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# How value, cost, and emotions drive electric motorcycle adoption in Vietnam: A cognitive–affective–conative approach

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ABSTRACT

Urban transportation in Vietnam, dominated by fossil fuel-powered motorbikes, is causing severe air pollution, contributing to climate change, and posing a threat to public health. In response to these challenges, promoting the transition from traditional motorbikes to electric motorcycles (EMs) is considered a sustainable transportation solution, aligning with the global trend toward green development. However, to expand market share and enhance the acceptance of electric motorcycles, a deeper understanding of consumer perception and behavior is essential. This study aims to develop and test a research model based on the cognitive–affective–conative framework. Data collected from 506 conventional motorbike users in Vietnam were analyzed using the SEM method. The study employs a second-order model, grounded in the cognitive–affective–conative framework, to evaluate the relationship between perceived value and perceived cost with the intention to use electric motorcycles, mediated by the role of anticipated emotions. The findings clarify the role of perceived value and perceived cost in shaping customers' anticipated emotions, which significantly influence their intention to switch to electric motorcycles. These insights not only provide valuable information for manufacturers and policymakers but also contribute to shaping development and marketing strategies for electric motorcycles in the future.

## 1. Introduction

Environmental degradation represents one of the most pressing challenges facing the world today, driven by a combination of global and regional factors. In addition to water and air pollution, biodiversity loss, and land degradation, climate change has become a severe threat to sustainable development (Ahmad et al., 2012). In particular, the rapidly increasing consumption of fossil fuels in industry and transportation has exacerbated this issue over the past decades. The negative impacts of climate change have resulted in substantial economic, social, and environmental losses worldwide (Wang et al., 2021; Young et al., 2010). The transportation sector currently accounts for approximately 60 % of global oil consumption and contributes around 25 % of total $CO_2$ emissions (Singh et al., 2014). Among its subsectors, road transport is responsible for nearly 80 % of energy consumption and generates about 10 % of the greenhouse gas emissions from the entire transportation industry (Obrecht et al., 2018). In Asia, the transportation sector accounts for 49.90 % of oil consumption and 8.40 % of $CO_2$ emissions (Phuong et al., 2024). In countries with high motorcycle dependency, such as Vietnam, fossil fuel-powered two-wheelers dominate the market (Huu & Ngoc, 2021) and contribute substantially to localized air pollution.

Air pollution has emerged as a critical concern in Vietnam. Several Vietnamese cities, such as Hanoi and Ho Chi Minh City, are consistently ranked among the most polluted cities globally in terms of air quality, with hazardous levels of fine particulate matter (PM2.5), posing severe risks to public health and urban sustainability. According to Ho et al. (2023), it is estimated that air pollution contributes to approximately

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70,000 fatalities annually and shortens the average life expectancy by 1.4 years. The Ministry of Transport (MoT) reported in 2024 that the transportation sector accounts for about 18 % of the country's total greenhouse gas emissions. Without appropriate measures, these emissions are projected to increase significantly, reaching around 64.3 million tons of $CO_2$ by 2025 and 88.1 million tons by 2030 (Trung et al., 2025). As a result, the Vietnamese government is implementing an action plan to transition the entire transportation system to green energy by 2050, aiming to achieve net-zero emissions (Mai et al., 2023). Therefore, the shift from internal combustion engine motorbikes to electric motorcycles is considered a key measure to improve air quality and mitigate environmental degradation (Schuitema et al., 2013). Electric motorcycles produce zero emissions during operation, helping to reduce greenhouse gas emissions and improve air quality in urban areas (Bonisoli et al., 2024). However, this transition has yet to yield substantial results, as the adoption rate of electric motorcycles remains relatively limited. As of 2024, more than 3 million electric bicycles and motorcycles are in use across Vietnam, with electric motorcycle penetration surpassing 10 % (B&Company, 2024). Therefore, in-depth research, particularly on consumer perceptions (Nguyen-Phuoc et al., 2023; Nguyen-Phuoc, Su, et al., 2025; Schuitema et al., 2013), is essential to uncover the underlying drivers and barriers to electric motorcycle adoption. Such knowledge is critical not only for bridging the gap between policy ambitions and actual consumer behavior but also for designing targeted interventions and policies that can accelerate the transition toward sustainable mobility.

Currently, research on consumers' intentions to adopt electric motorcycles has been attracting growing scholarly attention worldwide. Among these studies, factors from the technology acceptance model (TAM), such as perceived ease of use and perceived usefulness, have been successfully linked with the intention to use an electric motorcycle (Ho & Wu, 2021; Su et al., 2023). Additionally, the theory of planned behavior (TPB) has also been widely applied in research on electric motorcycles adoption (Aditya et al., 2024; Dewi & Susanti, 2023). Factors such as attitudes, subjective norms, and perceived behavioral control have been found to significantly influence the intention to use electric motorcycles (Aditya et al., 2024; Nguyen-Phuoc et al., 2023). These factors help clarify how consumers evaluate benefits, behavioral control, and social expectations when transitioning to environmentally friendly vehicles. Extending beyond these frameworks, Chen et al. (2021) applied behavioral reasoning theory (BRT) to capture both enabling and inhibiting factors, showing that such reasoning processes directly shape consumers' adoption intentions.

