention to use; H15: Perceived behavioral control positively affects behavioral intention to use; H16: Attitude toward electric positively affects behavioral intention to use.

First, environmental identity significantly influences perceived usefulness of EVs through individuals' recognition of environmental benefits. Nayum & Thøgersen [31] found that individuals with strong environmental identities are more likely to recognize and value the practical benefits of EVs, such as reduced emissions and lower carbon footprint. This relationship may vary between urban and rural residents, as urban dwellers typically show higher environmental consciousness due to direct exposure to air pollution and traffic congestion [52, 53]. Therefore:

H1: Environmental identity positively affects perceived usefulness of electric vehicles.

Second, environmental identity shapes attitudes toward EVs by aligning with personal values and environmental concerns. Li et al. [30], Li et al. [47] identified that pro-environmental motives are the most frequently claimed reasons for EV adoption, demonstrating how environmental identity directly influences attitudes. The impact of environmental identity on attitudes may be more pronounced in urban areas where environmental issues are more visible and immediate compared to rural settings [20]. Thus:

H2: Environmental identity positively affects attitude toward electric vehicles.

Third, environmental identity influences perceived ease of use through increased motivation to learn and adapt to new environmental technologies. Ahmad et al. [14] found that environmentally conscious individuals are more likely to overcome perceived difficulties in adopting EVs. This relationship might be particularly relevant in rural areas where charging infrastructure is less developed, as strong environmental identity can motivate individuals to overcome usage barriers [54]. Therefore:

H3: Environmental identity positively affects perceived ease of use of electric vehicles.

2.2. The Influence of Personal Innovativeness on EV Adoption

Personal innovativeness reflects an individual's willingness to embrace and experiment with new technologies. In the context of EV adoption, this characteristic plays a vital role in how people perceive and evaluate electric vehicles as an innovative transportation solution.

Personal innovativeness significantly influences the perceived usefulness of EVs through individuals' readiness to recognize the advantages of new technology. Abbasi et al. [39] found that consumer innovativeness significantly enhances intention to purchase EVs through performance expectancy, suggesting that more innovative individuals are better at recognizing the practical benefits of EVs. The impact may differ between urban and rural residents, as urban areas typically have higher exposure to technological innovations and greater access to EV-related information [51]. Their research revealed that adoption pioneers maintain stable, positive attitudes towards EVs and discuss broader topics like technological advantages, while laggards show more hesitation. Therefore:

H4: Personal innovativeness positively affects perceived usefulness of electric vehicles.

Moreover, personal innovativeness shapes attitudes toward EVs by influencing how individuals evaluate new transportation technologies. Li et al. [47] identified innovative motives as one of three key self-image motives significantly influencing consumers' EV adoption decisions. This relationship may be particularly pronounced in urban areas where there is greater exposure to EVs and charging infrastructure, allowing innovative individuals to form more positive attitudes through direct observation and experience. The urban-rural divide is evident as Singh et al. [32] found that performance expectancy and facilitating conditions have varying impacts across different geographical contexts. Thus:

H5: Personal innovativeness positively affects attitude toward electric vehicles.

2.3. The Impact of Social Network Influence on EV Adoption

Social network influence represents the impact of an individual's social connections, including friends, family, and peers, on their perceptions and decisions regarding EV adoption. This factor is particularly relevant in the context of innovative technologies like EVs, where social learning and peer experiences play crucial roles in adoption decisions.

Social network influence affects attitudes toward EVs through social learning and information sharing within communities. Ahmad et al. [14] found that social influence significantly impacts EV acceptance and uptake in Thailand, as individuals tend to form attitudes based on the experiences and opinions of their social circles. This influence may manifest differently in urban and rural settings. In urban areas, denser social networks and higher EV visibility create more opportunities for social learning, while rural communities might rely more heavily on close-knit relationships for information about new technologies [36]. Their research demonstrated that cultural factors and social influence play crucial roles in shaping adoption intentions across different geographical contexts. Therefore:

H6: Social network influence positively affects attitude toward electric vehicles.

Additionally, social network influence impacts perceived ease of use through shared experiences and practical knowledge transfer. Manutworakit & Choocharukul [13] found that social influence significantly influences purchase intention for EVs in Thailand, partly through its effect on how easy or difficult people perceive EV operation to be. The urban-rural distinction is particularly relevant here, as urban residents typically have more opportunities to observe and learn from existing EV users, while rural residents might face limited exposure to EV users in their social networks [55-57]. Their study highlighted that social influences and facilitating conditions vary significantly across different geographical contexts. Thus:

H7: Social network influence positively affects perceived ease of use of electric vehicles.

2.4. The Role of Trialability in EV Adoption

Trialability refers to the degree to which potential adopters can experiment with or test an innovation before making an adoption decision. In the context of EVs, trialability is particularly crucial as it allows individuals to gain first-hand experience with the technology, reducing uncertainty and adoption barriers.

Trialability significantly influences perceived ease of use by providing direct experience with EV operation and charging processes. Chonsalasin et al. [33] identified that the opportunity to test and experience EVs helps potential adopters better understand their operation and maintenance requirements, directly affecting their perception of how easy or difficult it would be to use an EV. The impact of trialability may vary significantly between urban and rural areas due to differences in access to EV test-drive opportunities. Urban residents typically have better access to EV dealerships and test-drive events, while rural residents may have limited opportunities for hands-on experience with EVs [23]. This urban-rural disparity in trialability opportunities can create different levels of perceived ease of use between these populations. For instance, Kumar & Chauhan [27] found that effort expectancy and facilitating conditions significantly impact consumer adoption intentions, highlighting the importance of practical experience in shaping perceptions. Therefore:

H8: Trialability positively affects perceived ease of use of electric vehicles.

2.5. Technology Acceptance Model Core Relationships in EV Adoption

The Technology Acceptance Model (TAM) posits several fundamental relationships between perceived ease of use, perceived usefulness, attitudes, and behavioral intentions. These relationships are particularly relevant in the context of EV adoption, where the technology represents a significant shift from conventional vehicles.

Perceived ease of use influences perceived usefulness, as users who find EVs easy to operate are more likely to recognize their practical benefits. Zhang et al. [26] found that perceived ease of use significantly influences consumers' purchase intentions through perceived usefulness, with this relationship varying between urban and rural contexts due to differences in charging infrastructure accessibility and technical support availability. This influence may be stronger in urban areas where better infrastructure makes EVs more practically useful [58, 59]. Therefore:

H9: Perceived ease of use positively affects perceived usefulness of electric vehicles.

The relationship between perceived ease of use and attitudes toward EVs is demonstrated through users' overall evaluation of the technology. Manutworakit & Choocharukul [13], Roemer & Henseler [60] found that effort expectancy (similar to perceived ease of use) significantly influences purchase intention for EVs in Thailand. This relationship might be stronger in rural areas where operational concerns like charging and maintenance are more prominent due to limited infrastructure [32, 61]. Thus:

H10: Perceived ease of use positively affects attitude toward electric vehicles.

Perceived ease of use directly impacts behavioral intention as it reduces adoption barriers. Ahmad et al. [14] found that effort expectancy significantly influences EV acceptance and uptake. The strength of this relationship may vary between urban and rural areas due to differences in support infrastructure and technical assistance availability [62-64]. Therefore:

H11: Perceived ease of use positively affects behavioral intention to use electric vehicles.

Perceived usefulness shapes attitudes toward EVs by highlighting their practical benefits. Kumar & Chauhan [27] demonstrated that performance expectancy (similar to perceived usefulness) significantly influences adoption intentions. This relationship might manifest differently in urban and rural contexts due to varying transportation needs and usage patterns [20]. Thus:

H12: Perceived usefulness positively affects attitude toward electric vehicles.

2.6. Determinants of Behavioral Intention in EV Adoption

The behavioral intention to adopt EVs is influenced by multiple factors that combine elements from TAM and TPB, creating a comprehensive understanding of adoption decisions across different geographical contexts.

Perceived usefulness directly influences behavioral intention through individuals' evaluation of EV benefits. Wang et al. [44] found that performance expectations positively influence consumers' intention to adopt EVs, while this effect varies between different geographical areas due to distinct utilitarian needs. For instance, urban users might focus on commuting efficiency, while rural users prioritize range and carrying capacity. Jain et al. [50] further confirmed that performance expectancy positively influences adoption intention, highlighting its crucial role in decision-making. Therefore:

H13: Perceived usefulness positively affects behavioral intention to use electric vehicles.

Subjective norm, representing social pressure and expectations, significantly impacts behavioral intentions. Gunawan et al. [28] found that subjective norm positively influences interest in using EVs, with this effect potentially varying between urban and rural communities due to different social structures and community influences. Urban areas might experience stronger social pressure due to environmental consciousness and trend-following behavior, while rural areas might be more influenced by practical community experiences [65, 66]. Thus:

H14: Subjective norm positively affects behavioral intention to use electric vehicles.

Perceived behavioral control, reflecting individuals' perceived ability to adopt and use EVs, influences behavioral intentions. Hull et al. [49] found that perceived behavioral control significantly affects EV adoption intention, with this relationship particularly relevant when comparing urban and rural contexts due to differences in infrastructure availability and support systems. This factor becomes especially crucial in rural areas where charging infrastructure and maintenance facilities might be limited [67, 68]. Therefore:

H15: Perceived behavioral control positively affects behavioral intention to use electric vehicles.

Finally, attitude toward EVs directly shapes behavioral intention through overall evaluation and predisposition. Singh et al. [32] demonstrated that positive attitudes toward EVs significantly enhance adoption intentions, with this relationship potentially varying between urban and rural populations due to different exposure levels and experiences with EVs. Manutworakit & Choocharukul [13] further confirmed that attitudes significantly influence purchase intention for EVs in Thailand, highlighting the importance of this relationship across different geographical contexts. Thus:

H16: Attitude toward electric vehicles positively affects behavioral intention to use electric vehicles.

2.7. Summary of Literature Review and Research Framework

The literature review establishes an integrated theoretical framework for examining EV adoption intentions across urban and rural contexts (Figure 1). The framework integrates three established theories - Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) - along with additional constructs specific to EV adoption.

The proposed model includes five exogenous variables:

- Environmental Identity (ENV): Influences Perceived Usefulness (H1), Attitude toward Electric Vehicles (H2), and Perceived Ease of Use (H3).
- Personal Innovativeness (PIN): Affects Perceived Usefulness (H4) and Attitude toward Electric Vehicles (H5).
- Social Network Influence (SOC): Impacts Attitude toward Electric Vehicles (H6) and Perceived Ease of Use (H7).
- Trialability (TRI): Influences Perceived Ease of Use (H8).
- Subjective Norms (SUN): Affects Behavioral Intention to Use (H14).

The model incorporates four mediating variables:

- Perceived Ease of Use (PEU): Influences Perceived Usefulness (H9), Attitude toward Electric Vehicles (H10), and Behavioral Intention to Use (H11).
- Perceived Usefulness (PUF): Affects Attitude toward Electric Vehicles (H12) and Behavioral Intention to Use (H13).
- Perceived Behavioral Control (PBC): Influences Behavioral Intention to Use (H15).
- Attitude toward Electric Vehicles (ATT): Affects Behavioral Intention to Use (H16).

The dependent variable, Behavioral Intention to Use (BIU), represents the ultimate outcome measure of EV adoption intention. This comprehensive framework enables examination of both direct and indirect effects on adoption intentions, while accounting for the distinct characteristics of urban and rural populations.

