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Modeling User Intentions for Electric Vehicle Adoption in Thailand: Incorporating Multilayer Preference Heterogeneity

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Abstract: *Background*: The automotive industry is pivotal in advancing sustainability, with electric vehicles (EVs) essential for reducing emissions and promoting cleaner transport. This study examines the determinants of EV adoption intentions in Thailand, integrating demographic and psychographic factors from Environmental psychology and innovation diffusion theory; *Methods*: Data from a structured questionnaire, administered to 4003 respondents at gas stations with EV charging facilities across Thailand, were analyzed using a Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM); *Results*: Findings indicate that younger adults, particularly those aged 25–34 years old and 45–54 years old, are more likely to adopt EVs, whereas conventional or hybrid vehicle owners are less inclined. Rural residency or travel also hinders adoption. Individuals with strong environmental values and openness to new technologies are more likely to adopt EVs; *Conclusions*: The proposed model quantified the relative importance of these factors and uncovered heterogeneity in user preferences, offering reliable and valuable insights for policymakers, EV manufacturers, and researchers. The study suggests targeted policies and enhanced charging infrastructure, especially in rural areas, and recommends leveraging environmental values and trialability through communication campaigns and test drive events. These insights can guide the development of targeted incentives, infrastructure expansion, communication strategies, and trialability programs to effectively promote wider EV adoption in Thailand and similar markets.

Keywords: environmental psychology; innovation diffusion theory; mixed-ordered probit model; random parameter; heterogeneity in means

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1. Introduction

The global automotive industry is undergoing a profound transformation, driven by a pressing need to address climate change and achieve sustainability goals. Electric vehicles (EVs) have emerged as a crucial element in this shift, offering a cleaner and more sustainable alternative to conventional combustion engine vehicles. This transition aligns with several Sustainable Development Goals (SDGs), including SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). Governments worldwide have recognized the importance of EVs and implemented various policies to incentivize their adoption, including tax credits, subsidies, infrastructure development, and emission regulations [1]. Thailand has also joined this global movement, aiming to become a regional hub for EV production and adoption. The government has set ambitious targets for EV production and sales, and introduced several policies to promote EV adoption, such as tax incentives and subsidies for both EV manufacturers and consumers [2].

Despite these efforts, the widespread adoption of EVs in Thailand faces significant challenges. Understanding the factors that influence user intentions to adopt EVs is crucial for developing effective policies and marketing strategies that can accelerate the transition to a more sustainable transportation system [3,4]. While previous research has investigated EV adoption intentions, most studies have relied on traditional methods like Structural Equation Modeling (SEM), which often assume homogeneous preferences among users. However, the decision to adopt an EV is complex and influenced by a diverse range of factors that vary across individuals [5–7]. This study departs from previous research by employing a more sophisticated econometric method—a Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM) [8]. The CMOPMHM approach addresses the limitations of traditional models by accounting for three critical aspects of user preferences: random parameters, heterogeneity in means, and correlation between random parameters [9]. By allowing the coefficients of some independent variables to vary randomly across individuals (random parameters) [10,11], the CMOPMHM captures the idea that people have different preferences and are influenced by factors differently [12]. For example, some individuals might be highly price-sensitive, while others might prioritize environmental impact. This understanding of preference heterogeneity can inform policies that are tailored to specific consumer segments [13]. For instance, subsidies could be designed to cater to the needs of price-sensitive consumers, while marketing campaigns could highlight the environmental benefits of EVs for eco-conscious consumers. The CMOPMHM further recognizes that the average effect of certain variables, represented by means of random parameters, can be influenced by other observed factors (heterogeneity in means). For example, the average effect of environmental concern on EV adoption intention might be higher among younger respondents, indicating a greater sensitivity to this factor within this demographic [13]. This insight can help policymakers target specific age groups with tailored information campaigns and incentives. Moreover, the CMOPMHM allows for correlation between random parameters, capturing the interdependence between individual preferences for different EV attributes [8]. For instance, individuals who are highly concerned about environmental impact might also be more sensitive to the purchase price, leading to a correlation between these two random parameters. Policymakers can leverage this understanding to design integrated incentive packages that address multiple consumer concerns simultaneously, making EVs more appealing to a broader range of potential buyers.

Furthermore, this study expands upon previous research by incorporating factors from Environmental Psychology [14] and innovation diffusion theory [15] to understand EV adoption intentions. While prior studies have often focused on frameworks like the Theory of Planned Behavior and the Technology Acceptance Model [16–18], this study explores a broader range of psychographic factors that influence EV adoption, including individuals' connection to nature, environmental identity, and their proclivity to adopt new technologies. It is important to note that the psychographic factors derived from Environmental psychology and innovation diffusion theory are not intended to reduce or replace demographic variables in explaining EV adoption intentions. Instead, they serve as complementary factors that provide a more comprehensive understanding of the decision-making process. While demographic variables offer crucial insights into socio-economic characteristics that influence EV adoption, psychographic factors capture deeper psychological and behavioral aspects that demographics alone cannot explain. For instance, two individuals with similar demographic profiles might have different EV adoption intentions due to varying environmental values or openness to new technologies. By incorporating both sets of factors, this study aims to provide a more nuanced and complete picture of the drivers behind EV adoption intentions. This comprehensive approach can lead to more effective and targeted strategies for promoting EV adoption, addressing both the socio-economic realities and the psychological motivations of potential EV adopters.

This study aims to identify the key factors that influence user intentions to adopt EVs in Thailand, considering both demographic factors and psychographic factors derived from Environmental psychology and innovation diffusion theory. Furthermore, it aims to quantify the relative importance of these factors and their interactions in shaping EV adoption intentions, as well as uncover the heterogeneity in user preferences and identify subgroups with distinct sensitivities to different EV attributes. By incorporating a sophisticated econometric method and a comprehensive set of explanatory variables, this study offers valuable insights for policymakers, EV manufacturers, and researchers. The findings contribute to a deeper understanding of the factors driving EV adoption in Thailand and provide a basis for developing targeted policies and strategies to accelerate the transition toward a more sustainable transportation system.

2. Literature Review

2.1. Factors Influencing EV Adoption

The adoption of electric vehicles (EVs), a key element in the global shift toward sustainable transportation (Table 1), is influenced by a complex interplay of demographic and psychographic factors. Demographic characteristics, such as age, education, occupation, and location, shape individuals' needs, resources, and exposure to new technologies [19]. Numerous studies have shown that younger individuals tend to be more receptive to EVs, possibly due to their greater familiarity with technological advancements and their heightened concern for environmental issues [20]. This age-related trend may be attributed to the formative experiences of younger generations, who have grown up with increasing awareness of climate change and technological solutions [21]. Education also plays a crucial role, with individuals possessing higher levels of education demonstrating a greater understanding of the environmental benefits of EVs and a higher likelihood of adoption [22]. This correlation may be due to increased access to information about EV technology and environmental issues, as well as potentially higher income levels associated with higher education [23]. Occupation and income level further influence affordability and the perceived practicality of EVs for daily commutes and travel needs [24]. Higher-income individuals may be more willing to bear the upfront costs of EVs, while certain occupations might align more closely with EV adoption due to factors such as company policies or professional image [25].

Additionally, home and travel locations, particularly the distinction between urban and rural environments, significantly impact EV adoption decisions. Urban areas, with their denser populations, shorter average driving distances, and greater access to charging infrastructure, are generally considered more conducive to EV adoption compared to rural areas [26]. The urban-rural divide in EV adoption may also be influenced by differences in exposure to EVs, availability of public transportation alternatives, and local environmental policies [27]. Prior experience with alternative fuel vehicles, such as hybrid electric vehicles (HEVs) and plug-in hybrid electric vehicles (PHEVs), may also positively influence individuals' willingness to adopt EVs, as familiarity with the technology and its perceived advantages can reduce barriers to adoption [28]. This effect can be understood through the lens of technology diffusion theory, where early adopters of related technologies are more likely to accept subsequent innovations [29].