Although research on electric motorcycle adoption has expanded considerably, existing studies often treat perceived value and perceived cost in a narrow or implicit manner, typically embedding them within broader constructs such as perceived usefulness or perceived behavioral control (e.g., Ho and Wu (2021), Nguyen-Phuoc et al. (2024)). As a result, the multidimensional nature of these factors remains underexplored, and their simultaneous role in shaping adoption intentions has received limited empirical attention. Moreover, prior studies have predominantly emphasized cognitive determinants, while overlooking the affective mechanisms, particularly anticipated emotions, through which consumers translate evaluations of value and cost into behavioral intentions. To address this gap, the present study develops an integrated model that conceptualizes perceived value and perceived cost as second-order constructs, and employs the cognitive–affective–conative (CAC) framework as its theoretical foundation. Specifically, the study focuses on how perceived value and perceived cost (cognition) influence anticipated emotions and attitude (affect), which in turn shape behavioral intention (conation). This approach enables a more comprehensive examination of how cognitive appraisals interact with affective responses to influence the intention to adopt electric motorcycles, thereby advancing theoretical understanding and offering actionable insights for policymakers and industry stakeholders. The specific objectives of this study are to:

- Develop and test an integrated model that conceptualizes perceived value and perceived cost as second-order constructs in explaining consumers' intention to adopt electric motorcycles.
- Apply the cognitive–affective–conative (CAC) framework to examine how cognitive evaluations of value and cost influence adoption intention through the mediating role of affective responses, particularly anticipated emotions.
- Contribute to both theory and practice by advancing understanding of consumer behavior in sustainable transport adoption and providing insights for policymakers and industry stakeholders in promoting electric motorcycles, especially in emerging economies.

The remainder of this paper is structured as follows. Section 2 presents the theoretical background and research hypotheses. Section 3 outlines the research methodology, including survey design, data collection, and analytical procedures. Section 4 reports the results, followed by Section 5, which discuss the theoretical and practical implications and the study's limitations. Finally, Section 6 concludes with a summary of the key findings and directions for future research.

## 2. Theoretical background and research hypotheses

### 2.1. Theoretical background

The cognitive–affective–conative framework is a model used in psychology and behavioral sciences to explain how people think, feel, and behave. It has been applied in various fields, especially in business, to understand decision-making processes. Several studies have used this theoretical framework as a foundation to explain consumers' cognitive and emotional processing and purchasing behavior (Lim & Kim, 2020). Kim et al. (2013) confirmed the relationship between user interaction motivation (cognitive), perceived value (affective), and satisfaction (conative) in the mobile environment. Ahn and Kwon (2020) applied the proposed model to examine the relationship between cognitive evaluation (i.e., perceived cost and perceived value), affective response (i.e., positive/negative anticipated emotions and attitudes), and conative formation (behavioral intention). Currently, the application of the cognitive–affective–conative framework in transport research remains limited. Some notable studies, such as that of Chen and Tseng (2010), have used this framework to explore the relationship between service quality and passenger loyalty to airport contexts. This limited application in the transport sector presents an opportunity to broaden the analytical tools available for understanding travel behavior, particularly by applying the cognitive–affective–conative framework to emerging modes such as electric motorcycles.

While theoretical models such as the theory of planned behavior (TPB), the unified theory of acceptance and use of technology (UTAUT), and the value–belief–norm theory (VBN) have been widely used to examine consumer behavior toward green mobility, they have limitations in capturing the emotional dynamics of decision-making. For instance, TPB focuses primarily on rational factors such as attitude, subjective norms, and perceived behavioral control, but does not explicitly account for anticipated emotions, which are increasingly recognized as influential in pro-environmental behavior. Similarly, UTAUT is technology-centric and tends to overlook affective components, while VBN emphasizes moral norms but underrepresents the cognitive cost-benefit evaluation from the consumer's perspective. In contrast, the cognitive–affective–conative (CAC) framework offers a more holistic structure by integrating cognition (e.g., perceived value and cost), affect (e.g., anticipated emotions and attitude), and conation (e.g., behavioral intention) (see Fig. 1). This layered structure is particularly well-suited for the current study, which aims to explore how value and cost perceptions influence both emotional responses and the intention to adopt electric motorcycles in an emerging economy context. Thus, the adoption of the CAC framework is not only novel but also theoretically justified and contextually relevant.