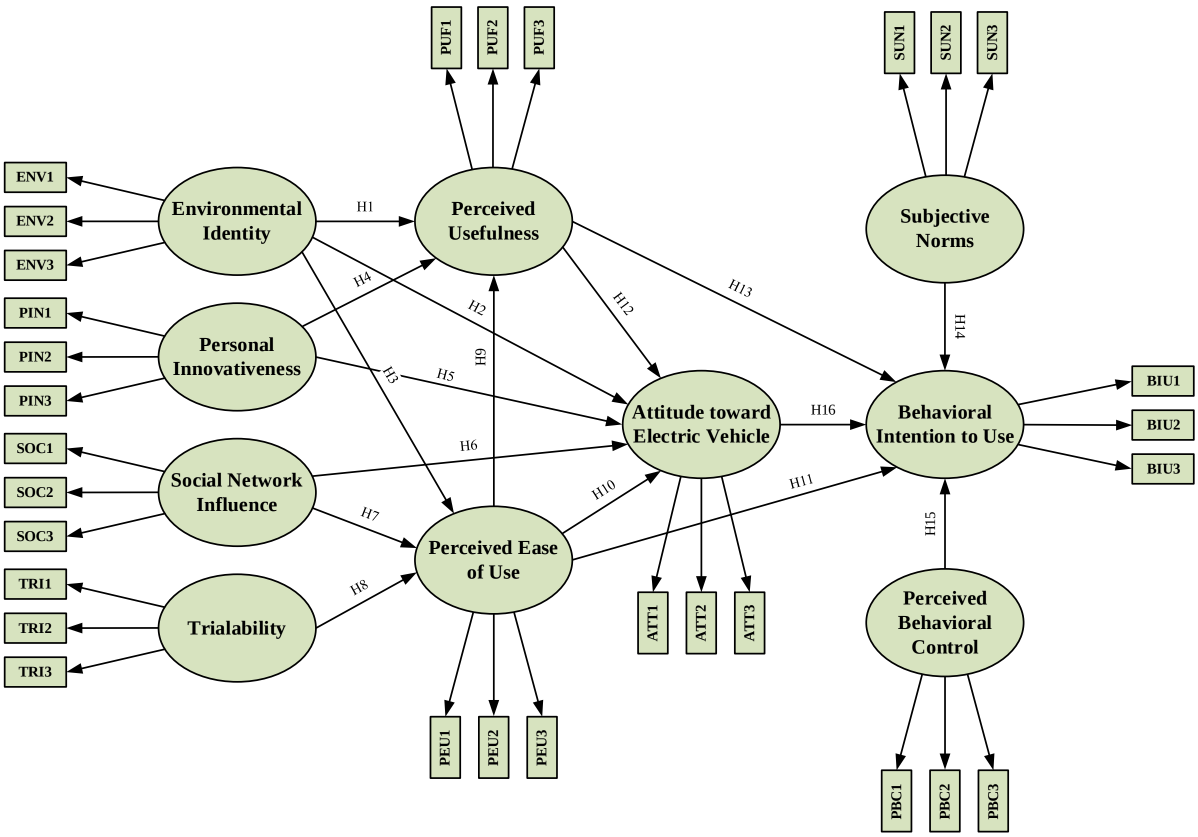

Figure 1. Conceptual frameworks and hypotheses

3. Material and Methods

3.1. Participants

The study targeted individuals aged 18 years and above who possess valid driving licenses, ensuring participants had the legal ability and practical experience to make informed decisions about vehicle adoption [33]. This criterion was particularly important as it ensured respondents could meaningfully evaluate the practical aspects of EV adoption based on their driving experience and transportation needs.

The sampling procedure employed simple random sampling to ensure representativeness and minimize selection bias. This method was chosen to provide equal opportunity for participation across both urban and rural populations in Thailand. The sampling frame included residents from various urban and rural areas, with urban areas defined according to Thailand's official administrative classification system as municipal regions (including city municipalities, town municipalities, and sub-district municipalities), while rural areas comprised non-municipal regions (Sub-district Administrative Organizations) [69, 70]. This classification follows Thailand's National Statistical Office definitions, which categorize areas based on population density, administrative functions, and infrastructure development. However, this administrative classification presented challenges in borderline cases, particularly in rapidly developing peri-urban areas. To address these ambiguous cases, additional criteria were applied, including distance from city centers (areas >40 km from major city centers were classified as rural) and population density thresholds (areas with <300 persons per square kilometer were classified as rural). In cases where these criteria produced contradictory classifications, the predominant land use pattern (agricultural versus commercial/residential) served as the deciding factor. Approximately 8% of the sample locations required this additional classification protocol, primarily in expanding metropolitan areas surrounding Bangkok, Chiang Mai, and Phuket. This refined classification approach ensured consistent categorization across all sampling points and aligned with similar methodological approaches used by Jiang et al. [20] in their urban planning perspective on EV adoption.

The sample size was determined following the structural equation modelling (SEM) guidelines, which recommend a minimum ratio of 20 observations per observed variable [40]. With 30 observed variables in the measurement model, the minimum required sample size was calculated as 600 respondents per model (urban and rural). To account for potential invalid responses and ensure robust analysis, we aimed to collect data from a larger sample. The final dataset comprised 3,595 valid responses (2,311 from urban areas and 1,284 from rural areas), exceeding the minimum requirement and providing sufficient statistical power for both urban and rural models.

3.2. Materials

The research instrument was designed as a structured questionnaire based on established theoretical frameworks including TAM, UTAUT, and TPB, along with extended factors identified in the literature review. The questionnaire items were adapted from validated scales in previous EV adoption studies [35, 71-73] to ensure content validity and reliability.

The questionnaire was structured into two main parts. Part one collected demographic information including gender, age, education level, occupation, vehicle ownership status, and current vehicle type. This demographic data was crucial for understanding the characteristics of urban and rural respondents and their current transportation patterns. Part two comprised items measuring the theoretical constructs: environmental identity (3 items), personal innovativeness (3 items), social network influence (3 items), trialability (3 items), perceived ease of use (3 items), perceived usefulness (3 items), subjective norm (3 items), perceived behavioral control (3 items), attitude toward electric vehicles (3 items), and behavioral intention to use (3 items).

All construct items in part two were measured using a seven-point Likert scale, where 1 represented "strongly disagree" and 7 represented "strongly agree." [25]. This scale was chosen to provide sufficient variance in responses while maintaining ease of understanding for respondents [44]. Prior to the main survey, the questionnaire underwent pilot testing with experts in the field to ensure clarity, relevance, and appropriate translation into the Thai language [74].

3.3. Procedure

The research employed a descriptive correlational design to examine EV adoption intentions across urban and rural areas. Data collection was strategically conducted at locations where potential EV adopters were likely to be encountered, specifically at gas stations and shopping malls equipped with EV charging stations. This approach ensured access to respondents who had some awareness of EV infrastructure and potential exposure to EV technology [11].

The sampling locations were selected based on the distribution of charging stations across Thailand's regions. As shown in our sampling frame, the study covered 14 provinces across different regions: Northern (Lampang, Chiang Mai), Central (Bangkok, Pathum Thani), Eastern (Chonburi, Ratchaburi, Chachoengsao), North-eastern (Ubon Ratchatani, Khon Kaen, Nakhon Ratchasima), and Southern (Phuket, Nakhon Si Thammarat) regions. Bangkok and its vicinity represented the highest proportion (28.91% from Bangkok alone) due to its concentrated charging infrastructure and population density [22]. It is important to acknowledge that the sampling approach based on charging station distribution presented potential limitations regarding geographical representation. Regions with fewer charging stations might be underrepresented in the sample, potentially introducing a bias toward areas with more developed EV infrastructure. To mitigate this limitation, additional sampling points were established in rural areas with limited charging infrastructure to ensure adequate representation of these populations.

The study employed quota sampling within each region to maintain proportional representation of urban and rural populations based on Thailand's demographic distribution. Furthermore, the demographic analysis revealed that the final sample achieved reasonable alignment with the national population distribution across regions, with slight adjustments made during data analysis through statistical weighting to account for minor discrepancies. This approach, while not eliminating all potential geographical bias, provided a pragmatic balance between accessing potential EV adopters and ensuring adequate representation of diverse geographical contexts. Similar geographical sampling challenges were noted by Peng et al. [9] in their comparative study of EV market share across different regions, highlighting the common methodological considerations in geographic analyses of EV adoption.

From an initial collection of 4,003 responses, the data underwent rigorous cleaning and validation processes. Responses were screened for completeness, engagement (through attention check questions), and outliers using Mahalanobis distance criterion. After data cleaning, 3,595 valid responses were retained (2,311 from urban areas and 1,284 from rural areas). As shown in Table 2, the demographic profile reveals notable differences between urban and rural respondents. Urban areas showed a higher proportion of males (63.9% versus 59.0% in rural areas), higher education levels (16.0% with Master's degrees compared to 8.9% in rural areas), and different vehicle type preferences (11.8% pickup trucks in urban areas versus 22.3% in rural areas). These demographic variations reflect the distinct characteristics and needs of urban and rural populations, particularly in terms of vehicle usage patterns and preferences.

Table 2. Demographic data

Characteristics	Category	Urban area (*n* = 2,311)		Rural area (*n* = 1,284)	
		Frequency	Frequency	Percentage	Percentage
Gender	Male	1363	821	63.9%	59.0%
	Female	948	463	36.1%	41.0%
Age	<25 years old	166	166	12.9%	7.2%
	25–34 years old	726	487	37.9%	31.4%
	35–44 years old	604	252	19.6%	26.1%
	45–54 years old	674	337	26.3%	29.2%
	Over 55 years old	141	42	3.3%	6.1%
Education	Elementary school	37	21	1.6%	1.6%
	Middle school (MS)	122	104	8.1%	5.3%
	High School/Vocational education	319	248	19.3%	13.8%
	High Vocational education	688	255	19.9%	29.8%
	Bachelor's Degree	930	444	34.6%	40.2%
	Master's Degree	205	205	16.0%	8.9%
	Doctoral Degree	10	7	0.5%	0.4%
Occupation	Government Employee	466	132	10.3%	20.2%
	Private Employee	787	285	22.2%	34.1%
	Business Owners	645	451	35.1%	27.9%
	Agriculturist	81	158	12.3%	3.5%
	Student	93	79	6.1%	4.0%
	General Employee	220	169	13.2%	9.5%
	Other	19	10	0.8%	0.8%
You are always driver?	No	391	427	33.3%	16.9%
	Yes	1920	857	66.7%	83.1%
Vehicle Type	Pick-up truck	273	286	22.3%	11.8%
	Private Car	1362	613	47.7%	58.9%
	Sport Utility Vehicle (SUV)	519	246	19.2%	22.5%
	Personal Purpose Vehicle (PPV)	116	84	6.5%	5.0%
	Multi-Purpose Vehicle (MPV)	41	55	4.3%	1.8%

Note: (N = 3,595).

3.4. Data Analysis

The analysis of EV adoption patterns between urban and rural areas followed a systematic four-step approach, as illustrated in Figure 2. The procedure began with data preparation and screening, followed by exploratory factor analysis (EFA) on the total sample to identify the underlying factor structure. The analysis then proceeded with confirmatory factor analysis (CFA) and structural equation modelling (SEM) conducted separately for urban and rural samples to examine group-specific patterns. Finally, measurement invariance testing was performed to validate cross-group comparisons. This sequential analytical approach ensured rigorous examination of the measurement model before proceeding to structural analysis, thereby establishing a reliable foundation for comparing EV adoption patterns between urban and rural population.

Exploratory Factor Analysis (EFA) serves as an essential preliminary step in scale development and validation, identifying the underlying factor structure of measured variables and examining their relationships. This method helps researchers understand how different items relate to their hypothesized constructs and verify the dimensionality of theoretical concepts. In this study, EFA was performed on the total sample (N = 3,595) using Principal Component Analysis with Varimax rotation. Prior to factor extraction, data suitability was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (threshold > 0.5) and Bartlett's test of sphericity ($p < 0.05$). The factor extraction process followed established criteria: factor loadings greater than 0.5, eigenvalues exceeding 1.0, and no significant cross-loadings (< 0.4) across factors. Items were allocated to factors based on their highest loading value, with a minimum explained variance threshold of 60% for the extracted factors. This exploratory phase served to validate the measurement instrument's factorial structure and confirm the distinctiveness of constructs such as environmental identity, personal innovativeness, and other theoretical components in the integrated model [30].