Beyond demographic characteristics, psychographic factors rooted in environmental psychology and innovation diffusion theory significantly contribute to EV adoption decisions. Individuals with a strong personal connection to nature and a sense of environmental responsibility are more likely to be concerned about the environmental impact of their transportation choices and seek cleaner alternatives like EVs [21]. This connection may be reinforced by personal experiences with environmental degradation or exposure to environmental education [30]. Barbarossa et al. [31] critically examine the interplay between environmental attitudes, personal values, green self-identity and EV adoption intentions, providing valuable insights into how these psychological factors influence consumer decision-making in the context of sustainable transportation.

Environmental identity, where individuals view environmental responsibility as a core aspect of their self-concept, also drives pro-environmental behaviors, including the adoption of sustainable technologies like EVs [32]. This identity-driven motivation can be particularly powerful as it aligns personal values with consumer choices, creating a sense of consistency and purpose in decision-making [33]. Huang et al. [3] offer further insights into the role of knowledge management in shaping consumer perceptions of EVs and their impact on adoption decisions, highlighting the importance of information dissemination in promoting EV uptake. Moreover, regular exposure to nature can enhance individuals' awareness of environmental issues and their impact on personal well-being, potentially leading to a greater appreciation for the benefits of EVs [34]. This exposure-effect relationship underscores the importance of accessible green spaces and nature-based education in fostering pro-environmental attitudes and behaviors [35].

Innovation diffusion theory provides further insights into the adoption process. Individuals are categorized as early adopters, early majority, late majority, and laggards based on their propensity to embrace new technologies. Early adopters, characterized by their willingness to take risks and try new things, play a crucial role in promoting the diffusion of innovations like EVs [36]. Trialability, the ease with which individuals can experiment with a new technology before committing to a purchase, also influences adoption decisions. Test drives, rental programs, and shared mobility services can increase the perceived trialability of EVs and reduce uncertainty, thereby promoting adoption [37–39]. Social network influence, particularly the opinions and experiences shared by friends, family, and peers, shapes individuals' perceptions and acceptance of new technologies [40]. Positive reviews and recommendations from trusted sources can encourage EV adoption, while negative feedback can create barriers. Recent studies have also highlighted the importance of government policies and incentives in shaping EV adoption intentions [41–43]. Chen et al. [44] offer new perspectives on the role of government policies in accelerating EV adoption in emerging markets, emphasizing the need for tailored approaches that consider local economic and social contexts.

Furthermore, the role of environmental concerns in driving EV adoption has been increasingly recognized [35,45]. As public awareness of climate change and air pollution grows, many consumers are viewing EV adoption as a way to reduce their personal environmental impact. This trend is particularly strong among younger generations and in urban areas where the effects of air pollution are more immediately felt.

A comprehensive meta-analysis by [42] provides a global perspective on these factors, highlighting the variability of influences across different global contexts and offering valuable insights for policymakers and researchers seeking to understand the complex dynamics of EV adoption. Additionally, Wang et al. [46] present an innovative model for predicting EV adoption rates using machine learning techniques, which could help policymakers better understand and address geographical disparities in adoption, potentially leading to more effective, targeted strategies for promoting EV use.

Table 1. Factors influencing EV adoption.

Category	Factor	Description	Reference
Demographic	Age	Younger individuals tend to be more receptive to EVs due to familiarity with technology and environmental awareness	Bjerkan, et al. [20], Singh, et al. [47]
	Education	Higher education levels correlate with a greater understanding of EV benefits and higher adoption likelihood	Bhat, et al. [22]
	Income/Occupation	Higher-income and certain occupations increase willingness to bear EV costs and align with adoption	Peng, et al. [24], Lodhia, et al. [25]
	Location	Urban areas are more conducive to EV adoption than rural areas due to infrastructure and driving patterns	Liu, et al. [26]

Table 1. *Cont.*

Category	Factor	Description	Reference
Psychographic	Environmental Connection	Strong personal connection to nature increases likelihood of seeking cleaner transportation alternatives	White, et al. [21], Singh, et al. [47], Higueras-Castillo, et al. [48]
	Environmental Identity	Viewing environmental responsibility as core to self-concept drives sustainable technology adoption	Rye, et al. [32], Singh, et al. [47]
	Nature Exposure	Regular exposure to nature enhances awareness of environmental issues and appreciation for EV benefits	Albatayneh, et al. [34], Higueras-Castillo, et al. [48]
Innovation Adoption	Early Adopter Tendency	Willingness to take risks and try new technologies promotes EV adoption	Singh, et al. [47]
	Trialability	Ability to experiment with EVs before purchase (e.g., test drives, rentals) reduces adoption uncertainty	Langbroek, et al. [36]
	Social Network Influence	Opinions and experiences of peers shape perceptions and acceptance of EVs	Feng, et al. [40], Higueras-Castillo, et al. [48]
Prior Experience	Alternative Fuel Vehicles	Experience with HEVs and PHEVs positively influences willingness to adopt EVs	Ziegler [28], Singh, et al. [47]

2.2. Ordered Probit Model Based on the Questionnaire Data

Ordered Probit models are a valuable tool for analyzing questionnaire data where the dependent variable, such as intention to adopt EVs, is ordinal. These models capture the inherent order in responses, such as "not at all likely (0–40%)", "somewhat likely, (40–60%)" "very likely, (60–100%)" while acknowledging that the distances between categories are not necessarily equal [12]. The model assumes a latent (unobserved) continuous variable underlying these observed ordinal responses, reflecting the underlying level of intention to adopt EVs.

While the standard ordered probit model provides a useful framework, it often falls short of capturing the complexity of individual preferences and decision-making processes by assuming homogeneous responses to independent variables. To address this limitation, advanced extensions of the ordered probit model, incorporating heterogeneity in user preferences through random parameters, heterogeneity in means, and correlation between random parameters, have been developed [11]. These extensions provide a more nuanced and realistic understanding of the factors driving EV adoption intentions and facilitate the development of more effective policy interventions and marketing strategies.

3. Questionnaire Design and Data Collection

The questionnaire employed in this study was structured in two distinct sections, designed to collect comprehensive data on respondents' characteristics and their attitudes toward electric vehicle (EV) adoption in Thailand. The first section gathered essential demographic information, including age, education level, occupation, home location (urban or rural), and travel patterns (urban or rural). This data allowed for an analysis of how demographic factors might influence EV adoption intentions. The second section is respondents' attitudes and perceptions using a seven-point Likert scale, where 1 represented "strongly disagree" and 7 represented "strongly agree." This scale is widely recognized for its effectiveness in capturing nuanced variations in attitudes and perceptions [17]. The attitudinal items were grounded in two established theoretical frameworks: Environmental psychology and innovation diffusion theory. Items related to Environmental Psychology assessed respondents' personal connection to nature, their environmental identity, and their perceived exposure to the natural environment. Items derived from innovation diffusion theory focused on capturing respondents' proclivities toward adopting new technologies, their willingness to experiment with new products, and the influence of their social networks on technology adoption decisions (Appendix A).

Prior to the main data collection, a rigorous validation process was undertaken to ensure the reliability and validity of the attitudinal measures derived from Environmental psychology and innovation diffusion theory in the Thai context. This process included a comprehensive literature review to identify established scales, which were then adapted for EV adoption in Thailand. A pilot study with 50 participants was conducted to assess the clarity and comprehensibility of the questionnaire items and to evaluate the preliminary reliability of the scales using Cronbach's alpha coefficients. Based on the pilot study results, necessary adjustments were made to the questionnaire.

Data collection was strategically conducted at gas stations equipped with EV charging stations to ensure a diverse sample that included both current EV users and traditional vehicle users. This setting allowed for a direct comparison of perceptions and intentions between these two groups. To ensure geographical representativeness across Thailand, a total of 4003 questionnaires were distributed across five major regions, with the sample size for each region proportionate to the distribution of EV registrations and charging infrastructure. For example, Bangkok, which accounts for 28.91% of the country's charging stations, received a corresponding 28.91% of the total questionnaires, ensuring that the sample reflected the actual distribution of EVs and charging facilities across the country. This approach aimed to capture a broad spectrum of perceptions and intentions toward EVs, providing a comprehensive picture of EV adoption trends in Thailand.

The data collection method, focusing on respondents at gas stations with EV charging facilities, may introduce some selection bias. This approach was chosen to capture data from both EV users and conventional vehicle users in a relevant context, ensuring that respondents have at least some exposure to EV infrastructure. However, this method may overrepresent individuals who are more likely to consider EVs. To mitigate this potential bias, several strategies were implemented. Firstly, data was collected across various regions of Thailand, ensuring geographical diversity and representativeness. Secondly, the large sample size (4003 respondents) helps to reduce the impact of potential bias. Thirdly, various vehicle types (i.e., ICE, HEV, PHEV, and EV) were included in the analysis to capture a range of perspectives. Within each gas station, respondents were approached randomly to avoid selection bias by the researchers. Additionally, data collection was conducted at different times of day and on different days of the week to capture a diverse range of respondents. While the possibility of some bias cannot be entirely eliminated, these measures were implemented to ensure the most representative sample possible given the data collection approach.

Table 2 shows a statistical snapshot of the respondents, revealing a sample consisting of 61.3% males, with the majority (63.2%) residing in rural areas and primarily engaged in private-sector employment (60.7%). The average age of the sample leans toward younger demographics, and educational backgrounds are diverse, with 38.7% holding Bachelor's degrees. Notably, 27.2% of respondents already own EVs, while a significant portion (49.5%) own conventional ICE vehicles. The average scores for questionnaire items related to Environmental Psychology ranged from 5.195 to 5.270, indicating a strong pro-environmental orientation. Similarly, the average scores for items related to innovation diffusion theory ranged from 4.811 to 5.177, suggesting a high level of openness to new technologies. Examining respondents' stated chances of adopting EVs reveals a mixed picture. While the largest group (28.23%) indicated an 80% chance of adopting EVs in the future, a substantial proportion (15.89%) reported a 0% chance, suggesting resistance or skepticism toward EV adoption. The remaining respondents fall across a spectrum of probabilities, with notable proportions indicating 20% (21.68%) and 40% (14.71%) chances.

Table 2. Descriptive statistic of the explanatory variables.

Variable	Description	Mean	S.D.	Min.	Max
	Respondents' demographic				
VGENDER	1 = Male, 0 = Female	0.613	0.487	0	1
AGE_25	1 = Yes, 0 = Others	0.092	0.289	0	1
AGE25_34	1 = Yes, 0 = Others	0.342	0.474	0	1
AGE35_44	1 = Yes, 0 = Others	0.240	0.427	0	1
AGE45_54	1 = Yes, 0 = Others	0.277	0.448	0	1
AGE_55 *	1 = Yes, 0 = Others	0.048	0.215	0	1
EDU_1 *	1 = Primary, 0 = Others	0.080	0.271	0	1
EDU_2	1 = High school/Vocational certificate, 0 = Others	0.158	0.364	0	1
EDU_3	1 = Associate degree/Higher vocational certificate, 0 = Others	0.256	0.436	0	1
EDU_4	1 = Bachelor, 0 = Others	0.387	0.487	0	1
EDU_5	1 = Master or Doctoral, 0 = Others	0.120	0.325	0	1
OCC_1	1 = Government Officer, 0 = Others	0.159	0.366	0	1
OCC_2	1 = Private Company Officer, 0 = Others	0.303	0.460	0	1
OCC_3	1 = Private Business, 0 = Others	0.304	0.460	0	1
OCC_4	1 = Agriculturist, 0 = Others	0.069	0.254	0	1
OCC_5	1 = Students, 0 = Others	0.046	0.209	0	1
OCC_6 *	1 = General Employees, 0 = Others	0.110	0.313	0	1
HOME_LO	1 = Rural, 0 = Urban	0.632	0.482	0	1
DRIVER	1 = Driver, 0 = Passenger	0.770	0.421	0	1
ICE	1 = Yes (Internal Combustion Engine), 0 = Others	0.495	0.500	0	1
HEV	1 = Yes (Hybrid), 0 = Others	0.116	0.320	0	1
PHEV	1 = Yes (Plug-in Hybrid), 0 = Others	0.117	0.322	0	1
EV *	1 = Yes (Battery Electric Vehicle), 0 = Others	0.272	0.445	0	1
PICKUP	1 = Yes, 0 = Others	0.162	0.368	0	1
CAR	1 = Yes, 0 = Others	0.548	0.498	0	1
SUV	1 = Yes, 0 = Others	0.208	0.406	0	1
PPV	1 = Yes, 0 = Others	0.055	0.228	0	1
MPV *	1 = Yes, 0 = Others	0.026	0.161	0	1
TRAVEL_L	1 = Rural, 0 = Urban	0.351	0.477	0	1
	Environmental Psychology				
NATURE1	I personally feel connected with nature and the environment.	5.211	1.377	1	7
NATURE2	Environmental conservation is important to me.	5.270	1.390	1	7
NATURE3	Spending time in nature is a meaningful experience for me.	5.250	1.377	1	7
ENV_IND1	Being environmentally responsible is part of my identity.	5.197	1.410	1	7
ENV_IND2	I tend to consider the environmental impact when making decisions.	5.230	1.382	1	7
ENV_IND3	I take actions to reduce the impact of greenhouse gas emissions.	5.202	1.398	1	7
NAT_EX1	Being regularly affected by the natural environment influences my feelings.	5.195	1.398	1	7
NAT_EX2	I familiarize myself with nature for its health benefits.	5.232	1.404	1	7
NAT_EX3	Nature affects my tranquility and influences my decisions.	5.214	1.380	1	7
	Innovation Diffusion Theory				
ADOP1	I tend to be an early adopter of new technologies.	4.811	1.557	1	7
ADOP2	I prefer to wait for technology to mature before using it.	5.046	1.511	1	7
ADOP3	I often adopt new technologies before they become widely known.	4.841	1.567	1	7
TRIAL1	I am more likely to use new technology if I can try it first.	5.177	1.397	1	7
TRIAL2	My readiness to try new technology is influenced by how easy it is to experiment with.	5.176	1.405	1	7
TRIAL3	I am open to experimenting with new technology before making a decision.	5.150	1.426	1	7
SOCIAL1	The opinions from my social network play a role in my adoption of new technology.	4.964	1.506	1	7

Table 2. *Cont.*

Variable	Description	Mean	S.D.	Min.	Max
SOCIAL2	I consider the experiences and advice from my friends and family.	5.010	1.463	1	7
SOCIAL3	Conversations within my social circle affect my decision to try new technology.	4.991	1.511	1	7

Note: * indicate reference categories. Chances for EV adoption: 0% = 636 (15.89%); 20% = 1504 (21.68%); 40% = 868 (14.71%); 60% = 589 (10.09%); 80% = 1130 (28.23%) and 100% = 376 (9.39%). Demographic variables were measured using categorical responses. Attitudinal variables related to Environmental psychology and innovation diffusion theory were measured using a 7-point Likert scale, where 1 represents "strongly disagree" and 7 represents "strongly agree". NATURE1-3 measure personal connection to nature, ENV_IND1-3 assess environmental identity, NAT_EX1-3 evaluate exposure to nature, ADOP1-3 measure technology adoption tendencies, TRIAL1-3 assess willingness to try new technologies, and SOCIAL1-3 measure the influence of social networks on technology adoption. The dependent variable (EV adoption intention) was measured on a scale from 0% to 100%, and later categorized into three levels for analysis.