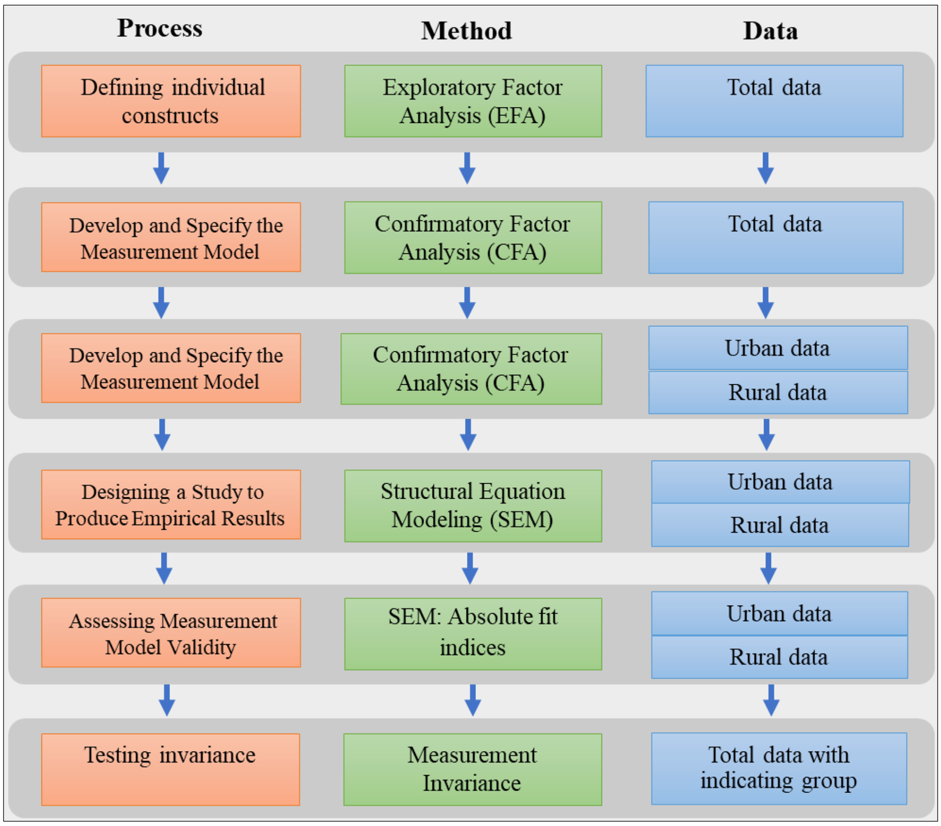

Figure 2. Data analysis procedures

Confirmatory Factor Analysis (CFA) represents a theory-driven confirmatory technique that examines whether the measured variables reliably reflect the hypothesized latent constructs. Unlike EFA, CFA tests a priori hypotheses about relations between observed variables and their underlying latent constructs, providing a more stringent evaluation of construct validity. In this study, CFA was conducted separately for urban (n = 2,311) and rural (n = 1,284) samples to validate the measurement model structure. Each target construct's convergent validity was assessed through examination of standardized factor loadings (λ) exceeding 0.7, Average Variance Extracted (AVE) greater than 0.5, and Composite Reliability (CR) exceeding 0.7. Discriminant validity was evaluated by comparing the square root of AVE with inter-construct correlations. The model's overall fit was assessed using multiple indices: chi-square per degree of freedom (χ^2/df < 5.0), Comparative Fit Index (CFI > 0.95), Tucker-Lewis Index (TLI > 0.95), Root Mean Square Error of Approximation (RMSEA < 0.08), and Standardized Root Mean Square Residual (SRMR < 0.08). These indices provided complementary information about model fit, with CFI and TLI indicating comparative fit, RMSEA assessing parsimony-adjusted fit, and SRMR showing absolute fit. Modification indices were consulted to identify potential model improvements while maintaining theoretical consistency [75].

Structural Equation Modelling (SEM) integrates measurement model validation with structural relationship testing. In this study, SEM was applied separately to urban (n = 2,311) and rural (n = 1,284) samples using Maximum Likelihood estimation. The measurement model represents the relationship between observed variables and latent constructs:

$$y = \Lambda\eta + \epsilon \tag{1}$$

where y represents the observed variables (questionnaire responses), Λ is the matrix of factor loadings, η represents the latent variables (Environmental Identity, Personal Innovativeness, etc.), and ϵ represents measurement errors. For example, the measurement model for Behavioral Intention (BI) can be expressed as:

$$BI_{observed} = \lambda_1\, BI_{observed} + \epsilon_{BI} \tag{2}$$

The structural model, examining relationships between latent constructs, is represented by:

$$\eta = B\eta + \Gamma\xi + \zeta \tag{3}$$

where B represents the matrix of path coefficients (*β)* between endogenous variables, *Γ* represents coefficients between exogenous and endogenous variables, *ξ* represents exogenous variables, and *ζ* represents structural errors. For instance, the relationship between Perceived Usefulness (PU) and Behavioral Intention (BI) (H13) is expressed as:

$$BI = \beta_{PU} \times PU + \zeta_{BI} \tag{4}$$

Model estimation involved: (1) parameter estimation using maximum likelihood, (2) assessment of critical ratios ($t > 1.96$, $p < 0.05$), (3) examination of standardized residuals (threshold < |2.58|), and (4) evaluation of modification indices. Model fit was assessed using χ^2/df, CFI, TLI, RMSEA, and SRMR indices.

Measurement invariance testing assesses whether the EV adoption measurement model maintains consistent meaning across urban and rural populations. In this study, two levels of measurement invariance were examined:

- Simultaneous Model Testing (Model 3): This baseline model tests whether the factor structure of EV adoption constructs (Environmental Identity, Personal Innovativeness, Social Network Influence, etc.) is conceptualized similarly across urban and rural groups. The model allows all parameters to be freely estimated across groups, establishing the basic requirement that both populations understand the EV adoption constructs in the same way.
- Parameter Equality Testing (Model 4): This constrained model examines whether factor loadings, intercepts, and structural paths remain equivalent across urban and rural populations. This level tests whether: The relationship between observed items and their constructs (λ) is similar. The baseline levels of EV adoption constructs are comparable and the structural relationships (β) between EV adoption factors operate similarly [34].

The comparison between these models tests the hypothesis: H0: The measurement and structural parameters are equivalent across urban and rural populations H1: The measurement and structural parameters differ between urban and rural populations

The hypothesis is tested using the chi-square difference test ($\Delta\chi^2$), where a significant difference indicates that urban and rural populations conceptualize or respond to EV adoption factors differently. Model fit is assessed using established criteria: χ^2/df, CFI, TLI, RMSEA, and SRMR [34].

4. Results

The descriptive statistics for all measurement items are presented in Table A1 (Appendix), providing mean values (M), standard deviations (SD), skewness (SK), and kurtosis (KU) for both urban (n = 2,311) and rural (n = 1,284) samples. Item analysis revealed distinct patterns between urban and rural respondents across all constructs. For the urban sample, mean scores ranged from 4.289 to 5.045 (on a 7-point scale), with standard deviations between 1.371 and 2.027. Skewness values ranged from -0.740 to -0.416, and kurtosis values from -0.977 to 0.471, indicating approximately normal distributions. The rural sample demonstrated consistently higher mean scores, ranging from 5.027 to 5.454, with standard deviations between 1.278 and 1.619. Skewness values (-1.257 to -0.833) and kurtosis values (0.118 to 1.575) for the rural sample also indicated acceptable normality. Reliability analysis using Cronbach's alpha showed strong internal consistency across all constructs, with values ranging from 0.880 to 0.950. Environmental Identity demonstrated high reliability (α = 0.925), followed by Perceived Usefulness (α = 0.946), Perceived Ease of Use (α = 0.936), and Behavioral Intention to Use (α = 0.950). These reliability coefficients exceed the recommended threshold of 0.7, indicating strong measurement consistency.

The measurement model was evaluated using Confirmatory Factor Analysis (CFA) for both urban and rural samples, with results presented in Table 3. For the urban sample (n = 2,311), standardized factor loadings (λ) ranged from 0.761 to 0.957, exceeding the threshold of 0.7. The squared multiple correlations (R^2) ranged from 0.579 to 0.916, indicating substantial explained variance in the observed variables. The Average Variance Extracted (AVE) values ranged from 0.549 to 0.829, surpassing the 0.5 threshold, while Composite Reliability (CR) values ranged from 0.785 to 0.936, exceeding the 0.7 benchmark. For the rural sample (n = 1,284), standardized factor loadings (λ) ranged from 0.728 to 0.932, with R^2 values between 0.530 and 0.869. The AVE values ranged from 0.585 to 0.899, and CR values from 0.809 to 0.964. All t-values were significant at $p < 0.001$ for both samples, indicating strong statistical significance of the parameter estimates. The measurement model demonstrated good fit indices for both urban (χ^2/df = 4.756, CFI = 0.987, TLI = 0.982, SRMR = 0.029, RMSEA = 0.040) and rural (χ^2/df = 3.042, CFI = 0.984, TLI = 0.978, SRMR = 0.041, RMSEA = 0.040) samples.

The measurement invariance testing results are presented in Table 4, demonstrating the comparison between urban and rural models through a two-step analysis. The simultaneous model (Model 3) established the baseline fit with $\chi^2 = 2530.235$ ($df = 638$), yielding satisfactory fit indices (CFI = 0.985, TLI = 0.980, SRMR = 0.035, RMSEA = 0.041 [90% CI = 0.039-0.042]). The constrained model (Model 4), with factor loadings, intercepts, and structural paths held equal across groups, produced $\chi^2 = 2940.291$ (df = 688), maintaining acceptable fit indices (CFI = 0.983, TLI = 0.978, SRMR = 0.061, RMSEA = 0.043 [90% CI = 0.041-0.044]). The chi-square difference test between Models 3 and 4 yielded $\Delta\chi^2 = 410.056$ ($\Delta df = 50$) with $p < 0.001$, indicating significant differences in measurement and structural parameters between urban and rural groups. This significant difference supports separate analysis of the structural relationships for urban and rural samples, suggesting that the EV adoption process operates differently across these populations.

Table 3. Parameters estimation of measurement model

Constructs and indicators	Urban area (n = 2,311)			Rural area (n = 1,284)		
	λ	***t*-value**	R^2	**λ**	***t*-value**	R^2
Environmental identity	**(AVE = 0.753, CR = 0.901)**			**(AVE = 0.805, CR = 0.925)**		
ENV1	0.881	135.727**	0.776	0.862	81.809**	0.744
ENV2	0.911	168.290**	0.830	0.883	91.783**	0.779
ENV3	0.900	167.510**	0.811	0.858	89.595**	0.737
Personal innovativeness	**(AVE = 0.591, CR = 0.812)**			**(AVE = 0.661, CR = 0.854)**		
PIN1	0.844	93.949**	0.712	0.790	56.892**	0.624
PIN2	0.805	84.712**	0.647	0.771	53.171**	0.595
PIN3	0.789	79.593**	0.623	0.744	48.822**	0.553
Social network influence	**(AVE = 0.713, CR = 0.882)**			**(AVE = 0.779, CR = 0.913)**		
SOC1	0.893	156.428**	0.797	0.857	82.295**	0.734
SOC2	0.865	119.680**	0.748	0.841	68.871**	0.707
SOC3	0.889	155.193**	0.790	0.835	76.073**	0.697
Trialability	**(AVE = 0.693, CR = 0.872)**			**(AVE = 0.686, CR = 0.867)**		
TRI1	0.814	53.008**	0.662	0.821	38.936**	0.674
TRI2	0.832	54.023**	0.692	0.831	39.436**	0.691
TRI3	0.838	52.218**	0.702	0.846	39.740**	0.715
Subjective norm	**(AVE = 0.657, CR = 0.851)**			**(AVE = 0.769, CR = 0.909)**		
SUN1	0.893	59.374**	0.797	0.848	33.891**	0.720
SUN2	0.828	53.180**	0.685	0.733	28.659**	0.537
SUN3	0.907	60.686**	0.823	0.845	33.082**	0.713
Perceived behavioral control	**(AVE = 0.549, CR = 0.785)**			**(AVE = 0.585, CR = 0.809)**		
PBC1	0.765	39.510**	0.585	0.745	23.917**	0.555
PBC2	0.768	39.882**	0.590	0.749	24.364**	0.562
PBC3	0.761	39.270**	0.579	0.728	23.983**	0.530
Perceived ease of use	**(AVE = 0.781, CR = 0.915)**			**(AVE = 0.851, CR = 0.945)**		
PEU1	0.925	253.031**	0.856	0.886	118.304**	0.784
PEU2	0.911	219.906**	0.830	0.884	120.104**	0.782
PEU3	0.932	270.960**	0.869	0.882	118.338**	0.778
Perceived usefulness	**(AVE = 0.829, CR = 0.936)**			**(AVE = 0.899, CR = 0.964)**		
PUF1	0.945	208.000**	0.893	0.897	95.268**	0.805
PUF2	0.951	322.304**	0.904	0.922	154.680**	0.851
PUF3	0.948	311.128**	0.898	0.913	143.675**	0.833
Attitude toward electric vehicles	**(AVE = 0.718, CR = 0.884)**			**(AVE = 0.755, CR = 0.902)**		
ATT1	0.834	117.388**	0.695	0.818	87.499**	0.670
ATT2	0.889	151.914**	0.790	0.868	91.413**	0.753
ATT3	0.882	147.475**	0.777	0.856	86.231**	0.733
Behavioral intention to use	**(AVE = 0.802, CR = 0.924)**			**(AVE = 0.877, CR = 0.955)**		
BIU1	0.907	211.005**	0.823	0.848	100.479**	0.719
BIU2	0.945	243.425**	0.893	0.905	105.071**	0.820
BIU3	0.957	303.494**	0.916	0.932	136.269**	0.869

Note: ** Significant at α = 0.001. λ Denotes Standardized Estimates.