4. Methodological Approach

4.1. Mixed-Ordered Probit Model

To investigate user intentions for electric vehicle adoption in Thailand while accommodating preference heterogeneity, this study used a mixed-ordered probit model with heterogeneity in means. The mixed-ordered probit model is a flexible econometric approach that allows for the modeling of ordinal dependent variables while accounting for individual-specific heterogeneity in preferences [49,50]

In the context of this study, the dependent variable is the user's intention to adopt electric vehicles, measured on an ordinal scale with three categories: low, neutral, and high chance of adopting electric vehicles. The mixed-ordered probit model assumes that an individual's observed response y_m is determined by an underlying latent variable Y_m, which is a function of observable characteristics X_m, and an error term ε_m:

$$Y_m = \beta X_m + \varepsilon_m, y_m = j, \text{ if } \mu_{j-1} < Y_m < \mu_j, j = 0,1,2 \tag{1}$$

where β is a vector of the estimable parameters, j denotes the integers representing the intention levels (i.e., Low, Neutral, and High), and μ_j is the threshold parameters that are ordered in nature, such that $\mu_{j-1} < \mu_j$ for determination of y_m.

To capture preference heterogeneity in this study, three layers of heterogeneity are empirically tested. The first layer allows the coefficients and the individual-specific effects to vary across individuals according to a specified distribution (e.g., normal, lognormal, triangular). This approach helps in discovering the significant random parameters [51]. The second layer of heterogeneity can be achieved by relaxing the assumption that any random parameters found are independent, thus allowing them to be correlated and influence the model outcome [8]. For the third layer, the heterogeneity in means approach [49] enables the model to accommodate varying preferences and their correlation with observable characteristics. Theoretically, the vector of random parameters for observation m can be further revised as [52]:

$$\beta_m = \beta + \eta Z_m + \Gamma \omega_m, \tag{2}$$

where β_m is a vector of random parameters corresponding to explanatory variables for observation m, β is the mean value of the random parameter vector, Z_m is a vector of explanatory variables for observation m that influence the means of the random parameter vectors, and η is a matrix of estimable parameters with each row of η corresponding to the loadings of a specific element of the vector β_m on the Z_m vector. That is, if a specific column entry in a row of η is zero, it implies that there is no shift in the mean of the corresponding row element of the β_m vector due to the row element of the Z_m vector corresponding to the column under consideration. Γ is a symmetric Cholesky matrix which is used to compute the standard deviation of the random parameters, and ω_m denotes a randomly distributed term with a mean value of zero and variance equal to σ^2.

Using Γ matrix, the standard deviation of the correlated random parameters is based on the diagonal and off-diagonal elements [10,53]:

$$\sigma_r = \sqrt{\sigma_{k,k}^2 + \sigma_{k,k-1}^2 + \sigma_{k,k-2}^2 + \ldots + \sigma_{k,1}^2}, \tag{3}$$

where σ_r denotes the standard deviation of the random parameter r, $\sigma_{k,k}$ is the Γ matrix's respective diagonal element, and $\sigma_{k,k}$, $\sigma_{k,k-1}$ $\sigma_{k,k-2}$, ... $\sigma_{k,1}$ denotes the lower triangular matrix's off-diagonal elements corresponding to the random parameter r. For each correlated random parameter, standard error and t-statistic of the standard deviation (σ_{rn}) are computed as [10,53]:

$$SE_{\sigma_r} = \frac{S_{\sigma_{rn}}}{\sqrt{N}}, \tag{4}$$

where $S_{\sigma_{rn}}$ is the standard deviation of the observation-specific σ_{rn}, and N is the total number of observations in the model estimation, and [53],

$$t_{\sigma_r} = \frac{\sigma_r}{SE_{\sigma_r}}, \tag{5}$$

This t-statistic serves the purpose whether the standard deviations of the correlated random parameters are statistically different from zero. And lastly, the correlation coefficient between two random parameters is derived as [53]:

$$Cor(x_{r,n}, x_{r',n}) = \frac{cov(x_{r,n}, x_{r',n})}{\sigma_{r,n}, \sigma_{r',n}}, \tag{6}$$

where $cov(x_{r,n}, x_{r',n})$ is the covariance between the two variables with random parameters r and r', and $\sigma_{r,n}$ and $\sigma_{r',n}$ are their standard deviation, respectively. The model parameters were estimated using the simulated maximum likelihood method, employing 500 Halton draws to obtain stable and reliable results [54,55]. To assess the impact of each explanatory variable on the probability of different user intention levels, average marginal effects were calculated across all observations. A one-unit increase in each explanatory variable was considered to quantify its influence on the likelihood of each intention level. The NLOGIT 6 software package was utilized to conduct the statistical modeling and analyses. The conceptual framework of the model is shown in Figure 1. The model development process involves several steps. First, each input variable is tested to determine if it produces significant random parameters, i.e., if it has a statistically significant standard deviation. This step helps identify which parameters should be treated as random and which should be treated as fixed. Once all the parameters have been tested, we obtain two sets of parameters: a set of random parameters with both mean and standard deviation estimates and a set of fixed parameters with only mean estimates. If two or more random parameters are found, the next step is to test the correlation between them. This step helps capture any potential interdependencies among the random parameters. Finally, we test whether the fixed parameters that are not significant (i.e., those with a p-value > 0.1) have a significant influence on the mean estimates of the random parameters. This step allows us to identify any potential heterogeneity in the means of the random parameters that can be explained by the fixed parameters. This step-by-step process ensures that the model captures the complex relationships among the input variables and provides a more accurate representation of the underlying decision-making process.

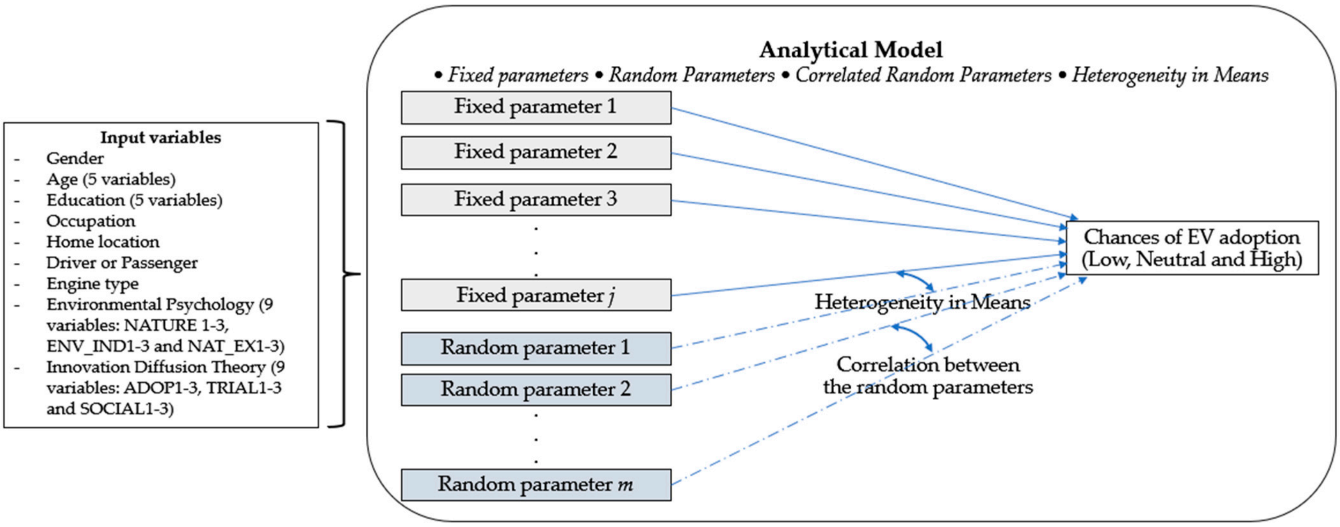

Figure 1. Conceptual framework.

4.2. Model Evaluation and Validation

To evaluate and validate the model fit, several goodness-of-fit measures will be employed in this study. The Akaike Information Criterion (AIC) and corrected AIC (AICc) will be used to assess the trade-off between model complexity and goodness-of-fit, with lower values indicating a better fit [56]. Additionally, McFadden R^2 statistic, corrected R_c^2, and Chi-square (χ^2) test were used [57]:

$$R^2 = 1 - \frac{LL(\beta)}{LL(0)} \quad (7)$$

$$R_c^2 = 1 - \frac{LL(\beta) - K}{LL(0)} \quad (8)$$

$$AIC = -2LL(\beta) + 2K \quad (9)$$

$$AIC_c = AIC + \frac{2K(K+1)}{(N-K-1)} \quad (10)$$

$$\chi^2 = -2[\mathrm{LL}(\beta_M) - \mathrm{LL}(\beta_N)] \quad (11)$$

where K is the number of parameters, N is the number of observations, $LL(\beta)$ is the log-loglikelihood at convergence, $LL(0)$ is the log-likelihood with only the constant term, and $\mathrm{LL}(\beta_M)$ and $\mathrm{LL}(\beta_N)$ are the log-likelihood at convergence for the model M and the competing model N, respectively. The χ^2 statistic is chi-square distributed with the degrees of freedom equal to the difference in the number of parameters in model M and model N.

5. Results

To determine the most suitable model for analyzing the relationship between independent variables and EV adoption intentions, we compared two ordered probit models with varying levels of categorization for the dependent variable. The first model utilized six categories directly corresponding to the original response options, while the second model consolidated these into three broader categories (0–40%, 40–60%, and 60–100%). Evaluating the goodness-of-fit using McFadden Pseudo R-squared and Akaike Information Criterion (AIC) revealed a superior fit for the three-categorical model. This model exhibited a higher R-squared value (0.406 compared to 0.241) and a significantly lower AIC (5230.7 compared to 10,518.5). These findings indicate that the three-categorical model explains a larger proportion of the variance in EV adoption intentions with a more parsimonious structure, achieving a better balance between model fit and complexity. The improved fit likely stems from grouping similar response categories, resulting in a more concise and meaningful representation of EV adoption likelihood. The improved fit likely stems from grouping similar response categories, resulting in a more concise and meaningful representation of EV adoption likelihood [57]. Therefore, we chose the three-categorical level ordered probit model for further interpretation and analysis, as it provides a more statistically sound and interpretable representation of the data.

While the AIC and AICc provide valuable insights for model comparison, they have limitations in differentiating between models, especially with large sample sizes. In this study, the initial comparison between six-category and three-category models showed minimal differences in AIC and AICc values. Therefore, additional factors were considered in the model selection process. The three-category model was ultimately chosen based on its parsimony, improved interpretability, better alignment with established theories of technology adoption, and practical significance in the context of EV adoption literature. This decision balances the trade-off between granularity and simplicity, providing a more concise representation of EV adoption intentions without significant loss of information. The three-category model not only simplifies the interpretation of results but also aligns more closely with the typical decision-making process in technology adoption, where consumers often categorize their intentions into broader groups (e.g., unlikely, neutral, likely) rather than finer gradations.

Based on the model goodness-of-fit comparison and validation results presented in Table 3, several key findings emerge. The Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM) appears to be the superior model among the five considered, as it exhibits the highest R-squared (0.418) and corrected R-squared (0.407) values, as well as the lowest Akaike Information Criterion (AIC) and corrected AIC (AICc) values (5135.560 and 5136.850, respectively). The likelihood ratio tests further support the superiority of the CMOPMHM model, with significant improvements observed compared with the mixed-ordered probit model with heterogeneity in means (MOPMHM) (p-value = 0.052). The MOPMHM model, in turn, outperforms the mixed-ordered probit model (MOPM) (p-value = 0.000), while the Correlated mixed-ordered probit model (CMOPM) shows a marginal improvement over the MOPM (p-value = 0.058) [7]. These findings suggest that incorporating both correlation and heterogeneity in the means significantly enhances the model's ability to capture the underlying data structure and provide a better fit to the observed user intentions for electric vehicle adoption in Thailand.

Table 3. Model goodness-of-fit comparison and validation.

Metric	OPM	MOPM	CMOPM	MOPMHM	CMOPMHM
N	4003	4003	4003	4003	4003
K	41	43	44	49	50
$LL(0)$	−4328.846	−4328.846	−4328.846	−4328.846	−4328.846
$LL(\beta)$	−2559.226	−2542.653	−2540.858	−2519.659	−2517.780
R^2	0.409	0.413	0.413	0.418	0.418
$R^2{}_c$	0.399	0.403	0.403	0.407	0.407
AIC	5200.452	5171.305	5169.716	5137.319	5135.560
AIC_c	5201.321	5172.261	5170.716	5138.558	5136.850
Likelihood ratio test superiority between models					
		MOPM vs. OPM	CMOPM vs. MOPM	MOPMHM vs. MOPM	CMOPMHM vs. MOPMHM
DOF		2	1	6	1
X^2		33.1467	3.58928	45.98626	3.75928
p-Value		0.000	0.058	0.000	0.052
Superior Model		MOPM	CMOPM	MOPMHM	CMOPMHM

N = Number of observations, K = Number of estimated parameters, $LL(0)$ = log-likelihood with constant only, $LL(\beta)$ = log-likelihood at convergence. OPM: Ordered Probit Model. MOPM: Mixed-Ordered Probit Model. CMOPM: Correlated Mixed-Ordered Probit Model. MOPMHM: Mixed-Ordered Probit Model with Heterogeneity in Means. CMOPMHM: Correlated Mixed-Ordered Probit Model with Heterogeneity in Means.

The results of the Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM), as shown in Table 4, reveal several significant factors influencing EV adoption intentions in Thailand. In terms of demographics, individuals aged 25–34 years old (coefficient = 0.727) and 45–54 (coefficient = 0.365) showed a higher likelihood of intending to adopt EVs compared to the reference age group (above 55 years). Similarly, government officers (coefficient = 0.205), private company officers (coefficient = 0.455), and students (coefficient = 1.993) displayed a greater propensity for EV adoption compared to other occupational categories. Identifying as a driver (coefficient = 0.166) was also positively associated with higher EV adoption intentions. Conversely, owning conventional ICE vehicles (coefficient = −2.773), HEVs (coefficient = −2.421), or PHEVs (coefficient = −2.431) was associated with a significantly lower likelihood of intending to adopt EVs. Residing or traveling in rural areas (coefficient = −0.295) also negatively impacted EV adoption intentions.

Table 4. Model results using the best model specification CMOPMHM.