Table 4. Model fit indices for invariance test

Description	χ^2	*df*	χ^2/df	CFI	TLI	SRMR	RMSEA (90% CI)	$\Delta\chi^2$	Δdf	*p-value*
Individual Groups:										
Model 1: Urban area	1493.393	314	4.756	0.987	0.982	0.029	0.040 (0.038-0.042)			
Model 2: Rural area	967.369	318	3.042	0.984	0.978	0.041	0.040 (0.037-0.043)			
Measurement of Invariance:										
Model 3: Simultaneous model	2530.235	638	3.966	0.985	0.980	0.035	0.041 (0.039-0.042)			
Model 4: Factor loading, intercepts, structural paths held equal across groups	2940.291	688	4.274	0.983	0.978	0.061	0.043 (0.041-0.044)	410.06	50	<0.01

The results of hypotheses testing through Structural Equation Modelling are presented in Table 5 and illustrated in Figures 3 and 4. All hypothesized relationships demonstrated statistical significance at $p < 0.001$ across both urban and rural models. In the urban model (n = 2,311), the structural relationships demonstrated good model fit (χ^2 = 1493.393, df = 314, χ^2/df = 4.756, CFI = 0.987, TLI = 0.982, SRMR = 0.029, RMSEA = 0.040). The strongest path coefficient was observed for the relationship between Perceived Ease of Use and Perceived Usefulness (β = 0.631, t = 62.910), followed by Perceived Usefulness to Behavioral Intention to Use (β = 0.445, t = 16.133). Environmental Identity to Attitude toward Electric Vehicles showed a moderate effect (β = 0.279, t = 10.856). The rural model (n = 1,284) also demonstrated satisfactory fit indices (χ^2 = 967.369, df = 318, χ^2/df = 3.042, CFI = 0.984, TLI = 0.978, SRMR = 0.041, RMSEA = 0.040). The strongest relationship was found between Perceived Ease of Use and Perceived Usefulness (β = 0.587, t = 35.528), followed by Perceived Usefulness to Behavioral Intention to Use (β = 0.353, t = 23.494). Environmental Identity to Perceived Ease of Use showed a notable effect (β = 0.350, t = 9.322). All sixteen hypotheses (H1-H16) were supported in both models, with varying magnitudes of path coefficients between urban and rural samples.

Table 5. Results of hypotheses testing (SEM)

Hypothesis path	Urban area			Rural area		
	β	***t*-value**	**Result**	***β***	***t*-value**	**Result**
H1: Environmental identity → Perceived usefulness	0.156	49.642**	Accepted	0.172	32.233**	Accepted
H2: Environmental identity → Attitude toward electric vehicles	0.279	10.856**	Accepted	0.108	5.505**	Accepted
H3: Environmental identity → Perceived ease of use	0.291	10.787**	Accepted	0.350	9.322**	Accepted
H4: Personal innovativeness → Perceived usefulness	0.153	44.892**	Accepted	0.175	28.710**	Accepted
H5: Personal innovativeness → Attitude toward electric vehicles	0.157	3.815**	Accepted	0.216	32.047**	Accepted
H6: Social network influence → Attitude toward electric vehicles	0.164	5.042**	Accepted	0.218	35.708**	Accepted
H7: Social network influence → Perceived ease of use	0.300	11.112**	Accepted	0.208	5.412**	Accepted
H8: Trialability → Perceived ease of use	0.222	36.264**	Accepted	0.256	26.370**	Accepted
H9: Perceived ease of use → Perceived usefulness	0.631	62.910**	Accepted	0.587	35.528**	Accepted
H10: Perceived ease of use → Attitude toward electric vehicles	0.263	50.329**	Accepted	0.244	39.718**	Accepted
H11: Perceived ease of use → Behavioral intention to use	0.135	4.808**	Accepted	0.172	38.269**	Accepted
H12: Perceived usefulness → Attitude toward electric vehicles	0.174	9.840**	Accepted	0.248	39.201**	Accepted
H13: Perceived usefulness → Behavioral intention to use	0.445	16.133**	Accepted	0.353	23.494**	Accepted
H14: Subjective norm → Behavioral intention to use	0.161	42.153**	Accepted	0.157	24.971**	Accepted
H15: Perceived behavioral control → Behavioral intention to use	0.118	32.071**	Accepted	0.131	20.076**	Accepted
H16: Attitude toward electric → Behavioral intention to use	0.121	50.960**	Accepted	0.141	38.901**	Accepted

*Note: → regression on, ** significant at α = 0.001. **β** denotes Standardized estimates.*

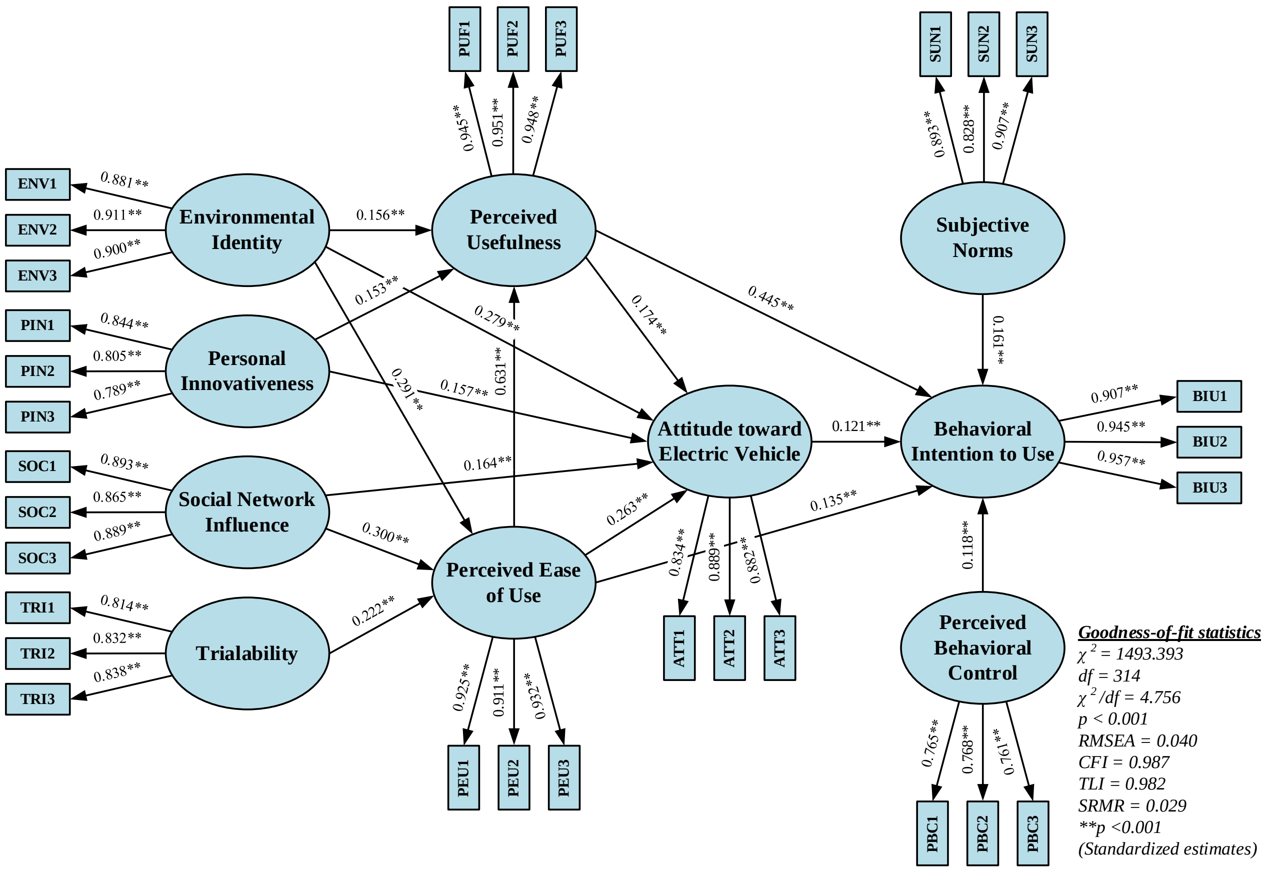

Figure 3. Structural equation modelling for electric vehicles adoption intention in urban areas

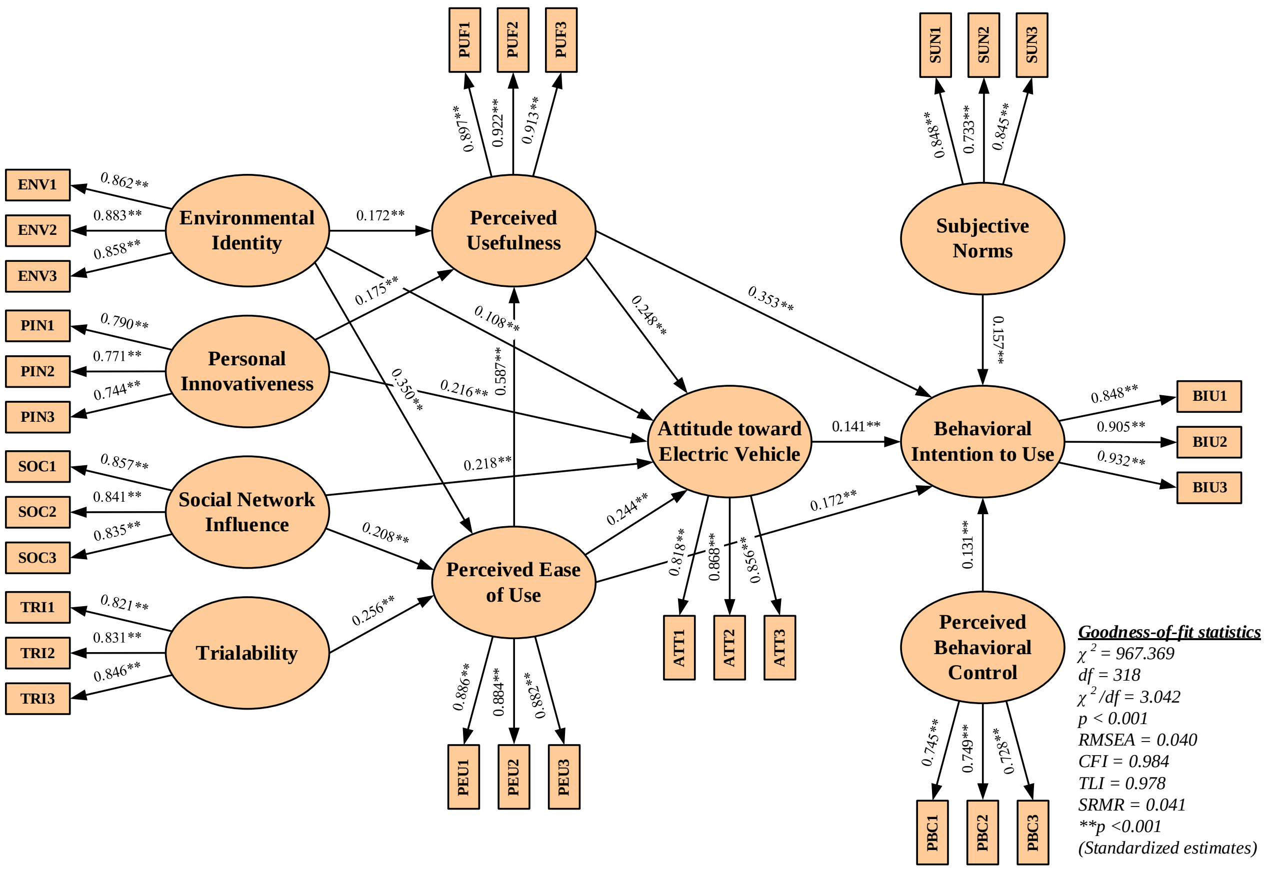

Figure 4. Structural equation modelling for electric vehicles adoption intention in rural areas

To further illustrate the differences in relationship strengths between urban and rural models, Figure 5 presents a comparative visualization of standardized path coefficients (β) across all hypotheses. The chart clearly demonstrates the distinct patterns in EV adoption mechanisms between geographical contexts. Notably, urban areas (orange bars) show substantially stronger effects in system-related relationships, particularly in H9 (Perceived ease of use → Perceived usefulness, β = 0.631) and H13 (Perceived usefulness → Behavioral intention to use, β = 0.445). In contrast, rural areas (purple bars) demonstrate stronger effects in relationships involving individual characteristics, such as H3 (Environmental identity → Perceived ease of use, β = 0.350) and H5 (Personal innovativeness → Attitude toward electric vehicles, β = 0.216).

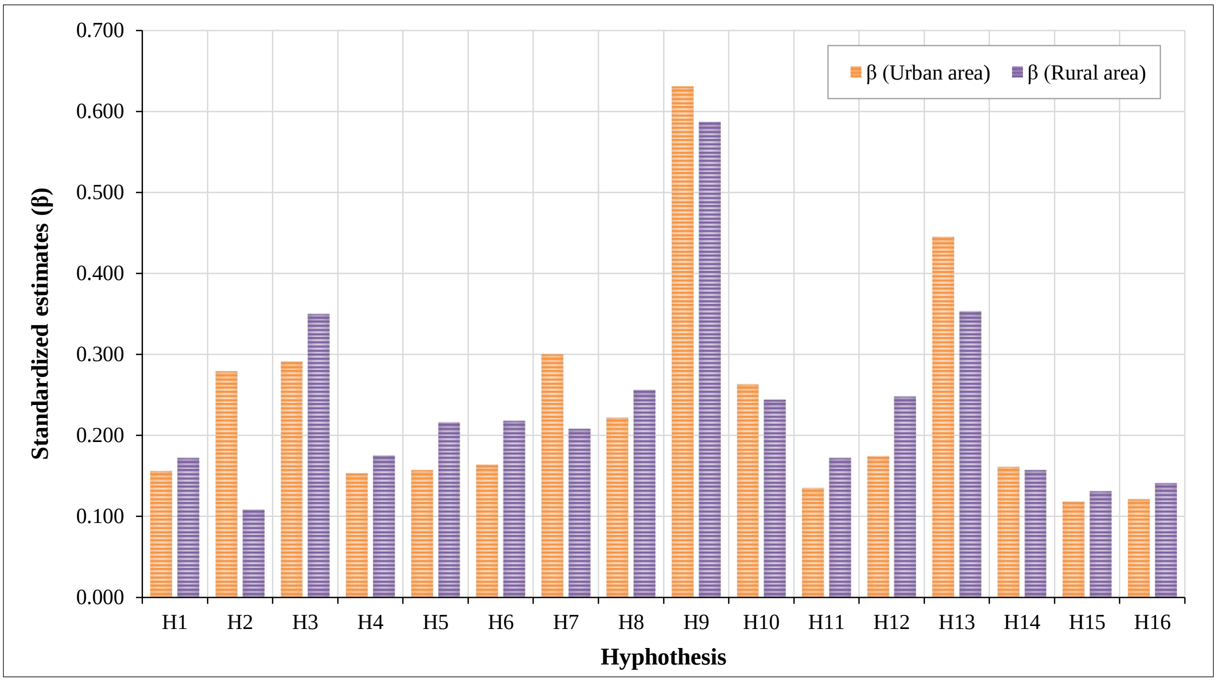

Figure 5. Comparison of standardized path coefficients (β) between urban and rural areas

5. Discussion

5.1. Overall Comparison of Urban and Rural Models

Analysis of the structural equation modelling results reveals distinct patterns in the strength of relationships between urban and rural contexts, providing comprehensive insights into how EV adoption mechanisms differ across geographical settings. The findings demonstrate that the pathways to EV adoption vary significantly between urban and rural populations, with different factors showing stronger influences in each context.

In rural areas, relationships involving individual characteristics and attitudes demonstrated notably stronger effects. Personal innovativeness exhibited more substantial influence on both attitude toward electric vehicles (β = 0.216 vs. 0.157) and perceived usefulness (β = 0.175 vs. 0.153). Similarly, environmental identity showed stronger effects on technical perceptions, particularly in its relationship with perceived ease of use (β = 0.350 vs. 0.291) and perceived usefulness (β = 0.172 vs. 0.156). These stronger effects suggest that rural EV adoption relies more heavily on individual characteristics and personal predispositions, possibly compensating for limited infrastructure and exposure to EVs [49].

Conversely, urban areas demonstrated stronger effects in relationships involving system interaction and utility. The core TAM relationships showed particularly robust effects in urban settings, with perceived ease of use more strongly influencing perceived usefulness (β = 0.631 vs. 0.587), and perceived usefulness having a greater impact on behavioral intention to use (β = 0.445 vs. 0.353). Environmental identity also showed a stronger influence on attitude toward electric vehicles in urban areas (β = 0.279 vs. 0.108), as did social network influence on perceived ease of use (β = 0.300 vs. 0.208). These patterns suggest that urban adoption is more driven by system-related perceptions and utility considerations, likely due to better infrastructure support and greater EV exposure [44].

5.2. Discussing Hypothesizes

H1, which proposed that environmental identity positively affects perceived usefulness of EVs, was supported in both urban (β = 0.156) and rural (β = 0.172) contexts, with rural areas showing a marginally stronger relationship. This finding reveals three key insights about the role of environmental identity in shaping perceptions of EV utility. The stronger effect in rural areas (β = 0.172) suggests that rural residents' environmental consciousness more powerfully influences their perception of EVs' practical benefits. This could be attributed to several factors. First, rural residents typically have more direct exposure to environmental changes through their closer connection to agricultural activities and natural landscapes, making them more sensitive to environmental benefits [76]. Second, rural areas often experience more visible effects of vehicle emissions due to less atmospheric dispersion compared to urban areas with higher buildings and better ventilation, potentially making environmental benefits more tangible [77]. Third, the longer average travel distances in rural areas might make rural residents more conscious of their vehicles' environmental impact, leading them to associate environmental identity more strongly with vehicle utility Jiang et al. [20]. The urban sample's slightly lower coefficient (β = 0.156) might reflect the more complex decision-making environment in cities. Urban residents, while environmentally conscious, might balance environmental benefits against other practical considerations such as parking availability and charging infrastructure [9]. This finding aligns with Li et al. [47], who found that while pro-environmental motives are frequently claimed, they operate alongside other practical considerations in urban settings.

H2, positing that environmental identity positively affects attitude toward EVs, revealed a notable contrast between urban (β = 0.279) and rural (β = 0.108) populations, with urban areas demonstrating a substantially stronger relationship. This disparity in effect sizes provides several meaningful insights into how environmental identity shapes attitudes toward EVs across different geographical contexts. The stronger effect in urban areas (β = 0.279) can be attributed to multiple factors. First, urban residents typically have greater exposure to environmental education and sustainability campaigns, which may strengthen the connection between their environmental identity and attitudes toward eco-friendly technologies [36]. Second, urban areas often experience more visible air pollution and traffic congestion, making the environmental benefits of EVs more immediately apparent and personally relevant [43, 78]. Third, the presence of more EVs in urban areas provides greater opportunities for positive attitude formation through observation and peer influence [51], who found that adoption pioneers in urban areas maintain more stable, positive attitudes toward EVs. The weaker relationship in rural areas (β = 0.108) might be explained by several contextual factors. First, rural residents may prioritize practical utility over environmental considerations due to their unique transportation needs, such as longer travel distances and the need for vehicles with higher carrying capacity [49]. Second, the limited visibility of EVs in rural areas might weaken the connection between environmental identity and attitudes toward EVs [79]. Third, the current lack of electric pickup trucks, which are popular in rural areas (22.3% of rural respondents use pickup trucks, see Table 2) [80], might create a disconnect between environmental identity and EV attitudes due to perceived incompatibility with rural lifestyle needs.

H3, which hypothesized that environmental identity positively affects perceived ease of use of EVs, showed significant effects in both contexts but with stronger influence in rural areas (β = 0.350) compared to urban areas (β = 0.291). This difference in effect sizes reveals important insights about how environmental identity influences perceptions of EV usability across different geographical settings. The stronger effect in rural areas (β = 0.350) can be explained by several mechanisms. First, individuals with strong environmental identity in rural areas might be more motivated to overcome perceived usage barriers, viewing potential difficulties as challenges worth addressing for environmental benefits [81]. Second, rural residents typically have more experience adapting to technological limitations due to infrastructure constraints, possibly making them more resilient in facing new technology adoption challenges [16]. Third, the higher dependence on personal vehicles in rural areas might motivate environmentally conscious individuals to invest more effort in understanding and mastering EV operation, despite potential infrastructure limitations [40]. The relatively lower but still substantial effect in urban areas (β = 0.291) might reflect different underlying dynamics. First, urban residents' environmental identity might have less influence on perceived ease of use because they have more external support systems and infrastructure, making ease of use less dependent on personal environmental commitment [44]. Second, the more complex urban driving environment might introduce additional considerations beyond environmental concerns, such as parking constraints and traffic congestion, which could moderate the relationship between environmental identity and perceived ease of use [82]. Third, the greater availability of alternative transportation options in urban areas might reduce the pressure to master EV usage, even among environmentally conscious individuals [20].

H4, which proposed that personal innovativeness positively affects perceived usefulness of EVs, was supported with similar magnitude effects in both urban (β = 0.153) and rural (β = 0.175) contexts, with rural areas showing a marginally stronger relationship. This finding reveals several important insights about how innovation orientation influences perceptions of EV utility across different geographical settings. The stronger effect in rural areas (β = 0.175) can be attributed to multiple mechanisms. First, innovative rural residents might be more proactive in seeking and processing information about EV benefits, compensating for the limited direct exposure to EVs in their environment [39]. Second, their innovative predisposition might enable better appreciation of EVs' advanced technological features, such as regenerative braking and smart charging capabilities, even without extensive first-hand experience [83, 84]. Third, innovative individuals in rural areas might be better at recognizing the long-term cost benefits of EVs, particularly given the typically longer travel distances in rural settings that could maximize fuel cost savings [44]. The slightly lower but significant effect in urban areas (β = 0.153) reflects different underlying dynamics. First, the greater availability of EV information and exposure in urban environments might reduce the relative importance of personal innovativeness in recognizing EV benefits [51]. Second, urban residents might rely more on observable evidence and peer experiences rather than their innovative predisposition when evaluating EV usefulness [85]. Third, the complex urban transportation environment might introduce additional considerations beyond technological innovation, such as parking availability and charging infrastructure, moderating the relationship between personal innovativeness and perceived usefulness [20].

H5, suggesting that personal innovativeness positively affects attitude toward EVs, revealed a notably stronger relationship in rural areas (β = 0.216) compared to urban areas (β = 0.157). This differential impact provides important insights into how innovation orientation shapes attitudes toward EVs across different geographical contexts. The stronger effect in rural areas (β = 0.216) can be explained through several mechanisms. First, in areas with limited EV presence, innovative individuals might form positive attitudes through their greater willingness to embrace novel technologies despite uncertainty [47]. Second, innovative rural residents might be more likely to challenge traditional vehicle preferences, particularly given that 22.3% of rural respondents use pickup trucks while EV alternatives are not yet available in this segment [86]. Third, the scarcity of EVs in rural areas might make personal innovativeness more crucial in attitude formation, as innovative individuals tend to form positive attitudes toward new technologies even with limited social validation [32]. Fourth, innovative rural residents might view the current limitations of EV infrastructure as temporary barriers rather than permanent obstacles, leading to more positive attitudes despite practical challenges. The moderate effect in urban areas (β = 0.157) reflects a different attitudinal formation process. First, the greater visibility of EVs in urban environments might reduce the role of personal innovativeness in attitude formation, as attitudes can be shaped more by direct observation and peer experiences 51]. Second, urban residents might form attitudes based on a broader range of factors beyond innovation, such as environmental concerns and practical considerations like parking availability [87]. Third, the higher availability of information and exposure to EVs in urban areas might make personal innovativeness less critical in overcoming uncertainty and forming positive attitudes [88].