Variables	Coefficient	t-Stat	Marginal Effect		
			Low	Neutral	High
Threshold μ	1.334	35.69			
Fixed-effect parameters					
Constant	−2.444	−8.55			
AGE_25	0.542	3.6	−0.0986	0.0023	0.0963
AGE25_34	0.727	5.96	−0.1395	0.0188	0.1207
AGE45_54	0.365	2.93	−0.0658	0.0037	0.0621
OCC_1	0.205	2.14	−0.0382	0.0036	0.0345
OCC_2	0.455	5.47	−0.0855	0.0090	0.0766
OCC_5	1.993	12.39	−0.2767	−0.1007	0.3774
DRIVER	0.166	2.89	−0.0315	0.0044	0.0270
ICE	−2.773	−37.37	0.4333	0.1056	−0.5389
HEV	−2.421	−26.28	0.3991	−0.0379	−0.3612
PHEV	−2.431	−28.64	0.3692	−0.0197	−0.3494
TRAVEL_L	−0.295	−5.43	0.0556	−0.0078	−0.0478
NATURE1	0.078	2.43	−0.0147	0.0019	0.0129
ENV_IND1	0.101	3.19	−0.0191	0.0024	0.0167
ENV_IND3	0.140	4.14	−0.0266	0.0034	0.0232
NAT_EX1	0.055	1.76	−0.0104	0.0013	0.0091
ADOP1	0.053	2.26	−0.0101	0.0013	0.0088
ADOP2	0.048	2.21	−0.0091	0.0012	0.0080
ADOP3	0.107	4.85	−0.0203	0.0026	0.0177
TRIAL1	0.066	2.23	−0.0125	0.0016	0.0109
TRIAL3	0.067	2.3	−0.0127	0.0016	0.0111
Random parameters					
AGE35_44	0.502	1.58	−0.0909	0.0065	0.0844
SD of Parameter Density Function	0.656	65.11			
EDU_3	1.332	4.96	−0.2182	−0.0226	0.2407
SD of Parameter Density Function	0.279	64.39			
Heterogeneity in means					
EDU_3: HOME_LO	0.352	3.22			
EDU_3: ENV_IND2	−0.151	−3.05			
EDU_3: TRIAL2	−0.119	−2.5			

Diagonal and off-diagonal matrix [t-stats], and correlation coefficients (in parenthesis)		
	AGE35_44	EDU_3
AGE35_44	0.656 [12.91] (1.000)	–
EDU_3	0.186 [3.82] (0.667)	0.208 [3.82] (1.000)

Table 4. *Cont.*

Variables	Coefficient	t-Stat	Marginal Effect		
			Low	Neutral	High
Model Statistic					
LL(0)	−4328.846				
LL(β)	−2517.780				
R^2	0.418				
$R^2{}_c$	0.407				
AIC	5135.560				
AIC_c	5136.850				

The potential correlations between age and other demographic and occupational variables were carefully considered in the model specification. Age was treated as a random parameter to allow for individual-specific variations in its effect on EV adoption intentions. Heterogeneity in the means of this random parameter was tested with respect to other demographic and occupational variables. Occupation was sub-categorized into several groups (e.g., government officers, private company officers, private business owners) to capture more nuanced effects. Interaction terms between age and occupation categories were also tested. The final model specification presented here represents the best balance between capturing relevant correlations and maintaining model parsimony and interpretability. The correlation matrix of the random parameters (Table 4) provides insights into the relationships between these variables in the context of EV adoption intentions.

Psychographic factors also played a significant role. Respondents with a stronger personal connection to nature (coefficient = 0.078), a strong environmental identity (coefficient = 0.101), and who actively take actions to reduce greenhouse gas emissions (coefficient = 0.140) demonstrated a higher likelihood of intending to adopt EVs.

These findings align closely with key concepts from innovation diffusion theory (IDT). The higher likelihood of EV adoption among younger adults (25–34 and 45–54 age groups) reflects IDT's concept of early adopters. The positive influence of environmental values (NATURE1-3, ENV_IND1-3) on EV adoption intentions demonstrates the perceived relative advantage of EVs as an environmentally friendly option, as well as their compatibility with individuals' values. The association between openness to new technologies (ADOP1-3) and EV adoption intentions aligns with IDT's concept of complexity, suggesting that those more comfortable with new technologies perceive EVs as less complex. The importance of being able to try new technologies before adoption (TRIAL1-3, with coefficients = 0.066 and 0.067 for TRIAL1 and TRIAL3) directly relates to IDT's concept of trialability. Additionally, the influence of social networks on technology adoption (SOCIAL1-3) aligns with IDT's concept of observability, highlighting the role of social influence in the adoption process. These connections between our findings and IDT provide a theoretical framework for understanding the factors driving EV adoption intentions in Thailand.

The model identified two random parameters: age (35–44) and education level (high vocational). This indicates that the effect of these variables on EV adoption intentions varies across individuals. For example, while the average effect of being in the 35–44 age group on EV adoption intention is positive (coefficient = 0.502), the standard deviation of the parameter density function (0.656) suggests considerable individual variation around this average. Similarly, while a high vocational education level generally has a positive effect on EV adoption intentions (coefficient = 1.332), the effect can vary considerably across individuals (standard deviation = 0.279).

Furthermore, the model revealed heterogeneity in the means for the random parameter "education level (high vocational)". This means that the average effect of having a high vocational education level on EV adoption intentions is influenced by other factors. Specifically, residing in a rural area (coefficient = 0.352), having strong environmental values (coefficient = −0.151), and valuing the ability to try new technologies before adoption (coefficient = −0.119) all affect the average effect of high vocational education on EV adoption intentions.

6. Discussions

6.1. Fixed Parameters

The results of the Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM), as shown in Table 4, reveal several significant factors influencing EV adoption intentions in Thailand. Examining the marginal effects, which represent the change in probability of intending to adopt an EV associated with a one-unit change in the independent variable, allows for a nuanced understanding of these relationships.

In terms of demographics, individuals aged 25–34 years old (marginal effect = 0.1207) and 45–54 years old (marginal effect = 0.0621) exhibit a higher probability of intending to adopt EVs compared to the older reference group (above 55 years). This aligns with the notion that younger individuals are often early adopters of new technologies and might be more open to EVs [58]. Furthermore, those identifying as drivers (marginal effect = 0.0270) demonstrate a greater inclination toward EV adoption, possibly reflecting a heightened awareness of the benefits and challenges associated with EVs. Interestingly, owning an ICE, HEV, or PHEV vehicle is significantly associated with a decreased likelihood of intending to adopt EVs, with marginal effects of −0.5389, −0.3612, and −0.3494, respectively. This might suggest satisfaction with existing vehicles, concerns about the range and charging infrastructure for EVs, or a lack of awareness regarding the advantages of fully electric technology [59]. Government officers (marginal effect = 0.0345), private company officers (marginal effect = 0.0766), and students (marginal effect = 0.3774) display a greater propensity for EV adoption compared to other occupational categories. This might reflect their socio-economic status, access to information, and potentially greater exposure to EV initiatives [60]. Government officers might be influenced by pro-EV policies, while private company officers and students might be more attuned to technological advancements and sustainability trends [61].

Residing or traveling in rural areas also has a negative association with EV adoption intentions (marginal effect = −0.0478). This likely stems from the limited charging infrastructure in rural areas, concerns about the suitability of EVs for longer driving distances and rural road conditions, and potentially lower exposure to EV promotion and information campaigns [26]. The analysis also confirms the positive influence of environmental values on EV adoption intentions. Individuals with a stronger personal connection to nature (marginal effect = 0.0129), a strong sense of environmental responsibility (marginal effect = 0.0167), and who actively take actions to reduce greenhouse gas emissions (marginal effect = 0.0232) exhibit a greater likelihood of intending to adopt EVs. This underscores the importance of highlighting the environmental benefits of EVs to resonate with environmentally conscious consumers [62]. Furthermore, individuals who are regularly exposed to and affected by the natural environment (marginal effect = 0.0091) are more likely to be drawn to EVs as a cleaner transportation option. This could reflect a heightened awareness of the impact of human activities on the environment [45].