H6, proposing that social network influence positively affects attitude toward EVs, demonstrated significant effects with notably different magnitudes between rural (β = 0.218) and urban (β = 0.164) populations. This variation in effect sizes reveals important insights about how social dynamics influence EV attitudes across different geographical contexts. The stronger effect in rural areas (β = 0.218) can be explained through several mechanisms. First, rural communities typically maintain stronger and more tight-knit social networks, making social influence more potent in shaping attitudes toward new technologies [42]. Second, the limited direct exposure to EVs in rural areas might increase reliance on social networks for information and opinion formation, making word-of-mouth and shared experiences particularly influential [89]. Third, rural residents might place greater trust in local social networks due to shared understanding of specific rural transportation needs and challenges [90]. Fourth, the higher perceived risk of EV adoption in areas with limited infrastructure might increase the importance of social validation in attitude formation, as residents look to their social networks for reassurance and practical advice [91]. The moderate effect in urban areas (β = 0.164) reflects different social dynamics. First, urban residents typically have access to more diverse information sources about EVs, potentially reducing their reliance on social networks for attitude formation [92]. Second, the greater visibility of EVs in urban environments might allow for more independent attitude formation based on direct observation rather than social influence [93]. Third, urban social networks tend to be more diffuse and heterogeneous, possibly diluting the impact of social influence on EV attitudes [74]. Fourth, the higher availability of charging infrastructure and support services in urban areas might reduce the need for social network validation in forming attitudes toward EVs. These findings extend previous research by Higueras-Castillo et al. [36], who identified the importance of social influence in EV adoption decisions.

H7, hypothesizing that social network influence positively affects perceived ease of use of EVs, revealed a stronger effect in urban areas (β = 0.300) compared to rural areas (β = 0.208). This notable difference in effect sizes provides important insights into how social networks influence perceptions of EV usability across different geographical settings. The stronger effect in urban areas (β = 0.300) can be attributed to several mechanisms. First, urban social networks are more likely to include existing EV users, providing direct, experiential knowledge about vehicle operation and charging processes [94]. Second, the higher density of urban populations creates more opportunities for peer learning and knowledge sharing about EV usage, particularly regarding charging locations and optimal driving practices [95]. Third, urban social networks might include more technologically savvy individuals who can offer practical advice about EV operation and troubleshooting [96]. Fourth, the presence of EV dealerships and service centres in urban areas might facilitate the spread of technical knowledge through social networks, enhancing perceived ease of use through shared experiences and solutions [78]. The moderate effect in rural areas (β = 0.208) reflects different social network dynamics. First, rural social networks might have fewer EV users, limiting the transfer of first-hand operational knowledge [48]. Second, the geographical dispersion of rural populations might reduce opportunities for regular interaction and knowledge sharing about EV usage [97]. Third, rural social networks might focus more on concerns about charging infrastructure limitations rather than actual usage experiences, potentially moderating their influence on perceived ease of use [40]. Fourth, the limited availability of EV service centres in rural areas might restrict the technical knowledge circulating within social networks, affecting perceptions of usage difficulty.

H8, proposing that trialability positively affects perceived ease of use of EVs, demonstrated significant effects with different magnitudes between rural (β = 0.256) and urban (β = 0.222) populations. This variation in effect sizes provides crucial insights into how hands-on experience influences perceptions of EV usability across different geographical contexts. The stronger effect in rural areas (β = 0.256) can be explained through several mechanisms. First, given the limited exposure to EVs in rural areas, direct trial experiences might have a more profound impact on reducing uncertainty about EV operation and charging processes [98, 99]. Second, rural residents might value hands-on experience more heavily due to their practical orientation and the need to verify vehicle capability for longer travel distances [44]. Third, trial experiences might be particularly influential in rural areas where charging infrastructure is limited, as it allows potential adopters to understand how to manage range anxiety and plan charging stops effectively [40]. Fourth, the higher proportion of pickup truck users in rural areas (22.3% versus 11.8% in urban areas) might make trialability especially important for understanding how EVs can meet their specific usage requirements [100]. The moderate effect in urban areas ($\beta = 0.222$) reflects different contextual factors. First, urban residents might have more diverse sources of information about EV usage, reducing their reliance on direct trial experiences [13]. Second, the greater visibility of EVs in urban environments might provide vicarious learning opportunities, complementing direct trial experiences [101]. Third, better access to charging infrastructure in urban areas might make EV operation seem less challenging even before trial experiences [33]. Fourth, urban residents might have more opportunities for casual exposure to EVs through car-sharing services or test drives, potentially diminishing the impact of any single trial experience.

H9, hypothesizing that perceived ease of use positively affects perceived usefulness of EVs, revealed the strongest effect among all hypothesized relationships, with notably higher magnitude in urban areas ($\beta = 0.631$) compared to rural areas ($\beta = 0.587$). This substantial difference in effect sizes provides critical insights into how perceptions of usability influence the recognition of EV benefits across different geographical contexts. The stronger effect in urban areas ($\beta = 0.631$) can be attributed to several mechanisms. First, the comprehensive charging infrastructure in urban areas might strengthen the connection between ease of use and perceived benefits, as users can more readily translate operational convenience into practical utility [26]. Second, urban driving patterns, characterized by shorter trips and frequent stops, might make the relationship between easy operation and perceived benefits more apparent, particularly regarding regenerative braking and energy efficiency [1, 41, 100]. Third, the availability of technical support and service centres in urban areas might enhance users' confidence in operating EVs, leading to better appreciation of their benefits [60]. Fourth, the higher density of charging stations in urban areas might make it easier for users to recognize how operational simplicity translates into practical advantages, particularly in terms of convenience and cost savings [102]. The relatively lower but still substantial effect in rural areas ($\beta = 0.587$) reflects different underlying dynamics. First, the limited charging infrastructure in rural areas might moderate how easily perceived usability translates into recognized benefits, despite users understanding the operation [40]. Second, longer travel distances in rural areas might create additional considerations beyond ease of use, such as range anxiety and charging planning, affecting the perception of practical benefits [27]. Third, the specific vehicle needs of rural residents, such as cargo capacity and all-terrain capability, might introduce additional factors mediating the relationship between ease of use and perceived usefulness [80]. Fourth, the less developed EV ecosystem in rural areas might make it harder for users to fully realize the benefits of EVs even when they find them easy to use.

H10, proposing that perceived ease of use positively affects attitude toward EVs, demonstrated significant effects with slightly different magnitudes between urban ($\beta = 0.263$) and rural ($\beta = 0.244$) populations. This variation in effect sizes reveals important insights about how perceptions of usability shape attitudes toward EVs across different geographical contexts. The stronger effect in urban areas ($\beta = 0.263$) can be explained through several mechanisms. First, the more developed charging infrastructure in urban areas might allow easier operation to more directly translate into positive attitudes, as users face fewer barriers to regular EV use [25]. Second, urban residents' typically shorter travel distances might make operational ease more salient in attitude formation, as they encounter fewer range-related challenges [103, 104]. Third, the availability of technical support services in urban areas might enhance the relationship between perceived ease of use and attitudes by reducing concerns about potential operational difficulties [105]. Fourth, the higher visibility of successful EV usage in urban environments might reinforce the connection between operational simplicity and positive attitudes [27]. The slightly lower effect in rural areas ($\beta = 0.244$) reflects different contextual factors. First, rural residents might weigh other considerations more heavily in attitude formation, such as vehicle capability and range, even when they perceive EVs as easy to use [52]. Second, the limited charging infrastructure in rural areas might moderate how perceived ease of use translates into positive attitudes, as operational simplicity alone may not overcome infrastructure-related concerns [106]. Third, the specific transportation needs of rural residents, such as longer travel distances and varied terrain, might introduce additional factors in attitude formation beyond operational ease [107]. Fourth, the less developed EV ecosystem in rural areas might create a gap between perceived ease of use and overall attitudes, as practical implementation challenges remain despite understanding EV operation. These findings extend previous research by Zhang et al. [26], who found that perceived ease of use significantly influences consumers' purchase intentions.

H11, suggesting that perceived ease of use positively affects behavioral intention to use EVs, revealed a stronger effect in rural areas ($\beta = 0.172$) compared to urban areas ($\beta = 0.135$). This difference in effect sizes provides important insights into how perceptions of usability directly influence adoption intentions across different geographical contexts. The stronger effect in rural areas ($\beta = 0.172$) can be attributed to several mechanisms. First, given the limited charging infrastructure and support services in rural areas, the perception that EVs are easy to use might play a more crucial role in building confidence for adoption [14]. Second, rural residents might place greater emphasis on operational simplicity due to the need for self-reliance in areas with fewer technical support options [79]. Third, the longer travel distances typical in rural areas might make perceived ease of use more critical in adoption decisions, as users need confidence in managing charging and range over extended journeys [63]. The lower effect in urban areas ($\beta = 0.135$) reflects different contextual influences. First, urban residents might have more factors influencing their adoption intentions beyond ease of use, such as environmental concerns and social influence [37]. Second, the better availability of charging infrastructure and technical support in urban areas might reduce the importance of perceived ease of use in adoption decisions [17, 108]. Third, the shorter travel distances and more predictable usage patterns in urban environments might make operational ease less critical in the decision to adopt [109]. Fourth, the greater availability of alternative transportation options in urban areas might reduce the pressure to master EV operation as the sole transportation solution.

H12, proposing that perceived usefulness positively affects attitude toward EVs, demonstrated notably different effects between rural (β = 0.248) and urban (β = 0.174) populations. This variation in effect sizes reveals important insights about how the recognition of EV benefits shapes attitudes across different geographical contexts. The stronger effect in rural areas (β = 0.248) can be explained through several mechanisms. First, rural residents might form stronger attitudes based on perceived usefulness due to their typically higher vehicle dependency and longer travel distances, making practical benefits more salient in attitude formation [100]. Second, the potential for greater fuel cost savings over longer rural travel distances might strengthen the relationship between perceived usefulness and attitudes [110]. Third, rural residents might place greater emphasis on utility aspects when forming attitudes due to their more practical orientation toward vehicle use, particularly given their higher reliance on vehicles for both personal and commercial purposes [49]. The lower effect in urban areas (β = 0.174) reflects different underlying dynamics. First, urban residents might have more diverse factors influencing their attitudes toward EVs, such as environmental concerns and social status, reducing the relative importance of perceived usefulness [26]. Second, the availability of alternative transportation options in urban areas might make practical benefits less central to attitude formation [63]. Third, shorter urban travel distances might make some EV benefits, such as fuel cost savings, less prominent in attitude formation [5]. Fourth, the better developed charging infrastructure in urban areas might shift attitude formation focus from practical utility to other considerations such as environmental impact or technological innovation. These findings extend previous research by Manutworakit & Choocharukul [13], who found that performance expectancy significantly influences purchase intention for EVs in Thailand. The current study demonstrates that this influence operates differently across geographical contexts, with rural areas showing a stronger connection between perceived usefulness and attitudes, possibly due to their greater focus on practical vehicle utility.

H13, suggesting that perceived usefulness positively affects behavioral intention to use EVs, revealed a notably stronger effect in urban areas (β = 0.445) compared to rural areas (β = 0.353). This substantial difference in effect sizes provides crucial insights into how the recognition of EV benefits directly influences adoption intentions across different geographical contexts. The stronger effect in urban areas (β = 0.445) can be attributed to several mechanisms. First, urban residents might more readily translate perceived benefits into adoption intentions due to better supporting infrastructure that makes these benefits immediately realizable [111]. Second, the higher density of charging stations in urban areas might strengthen the relationship between perceived usefulness and adoption intention by reducing range anxiety concerns [112]. Third, urban driving patterns, characterized by frequent short trips and stop-and-go traffic, might make EV benefits such as regenerative braking and lower operating costs more immediately apparent and influential in adoption decisions [74]. Fourth, the presence of more EVs in urban areas might provide greater validation of perceived benefits, strengthening their influence on adoption intentions [5, 113]. The relatively lower effect in rural areas (β = 0.353) reflects different contextual challenges. First, despite recognizing EV benefits, rural residents might face more practical barriers to translating this perception into adoption intentions, such as limited charging infrastructure [114]. Second, the specific vehicle needs in rural areas, particularly the preference for pickup trucks, might moderate how perceived usefulness translates into adoption intentions due to limited EV options [115]. Third, longer travel distances in rural areas might create additional considerations beyond perceived usefulness, such as charging availability and range capability [50]. Fourth, the less developed EV ecosystem in rural areas might create a gap between recognizing benefits and forming adoption intentions due to implementation concerns.