Furthermore, the ability to try new technologies before making a purchase decision emerges as a significant driver of EV adoption intentions (marginal effect = 0.0109). This emphasizes the need for strategies that enhance the trialability of EVs, such as test drive events, rental programs, and showcasing EVs in public spaces [63]. Providing opportunities for potential users to experience the benefits and address their concerns firsthand can significantly increase their willingness to consider EV adoption. Individuals who self-identify as early adopters of new technologies (marginal effect = 0.0088) exhibit a greater likelihood of intending to adopt EVs, reflecting their openness to innovation [3].

6.2. Random Parameters, Heterogeneity in Means and Diagonal and Off-Diagonal Matrix

The model identified two random parameters: age (35–44 years old; Figure 2) and education level (high vocational). This indicates that the effect of these variables on EV adoption intentions varies across individuals. For example, while the average effect of being in the 35–44 age group on EV adoption intention is positive (coefficient = 0.502), the standard deviation of the parameter density function (0.656) suggests considerable individual variation around this average. Similarly, while a high vocational education level generally has a positive effect on EV adoption intentions (coefficient = 1.332), the effect can vary considerably across individuals (standard deviation = 0.279).

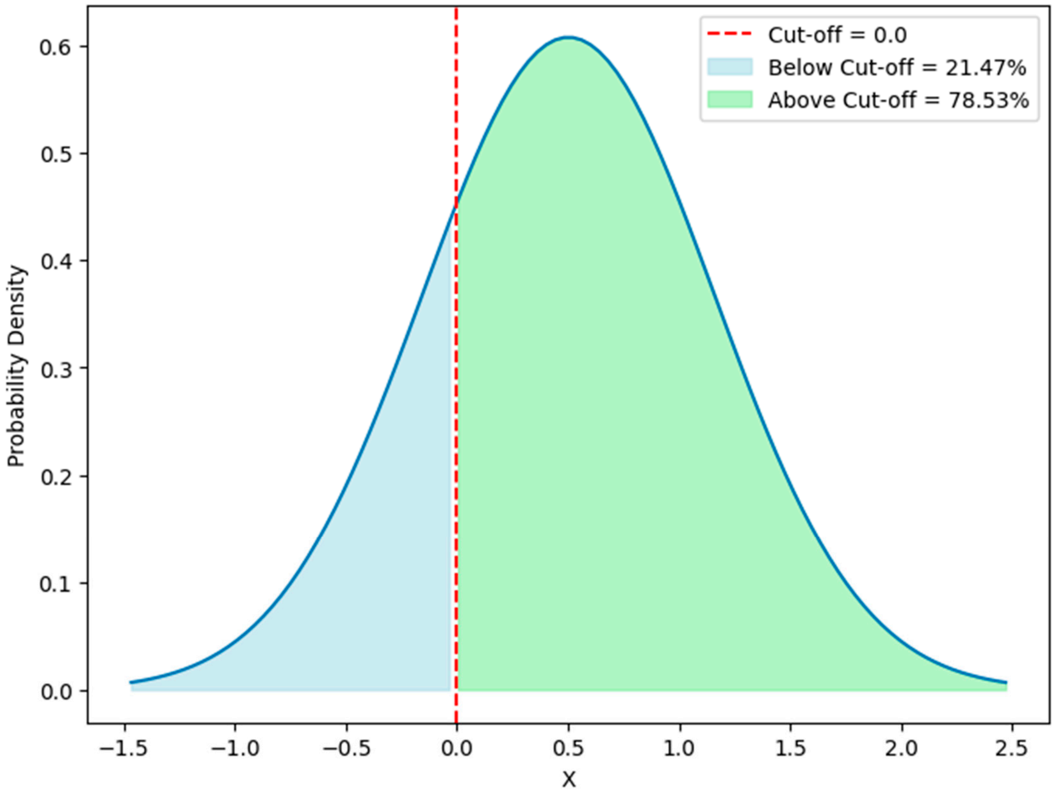

Figure 2. Distributional split the random parameters AGE35_44.

Furthermore, the model revealed heterogeneity in the means for the random parameter "education level (high vocational)". This means that the average effect of having a high vocational education level on EV adoption intentions is influenced by other factors. Specifically, residing in a rural area (coefficient = 0.352), having strong environmental values (coefficient = −0.151), and valuing the ability to try new technologies before adoption (coefficient = −0.119) all affect the average effect of high vocational education on EV adoption intentions. These findings highlight the complex interplay of demographic, attitudinal, and contextual factors in shaping individual EV adoption decisions.

The positive correlation between the random parameters (0.667) indicates that individuals for whom age (35–44 years old) has a stronger positive effect on EV adoption intentions are also more likely to be positively influenced by having a high vocational education level. This suggests a potential interaction between these factors, where both age and education level contribute to a greater openness to EV adoption.

7. Conclusions and Policy Implications

This study aimed to understand the electric vehicle (EV) adoption intentions in Thailand, moving beyond traditional models by incorporating a sophisticated econometric approach and a comprehensive set of explanatory variables. The research sought to identify the key factors driving EV adoption intentions, quantify their relative importance, and uncover the heterogeneity in user preferences to provide valuable insights for policymakers, EV manufacturers, and researchers. This study makes a significant contribution to the existing literature by employing a Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM) to analyze EV adoption intentions in Thailand, incorporating both demographic factors and psychographic factors derived from Environmental psychology and innovation diffusion theory.

After model comparisons, the three-categorical level CMOPMHM emerged as the best-fitting model, providing a nuanced understanding of the factors affecting EV adoption intentions. The model revealed that younger age groups, specific occupations, and identifying as a driver were positively associated with higher EV adoption intentions. Conversely, owning a conventional ICE, HEV, or PHEV vehicle, as well as residing or traveling in rural areas, significantly decreased the likelihood of intending to adopt EVs. Furthermore, the study highlighted the positive influence of environmental values, including a personal connection to nature, environmental identity, and pro-environmental actions, on EV adoption intentions. The importance of trialability was also emphasized, suggesting that providing opportunities for potential users to experience EVs firsthand can significantly increase their willingness to consider adoption.

The Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM) revealed several key insights. Younger adults, particularly those aged 25–34 years old (marginal effect = 0.1207) and 45–54 (marginal effect = 0.0621), showed a significantly higher probability of EV adoption compared to older age groups. Occupational influence was evident, with government officers, private company officers, and students displaying a greater propensity for EV adoption. Current vehicle ownership significantly impacted adoption intentions, with owners of conventional ICE vehicles, HEVs, or PHEVs less likely to consider EVs. A notable rural-urban divide was observed, with rural residency or travel negatively impacting EV adoption intentions. Environmental values, including strong environmental identity and active engagement in reducing greenhouse gas emissions, positively influenced EV adoption intentions. Early adopters of new technologies and those valuing the ability to try new technologies before adoption showed higher likelihoods of intending to adopt EVs. The CMOPMHM approach uncovered significant heterogeneity in preferences, particularly for the 35–44 age group and those with high vocational education. The random parameter for the 35–44 age group (coefficient = 0.502, standard deviation = 0.656) indicated considerable variation in this group's EV adoption intentions. For those with high vocational education, the heterogeneity in means revealed that rural residency, environmental values, and trialability all influenced the effect of education on EV adoption intentions. This highlights the complex interplay of factors affecting EV adoption and underscores the need for nuanced, targeted approaches in policy and marketing strategies.

These findings offer valuable guidance for policymakers and EV marketers seeking to design effective strategies to promote wider EV adoption. Policy interventions should consider targeted incentives tailored to specific demographic groups, particularly those demonstrating a higher propensity for EV adoption. For example, the substantial marginal effects associated with students (0.3774) and private company officers (0.0766) suggest that these groups could be effectively targeted with tailored incentive programs, such as reduced tuition fees for students who purchase EVs or preferential loan rates for EV purchases by private company employees. Expanding public charging infrastructure in urban areas while simultaneously investing in charging networks along major highways and in rural communities is crucial to address the range anxiety associated with EVs and cater to the needs of rural residents (who exhibited a negative marginal effect of -0.0478).

Furthermore, communication strategies should leverage the positive influence of environmental values on EV adoption intentions. Public awareness campaigns can effectively highlight the environmental benefits of EVs, such as reduced greenhouse gas emissions and improved air quality, to resonate with environmentally conscious consumers, who demonstrated a strong connection to nature (marginal effect = 0.0129) and a strong sense of environmental responsibility (marginal effect = 0.0167). Collaborative efforts between government agencies and EV manufacturers can foster the development of innovative trialability programs, such as expanded test drive events, short-term rental programs, and interactive EV showcases in public spaces. These initiatives can address the concerns of individuals who value the ability to try new technologies before adoption (marginal effect = 0.0109) and provide a firsthand experience of the benefits and practicality of EVs.

The insights derived from our Correlated Mixed-Ordered Probit Model with Heterogeneity in Means (CMOPMHM) offer valuable guidance for policymakers and industry stakeholders seeking to promote EV adoption in Thailand. However, translating these insights into real-world applications comes with both opportunities and challenges. The model's ability to capture preference heterogeneity allows for more nuanced, demographic-specific policies, such as tailored incentives for the 25–34-year-old and 45–54-year-old age groups who show higher EV adoption intentions. The negative impact of rural residency on EV adoption intentions highlights the need for strategic charging infrastructure expansion in rural areas. The strong influence of environmental values suggests that EV marketing campaigns emphasizing environmental benefits could be particularly effective. Additionally, the positive impact of technology adoption tendencies indicates that programs enhancing general technological literacy could indirectly boost EV adoption. The significance of trialability suggests that expanding opportunities for potential adopters to experience EVs firsthand could significantly impact adoption rates.

Despite these practical implications, implementing such a sophisticated model faces several challenges. Collecting extensive, high-quality data on a regular basis for real-time decision-making can be resource-intensive and logistically challenging. The complexity of the CMOPMHM may make it difficult for non-technical stakeholders to interpret and apply the results, potentially limiting its practical use in policy-making processes. The rapidly evolving EV market necessitates frequent updating of the model's parameters to remain relevant, which could be time-consuming and costly. While our model provides insights specific to Thailand, its applicability to other markets may be limited due to cultural, economic, and infrastructural differences. Developing targeted policies and programs based on the model's insights may require significant financial investments, which could be challenging in resource-constrained environments. Collecting the detailed individual-level data required for such models may raise privacy concerns, necessitating careful data management practices. Balancing the model's complexity with actionable insights presents a significant challenge in translating theoretical findings into simple, implementable policies without losing critical details.

Addressing these challenges will require close collaboration between researchers, policymakers, and industry stakeholders. Regular model updates, simplified interpretation tools, and pilot programs to test model-derived strategies could help bridge the gap between theoretical insights and practical application. Despite these challenges, the rich insights provided by the CMOPMHM offer a valuable foundation for developing more effective, targeted strategies to accelerate EV adoption in Thailand and potentially in similar markets.

While this study provides valuable insights into EV adoption intentions in Thailand, it is essential to acknowledge its limitations. The study focused solely on individual intentions and did not consider other factors that might influence actual EV adoption, such as vehicle affordability, charging infrastructure availability, and government policies. Future research could explore these factors in greater depth and investigate the relationship between intentions and actual adoption behavior. Despite the valuable insights provided by the current findings, the data collection method at gas stations with EV charging facilities may potentially introduce some degree of individual selection bias. Future research could benefit from expanding data collection methods to include a broader range of respondents and locations, further enhancing the generalizability of the findings.

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Data Availability Statement: Data available on request due to restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Questionnaire

Factors affecting the decision to use electric vehicles in Thailand			
The purpose of this questionnaire is to survey factors that impact the decision to use electric vehicles in Thailand. The aim is to analyze various factors that influence the choice of electric vehicles.			
Please mark √ in front of the answer or score box that matches your opinion.			
Section 1 General information of respondents and travel behavior data			
(1.1) Gender	❍ Male	❍ Female	
(1.2) Age	❍ Less than 25 years old ❍ 45–54 years old	❍ 25–34 years old ❍ 55 years old and above	❍ 35–44 years old
(1.3) Highest education level	❍ Primary school ❍ Bachelor's degree	❍ High school/Vocational certificate ❍ Master or Doctoral	❍ Associate degree/Higher vocational certificate
(1.4) Occupation	❍ Government officer ❍ Agriculturist	❍ Private company officer ❍ Students	❍ Private business ❍ General employees
(1.5) Current residence	❍ Rural	❍ Urban	
(1.6) Are you always the driver when traveling?	❍ No	❍ Yes	
(1.7) Current engine type	❍ Internal combustion engine ❍ 100% electric (battery electric vehicle)	❍ Hybrid	❍ Plug-in hybrid
(1.8) Current vehicle type	❍ Pickup truck ❍ PPV	❍ Personal car ❍ MPV	❍ SUV
(1.9) Area of most frequent driving	❍ Urban	❍ Rural	
(1.10) Chance that you will decide to buy an electric vehicle in the future	❍ 0% ❍ 60%	❍ 20% ❍ 80%	❍ 40% ❍ 100%

Section 2 Environmental psychology and innovation diffusion theory								
	Questionnaire item	**Level of agreement**						
		Strongly agree <--> strongly disagree						
		7	**6**	**5**	**4**	**3**	**2**	**1**
Environmental psychology								
	Personal connection to nature							
2.1	I personally feel connected with nature and the environment.	7	6	5	4	3	2	1
2.2	Environmental conservation is important to me.	7	6	5	4	3	2	1
2.3	Spending time in nature is a meaningful experience for me.	7	6	5	4	3	2	1
	Environmental identity							
2.4	Being environmentally responsible is part of my identity.	7	6	5	4	3	2	1
2.5	I tend to consider the environmental impact when making decisions.	7	6	5	4	3	2	1
2.6	I take actions to reduce the impact of greenhouse gas emissions.	7	6	5	4	3	2	1
	Nature exposure							
2.7	Being regularly affected by the natural environment influences my feelings.	7	6	5	4	3	2	1
2.8	I familiarize myself with nature for its health benefits.	7	6	5	4	3	2	1
2.9	Nature affects my tranquility and influences my decisions.	7	6	5	4	3	2	1
Innovation diffusion theory								
	Adopter categories							
2.10	I tend to be an early adopter of new technologies.	7	6	5	4	3	2	1
2.11	I prefer to wait for technology to mature before using it.	7	6	5	4	3	2	1
2.12	I often adopt new technologies before they become widely known.	7	6	5	4	3	2	1
	Trialability							
2.13	I am more likely to use new technology if I can try it first.	7	6	5	4	3	2	1
2.14	My readiness to try new technology is influenced by how easy it is to experiment with.	7	6	5	4	3	2	1
2.15	I am open to experimenting with new technology before making a decision.	7	6	5	4	3	2	1
	Social network influence							
2.16	The opinions from my social network play a role in my adoption of new technology.	7	6	5	4	3	2	1
2.17	I consider the experiences and advice from my friends and family.	7	6	5	4	3	2	1
2.18	Conversations within my social circle affect my decision to try new technology.	7	6	5	4	3	2	1

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