H14, proposing that subjective norm positively affects behavioral intention to use EVs, revealed similar effects between urban (β = 0.161) and rural (β = 0.157) populations. Despite the similar magnitudes, the underlying mechanisms through which subjective norms influence adoption intentions appear to operate differently in each context. The effect in urban areas (β = 0.161) can be explained through several mechanisms. First, the higher visibility of EVs in urban environments might strengthen social normative pressures as EV adoption becomes increasingly associated with environmental consciousness and technological sophistication [28]. Second, urban residents might experience stronger normative influences due to more frequent exposure to EV-related social messaging and peer adoption behaviours [116]. Third, the presence of early adopters in urban areas might create social proof that influences others' adoption intentions through demonstrated feasibility [51]. Fourth, urban social networks, though more diverse, might exert consistent normative pressure due to shared exposure to environmental concerns and sustainability initiatives [82]. The comparable effect in rural areas (β = 0.157) reflects different social dynamics. First, while rural social networks might be smaller, their influence could be more intense due to stronger community ties and shared understanding of local transportation needs [36]. Second, the scarcity of EVs in rural areas might make social approval particularly important in adoption decisions, as potential adopters seek validation from their community [56]. Third, rural residents might rely more heavily on subjective norms to evaluate the practicality of EV adoption, given the limited opportunities for direct observation [117]. Fourth, the close-knit nature of rural communities might make social acceptance of new technology adoption particularly influential in decision-making processes.

H15, hypothesizing that perceived behavioral control positively affects behavioral intention to use EVs, demonstrated slightly different effects between rural (β = 0.131) and urban (β = 0.118) populations. This variation in effect sizes provides important insights into how perceptions of control over EV adoption influence behavioral intentions across different geographical contexts. The stronger effect in rural areas (β = 0.131) can be attributed to several mechanisms. First, rural residents might place greater emphasis on perceived control due to the more challenging EV adoption environment, including limited charging infrastructure and longer travel distances [118]. Second, the higher proportion of self-reliant vehicle usage in rural areas might make perceived behavioral control more crucial in forming adoption intentions [58]. Third, the limited availability of technical support services in rural areas might increase the importance of feeling confident in one's ability to manage EV operation [40]. Fourth, rural residents' need to navigate longer distances and varied terrain might make their sense of control over the vehicle's operation and charging management particularly influential in adoption decisions [119]. The slightly lower effect in urban areas (β = 0.118) reflects different contextual factors. First, urban residents might feel less dependent on personal behavioral control due to better access to support infrastructure and technical assistance [120]. Second, the presence of more comprehensive charging networks in urban areas might reduce the importance of perceived control in adoption decisions [121]. Third, shorter travel distances and more predictable urban driving patterns might make control perceptions less critical in forming adoption intentions [27]. Fourth, the availability of alternative transportation options in urban areas might reduce the pressure to feel complete control over EV operation when considering adoption.

H16, proposing that attitude toward EVs positively affects behavioral intention to use EVs, demonstrated slightly stronger effects in rural areas (β = 0.141) compared to urban areas (β = 0.121). This difference in effect sizes reveals important insights about how attitudes translate into adoption intentions across different geographical contexts. The stronger effect in rural areas (β = 0.141) can be explained through several mechanisms. First, rural residents might form more carefully considered attitudes due to the higher stakes of EV adoption in areas with limited charging infrastructure, making these attitudes more predictive of actual adoption intentions [103]. Second, the greater financial investment relative to rural income levels might strengthen the attitude-intention relationship, as attitudes need to be stronger to overcome economic barriers [8]. Third, the practical challenges of EV adoption in rural areas might make positive attitudes more meaningful predictors of intention, as they likely reflect careful consideration of both benefits and barriers [49]. Fourth, the limited exposure to EVs in rural areas suggests that positive attitudes might be based more on thoughtful evaluation rather than social trends, making them more strongly linked to behavioral intentions [100]. The slightly lower effect in urban areas (β = 0.121) reflects different underlying dynamics. First, urban residents might face fewer barriers between attitudes and intentions due to better infrastructure support, potentially reducing the strength of the attitude-intention relationship [29]. Second, urban attitudes might be more influenced by temporary factors such as trends or peer influence, making them less strongly connected to actual adoption intentions [51]. Third, the complex urban transportation environment might introduce additional factors between attitudes and intentions, such as parking availability and traffic conditions.

6. Conclusion and Implications

6.1. Conclusions

This study investigated the urban-rural differences in electric vehicle (EV) adoption intentions in Thailand, addressing a critical gap in understanding how geographical contexts influence adoption patterns. While previous research has examined EV adoption factors independently, limited attention has been paid to comparing urban and rural adoption mechanisms through an integrated theoretical framework. The study combined the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT) with additional constructs, including environmental identity and trialability, to comprehensively examine adoption intentions. Data were collected from 3,595 respondents (2,311 urban and 1,284 rural) across Thailand, selected based on the distribution of charging stations in different provinces. The analysis employed a rigorous multi-step approach including exploratory factor analysis, confirmatory factor analysis, structural equation modelling, and measurement invariance testing. The findings revealed significant differences in adoption mechanisms between urban and rural populations, with urban areas showing stronger effects in system-related perceptions and utility considerations, while rural areas demonstrated stronger influences of individual characteristics and social factors. This research contributes to both theory and practice by providing insights for developing targeted EV promotion strategies that account for geographical differences, particularly relevant for Thailand's goal of achieving 30% EV production by 2030.

The findings revealed three critical patterns in EV adoption mechanisms across geographical contexts. First, core technical perceptions demonstrated stronger effects in urban areas, with perceived ease of use more strongly influencing perceived usefulness (β = 0.631) and perceived usefulness having greater impact on behavioral intention (β = 0.445) compared to rural areas (β = 0.587 and β = 0.353, respectively). This suggests that urban residents' adoption intentions are more heavily influenced by system utility considerations, likely due to better infrastructure support and greater EV exposure. Second, individual characteristics showed more substantial effects in rural areas, particularly in relationships involving personal innovativeness and environmental identity. Personal innovativeness more strongly influenced attitudes toward EVs in rural areas (β = 0.216 vs. 0.157 in urban areas), while environmental identity demonstrated stronger effects on perceived ease of use (β = 0.350 vs. 0.291). Third, social influence mechanisms operated differently across contexts, with rural areas showing stronger effects on attitudes (β = 0.218 vs. 0.164) but weaker effects on perceived ease of use (β = 0.208 vs. 0.300) compared to urban areas. These findings highlight the distinct adoption pathways in urban and rural contexts, emphasizing the need for differentiated approaches to promoting EV adoption across geographical settings.

6.2. Policy Recommendations

6.2.1. Recommendations for Urban Areas

Based on the structural equation modelling results, urban residents' EV adoption intentions are most strongly influenced by the relationship between perceived ease of use and perceived usefulness (H9, $\beta = 0.631$), followed by perceived usefulness to behavioral intention (H13, $\beta = 0.445$), and social network influence on perceived ease of use (H7, $\beta = 0.300$). These findings suggest three key policy directions for urban areas:

First, policies should focus on enhancing the perceived ease of EV operation and charging, as indicated by high factor loadings on charging process comprehension ($\lambda = 0.932$) and learning ease ($\lambda = 0.925$). Recommended policies include:

- Establishing EV Experience Centres in major urban shopping malls where potential users can learn about EV operation through interactive displays and simulators
- Implementing a standardized EV charging interface across urban areas with clear, user-friendly instructions
- Developing mobile applications that integrate real-time charging station availability, reservation systems, and payment options for example, Norway has successfully implemented similar programs through their "EV Experience Centres" in Oslo, where potential adopters can learn about EVs in a no-pressure environment [122].

Second, given the strong influence of perceived usefulness on adoption intention ($\beta = 0.445$) and high factor loadings on daily transportation benefits ($\lambda = 0.951$), policies should emphasize practical advantages through:

- Creating dedicated EV lanes and priority parking spaces in urban centres
- Implementing dynamic road pricing with significant discounts for EVs
- Developing integrated smart city systems that enable EVs to access real-time traffic information and optimal routing Singapore's Green Vehicle Rebate scheme and EV-priority parking system provides a successful model for such initiatives [44].

Third, leveraging the significant impact of social networks ($\beta = 0.300$) through:

- Establishing EV owner ambassador programs where experienced users share their experiences
- Creating community-based EV sharing programs in urban neighbourhoods
- Supporting EV owner clubs and regular meet-ups through municipal facilities and resources Similar programs in Shanghai, China, have effectively utilized social networks to promote EV adoption through community-based initiatives [46].

6.2.2. Recommendations for Rural Areas

Based on the structural equation modelling results, three key areas require policy attention in rural contexts:

First, considering H4 and H5 results, where personal innovativeness showed strong effects on both perceived usefulness ($\beta = 0.175$) and attitude toward EVs ($\beta = 0.216$), with high factor loadings on early technology adoption (PIN1: $\lambda = 0.790$) and innovation preference (PIN2: $\lambda = 0.771$), policies should focus on supporting early adopters and innovation-oriented individuals:

- Creating "Rural EV Pioneer" programs that provide additional incentives for first adopters in each rural district
- Establishing mobile EV demonstration units that travel between rural communities
- Developing special financial packages for innovative agricultural businesses transitioning to electric vehicles For example, South Korea's Rural EV Leadership Program provides enhanced subsidies and recognition for early adopters in rural communities [123].

Second, based on H3 and H7 results, where environmental identity strongly influences perceived ease of use ($\beta = 0.350$) and social networks affect attitudes ($\beta = 0.218$), supported by high loadings on environmental responsibility (ENV1: $\lambda = 0.862$) and social network opinions (SOC1: $\lambda = 0.857$), policies should leverage community-based approaches:

- Implementing "Community Charging Hubs" that combine charging stations with local gathering spaces
- Developing rural EV cooperatives where communities can share charging infrastructure and maintenance resources
- Creating educational programs that connect environmental benefits to local agricultural sustainability New Zealand's Rural Community Charging Initiative provides a successful model, where farming communities collectively manage charging infrastructure [49].

Third, addressing H12 results, where perceived usefulness strongly influences attitudes ($\beta = 0.248$), with high loadings on transportation needs (PUF2: $\lambda = 0.922$) and practical benefits (PUF3: $\lambda = 0.913$), policies should emphasize practical benefits specific to rural contexts:

- Providing enhanced subsidies for electric pickup trucks and agricultural EVs
- Establishing mobile charging solutions for remote areas
- Developing battery swap stations along major rural routes Japan's Rural Transportation Electrification Program demonstrates successful implementation of similar policies, particularly in supporting agricultural EV applications [124].

6.2.3. Implementation Strategy and Action Plan

The policy recommendations require strategic phasing to ensure effective implementation, considering the distinct characteristics of urban and rural areas. The implementation can be structured into three phases:

Phase 1 (Immediate: 1-2 years): Urban areas should prioritize establishing EV Experience Centres (leveraging the strong PEU→PU relationship, $\beta = 0.631$) and implementing standardized charging interfaces in high-traffic areas. Meanwhile, rural areas should focus on the "Rural EV Pioneer" program (building on strong personal innovativeness effects, $\beta = 0.216$) and establishing initial community charging hubs. The high factor loadings on charging process comprehension (PEU3: $\lambda = 0.932$ urban, $\lambda = 0.882$ rural) suggest that these infrastructure-focused initiatives will significantly impact adoption rates [61].

Phase 2 (Medium-term: 2-4 years): Urban implementation should expand to include integrated smart city systems and EV-priority zones, capitalizing on the strong perceived usefulness effect ($\beta = 0.445$). Rural areas should develop cooperative charging networks and mobile charging solutions, addressing the high loading on transportation needs (PUF2: $\lambda = 0.922$). Thailand could follow Singapore's phased approach, which achieved a 30% increase in EV adoption through similar sequential implementation [125].

Phase 3 (Long-term: 4-5 years): Both areas should focus on community engagement programs, with urban areas developing EV owner ambassador networks (social network influence $\beta = 0.300$) and rural areas establishing agricultural EV demonstration programs. The high loadings on social network opinions (SOC1: $\lambda = 0.893$ urban, $\lambda = 0.857$ rural) suggest these programs will effectively drive sustained adoption.

The policy recommendations require strategic phasing to ensure effective implementation, considering the distinct characteristics of urban and rural areas. The implementation can be structured into three phases: immediate (1-2 years), medium-term (2-4 years), and long-term (4-5 years). In the immediate phase, urban areas should prioritize establishing EV Experience Centres, leveraging the strong relationship between perceived ease of use and perceived usefulness ($\beta = 0.631$), while rural areas should focus on "Rural EV Pioneer" programs, building on strong personal innovativeness effects ($\beta = 0.216$). The medium-term phase should expand to integrated smart city systems in urban areas and cooperative charging networks in rural areas, capitalizing on the high loadings for transportation needs (PUF2: $\lambda = 0.922$). The long-term phase should emphasize community engagement programs across both areas, supported by strong social network influence ($\beta = 0.300$ urban, $\beta = 0.218$ rural).

For policy decision-makers, the findings offer crucial insights for effective implementation. First, resource allocation should prioritize high-impact initiatives based on regional coefficients - for instance, emphasizing ease-of-use programs in urban areas ($\lambda = 0.932$ for charging comprehension) and community-based approaches in rural areas ($\lambda = 0.857$ for social network opinions). Second, infrastructure development should follow a progressive pattern that aligns with adoption rates, starting with high-traffic urban areas and gradually expanding to rural regions. Third, continuous monitoring and evaluation systems should be established to track implementation effectiveness, using the model's parameters as baseline metrics. Fourth, policy-makers should develop region-specific communication strategies that emphasize the most influential factors identified in each area - system utility in urban areas and personal innovation in rural areas [126].

Other developing countries, particularly in Southeast Asia, can adapt these recommendations to their contexts while accounting for local variations. Countries like Vietnam, Indonesia, and Malaysia, which share similar urban-rural divisions, can benefit from Thailand's implementation experience while customizing approaches to their specific needs. The adaptation process should consider four key elements: First, infrastructure readiness assessment using standardized metrics like those employed in this study. Second, economic calibration of incentive structures based on local income levels and cost-of-living differences between urban and rural areas. Third, integration of cultural and social factors specific to each country, particularly in designing community engagement programs. Fourth, development of monitoring frameworks that track implementation progress using comparable parameters to enable cross-country learning and optimization. For example, Vietnam could prioritize urban charging infrastructure development while focusing on agricultural EV applications in rural areas, like Thailand's dual-track approach but adapted to their specific transportation patterns.

While the proposed strategies offer a comprehensive framework for promoting EV adoption across different geographical contexts, their implementation faces several feasibility challenges that must be addressed. The economic and infrastructural constraints are particularly significant in rural areas and warrant careful consideration. From an economic perspective, the "Rural EV Pioneer" program and community charging hub initiatives require substantial initial investment despite their long-term benefits. Based on data from similar programs in South Korea, the estimated cost per rural charging station is approximately 1.5-2 times higher than urban installations due to grid extension requirements and lower utilization rates. This economic challenge can be addressed through public-private partnership models, where government subsidies cover 50-60% of initial costs while private operators manage ongoing operations. This approach has proven successful in New Zealand's Rural Community Charging Initiative, achieving 30% cost reductions through community co-investment. Infrastructural constraints in rural areas present additional challenges, particularly regarding grid capacity and technical expertise. Many rural regions in Thailand have limited electricity distribution infrastructure that may require significant upgrades to support EV charging networks. To address this constraint, the implementation strategy should incorporate distributed energy resources, including solar-powered charging stations with battery storage systems. These systems can operate with minimal grid dependency, reducing infrastructure upgrade costs by approximately 40% based on similar implementations in rural Japan. The proposed phased implementation approach accounts for these constraints by prioritizing high-impact, lower-cost initiatives in the immediate phase while establishing the foundation for more resource-intensive projects in later phases. This pragmatic approach aligns with Bhat & Guo [127] findings on the importance of progressive infrastructure development to match adoption rates across different geographical contexts. Additionally, the feasibility of these strategies is enhanced by Thailand's existing electrification programs and renewable energy initiatives, which can be leveraged to support EV infrastructure development. By integrating EV promotion with broader rural electrification efforts, significant cost efficiencies can be achieved through shared infrastructure investments and maintenance systems.

6.3. Limitations and Future Research

The primary limitation of this study lies in its cross-sectional nature, which captures EV adoption intentions at a single point in time. This approach, while providing valuable insights into urban-rural differences, cannot account for how these intentions evolve as charging infrastructure develops and EV technology advances [128]. Moreover, the timing of data collection coincided with the early stages of Thailand's EV infrastructure development, particularly in rural areas, which may have influenced respondents' perceptions of practical utility and ease of use. Future research should employ longitudinal designs to track changes in adoption intentions as infrastructure develops. Hull et al. [49] suggest that adoption patterns may shift significantly as charging networks expand and new EV models become available, particularly in rural areas. Therefore, a longitudinal study tracking the same urban and rural populations over Thailand's EV infrastructure development period (2024-2030) would provide valuable insights into how the relationships identified in this study evolve with improving infrastructure and increasing EV exposure.

A significant limitation of this study is the absence of detailed analysis regarding socioeconomic factors and cultural attitudes that may influence EV adoption differently across urban and rural populations. While the structural relationships between adoption constructs were thoroughly examined, the study did not explicitly incorporate income disparities, education levels, or cultural predispositions toward new technologies as moderating variables. This limitation is particularly relevant in the Thai context, where rural areas represent approximately 49% of the population but account for 79% of the country's poor. In 2019, rural household monthly income averaged only 68% of urban household income, creating substantial differences in purchasing power and technology investment capacity [129]. Additionally, rural populations in Thailand typically have lower levels of formal education, higher dependency ratios, and more challenging living conditions that may fundamentally alter their approach to high-cost innovations like electric vehicles. These socioeconomic realities likely influence the practical applicability of adoption models, particularly when examining relationships between perceived usefulness, cost considerations, and behavioral intentions. While the study identified stronger effects of individual characteristics in rural areas, it did not fully account for how economic constraints might moderate or even override these relationships. Future research should incorporate explicit socioeconomic stratification in sampling design and employ mixed-methods approaches to explore how financial constraints and cultural perceptions interact with the identified adoption factors. Longitudinal studies examining adoption patterns as rural economic conditions evolve would also provide valuable insights for policymakers seeking to implement targeted incentive programs that address the unique challenges of rural communities while leveraging their stronger social networks and environmental connections

7. Declarations

7.1. Author Contributions

Conceptualization, D.C. and T.C.; methodology, D.C. and N.L.; software, V.R.; validation, T.C. and N.L.; formal analysis, D.C.; investigation, S.J.; data curation, T.C.; writing—original draft preparation, T.C.; writing—review and editing, T.C. and D.C.; visualization, D.C. and T.C.; supervision, V.R.; project administration, S.J.; funding acquisition, T.C. 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

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7.4. Institutional Review Board Statement

This research was approved by the Ethics Committee for Research Involving Human Subjects, Rajamangala University of Technology Isan (Project Code: HEC-01-66-075).

7.5. Conflicts of Interest

The authors declare no conflict of interest.

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Appendix I

Table A1. Questionnaire items and Statistical summary

Item	Questionnaire item	Urban area (n = 2,311)				Rural area (n = 1,284)			
		M	SD	SK	KU	M	SD	SK	KU
	Environmental identity (Cronbach's α = 0.925)								
ENV1	Being environmentally responsible is part of my identity	4.963	1.410	-0.613	0.116	5.449	1.381	-1.144	1.171
ENV2	I tend to consider environmental impacts when making decisions	5.010	1.380	-0.740	0.471	5.453	1.362	-1.220	1.553
ENV3	I take actions to reduce greenhouse gas emissions	4.959	1.392	-0.670	0.213	5.454	1.363	-1.175	1.342
	Personal innovativeness (Cronbach's α = 0.880)								
PIN1	I am usually among the first to try new technologies	4.737	1.441	-0.532	0.015	5.104	1.555	-0.850	0.202
PIN2	I prefer to wait for technology to mature before using it	4.887	1.454	-0.649	0.247	5.244	1.551	-0.849	0.247
PIN3	I often adopt new technologies before they become widely known	4.768	1.442	-0.416	-0.174	5.176	1.544	-0.833	0.203
	Social network influence (Cronbach's α = 0.924)								
SOC1	Opinions from my social network play a role in my acceptance of new technologies	4.797	1.523	-0.559	-0.328	5.234	1.437	-0.881	0.420
SOC2	I consider experiences and advice from my friends and family	4.882	1.497	-0.705	0.001	5.195	1.403	-0.880	0.431
SOC3	Conversations within my social circle influence my decision to try new technologies	4.807	1.515	-0.600	-0.204	5.277	1.468	-0.915	0.317
	Trialability (Cronbach's α = 0.917)								
TRI1	I am more likely to use new technology if I can try it first	5.045	1.371	-0.738	0.405	5.350	1.409	-1.108	1.099
TRI2	My willingness to try new technology is affected by the ease of trial	4.998	1.366	-0.712	0.383	5.387	1.420	-1.112	0.996
TRI3	I am open to experimenting with new technology before making a decision	4.950	1.388	-0.596	0.139	5.388	1.429	-1.128	0.964
	Subjective norm (Cronbach's α = 0.906)								
SUN1	People who are important to me think I should use electric vehicles	4.534	1.724	-0.495	-0.724	5.318	1.499	-1.147	0.900
SUN2	I feel pressure from friends and family to use electric vehicles	4.289	1.794	-0.467	-0.864	5.027	1.610	-0.875	0.118
SUN3	I believe others who are important to me would approve of my choice to use electric vehicles	4.681	1.562	-0.523	-0.424	5.123	1.501	-0.936	0.516
	Perceived behavioral control (Cronbach's α = 0.940)								
PBC1	I feel confident in my ability to use electric vehicles	4.940	1.481	-0.563	-0.249	5.320	1.416	-1.166	1.249
PBC2	I believe I have control over the decision to use electric vehicles	4.891	1.465	-0.563	-0.205	5.296	1.393	-1.176	1.382
PBC3	I feel that using electric vehicles is entirely within my control	4.828	1.486	-0.452	-0.354	5.311	1.447	-1.082	0.956
	Perceived ease of use (Cronbach's α = 0.936)								
PEU1	Learning to use electric vehicles would be easy for me	4.832	1.632	-0.578	-0.414	5.456	1.565	-1.190	0.898
PEU2	I believe using electric vehicles would require minimal effort from me	4.695	1.767	-0.552	-0.663	5.410	1.594	-1.117	0.694
PEU3	The process of charging and using electric vehicles seems easy for me	4.777	1.642	-0.606	-0.380	5.288	1.482	-1.101	0.954
	Perceived usefulness (Cronbach's α = 0.946)								
PUF1	Using electric vehicles would enhance my overall travel experience	4.769	1.656	-0.558	-0.553	5.279	1.545	-1.025	0.617
PUF2	I believe using electric vehicles would be beneficial for my daily transportation needs	4.827	1.704	-0.574	-0.605	5.460	1.590	-1.180	0.734
PUF3	Using electric vehicles would be a good option to meet my transportation needs	4.786	1.753	-0.549	-0.675	5.434	1.619	-1.167	0.707
	Attitude toward electric vehicles (Cronbach's α = 0.911)								
ATT1	I have a positive attitude toward using electric vehicles	5.026	1.393	-0.623	0.069	5.359	1.278	-1.028	1.423
ATT2	Using electric vehicles aligns with my personal values	4.803	1.512	-0.605	-0.219	5.366	1.396	-1.257	1.575
ATT3	I view using electric vehicles as a desirable choice	4.796	1.537	-0.513	-0.384	5.360	1.381	-1.075	1.040
	Behavioral intention to use (Cronbach's α = 0.950)								
BIU1	I intend to use electric vehicles in the future	4.685	2.027	-0.576	-0.969	5.215	1.725	-1.066	0.304
BIU2	It is very likely that I will adopt electric vehicles for regular use	4.589	1.887	-0.449	-0.977	5.281	1.601	-1.087	0.532
BIU3	I am likely to consider using electric vehicles to meet my transportation needs	4.692	1.840	-0.513	-0.870	5.283	1.612	-1.082	0.526

Note: M denotes average; SD denotes standard deviation; SK denotes skewness; KU denotes kurtosis