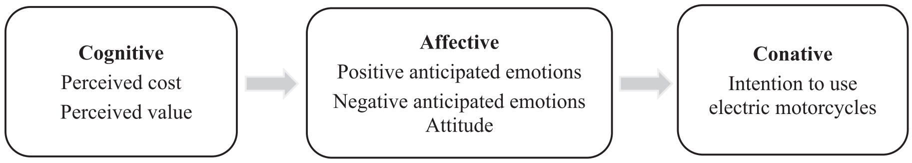


**Fig. 1.** The cognitive–affective–conative framework.

## 2.2. Research hypotheses

### 2.2.1. Cognitive

Perceived value is defined as the customer's overall assessment of the usefulness of a product or service based on their perception of what is received (benefits) and what is given up (sacrifices) (Boksberger & Melsen, 2011). Sheth et al. (1991) introduced a five-dimensional value model, including economic value, hedonic value, social value, altruistic value, and functional value, which serves as an important foundation for developing perceived value measurement scales. In the context of green consumption, Koller et al. (2011) analyzed the components of perceived value, including functional value, economic value, social value, and hedonic value, to determine their impact on consumer loyalty. Similarly, in the context of online shopping, Zhang et al. (2021) applied functional value, hedonic value, and social value to assess purchase intention. Based on this theoretical foundation, the present study considers perceived value as a second-order construct, formed by the first-order constructs of economic value, hedonic value, social value, altruistic value, and functional value.

Previous studies have shown that perceived value influences decision-making before the purchase decision stage, as well as customer satisfaction and behavioral intention in the post-purchase evaluation stage (Parasuraman & Grewal, 2000). However, customers may feel an increased level of trust and develop a positive attitude toward a product through search efforts, as it saves them time and reduces perceived risk (Harridge-March, 2006). The perceived value of such customers has been found to be a strong determinant of their attitude toward shopping. Therefore, this study will delve into how perceived value influences customer attitudes toward electric motorcycles in the current market context. It will examine different aspects of perceived value. Perceived value of specific events (e.g., perceptions of service related to restaurant consumption) triggers certain emotions, which in turn affect consumer behavior, following the cognitive–affective–conative framework. That is, higher (or lower) levels of perceived value evoke more positive (or negative) emotions and vice versa (Song & Qu, 2019). According to Ahn and Kwon (2020) the perceived value of green hotel customers significantly and positively influences their anticipated emotions. Given that positive anticipated emotion is typically triggered by expected success and negative anticipated emotion by expected failure, perceived value is expected to enhance positive anticipated emotion while reducing negative anticipated emotion. To explore customers' intention to use electric motorcycles, this study will examine how perceived value influences anticipated emotions and customer attitudes.

**H1.** Perceived value has a significant and positive direct impact on positive anticipated emotion.

**H2.** Perceived value has a significant and positive direct impact on attitude.

**H3.** Perceived value has a significant and negative direct impact on negative anticipated emotion.

Perceived cost refers to the costs imposed on customers in manufacturing or service companies, whether monetary or non-monetary (time and effort). These costs should be integrated as perceived costs and subsequent costs, including perceived quality as well as other internal and external characteristics of the perceived service and product (Eftekhari et al., 2015). Four types of costs are considered to negatively affect the customer's green brand relationship: price, effort, evaluation costs, and performance risk (Ahn & Kwon, 2020). Among these, price is a particularly important factor in business research. For instance, in the field of online shopping, price has been identified as a key factor influencing customers' purchase intentions (Kim et al., 2012). Effort, a common element in cost perception, has been shown to impact individual decision-making, such as in the education sector. In the study by Zhang et al. (2023), effort significantly influenced students' school selection intentions. Evaluation costs, which involve the mental effort required to gather and analyze information to minimize uncertainty, have been identified in studies on green hotels (Burnham et al., 2003). Finally, performance risk reflects uncertainty regarding a product's functionality, particularly in the context of product innovation. This often leads to concerns that the product may not perform as expected after the trial phase (Gunawan et al., 2022).

In this study, perceived cost is defined as the extent to which an individual believes they have to incur costs when using a system (Kleijnen et al., 2004) argued that perceived cost negatively impacts an individual's attitude toward system usage. Furthermore, perceived cost negatively influences consumer attitudes, as cost considerations often become a priority when selecting a product. Additionally, perceived cost may have a significant negative impact on customers' positive anticipated emotion and a significant negative influence on their negative anticipated emotion (Papista & Krystallis, 2013). Therefore, we propose the following hypotheses:

**H4.** Perceived cost has a significant and negative direct impact on positive anticipated emotion.

**H5.** Perceived cost has a significant and negative direct impact on attitude.

**H6.** Perceived cost has a significant and positive direct impact on negative anticipated emotion.

### 2.2.2. Affective

Within the cognitive–affective–conative framework (Oliver, 1999), anticipated emotions are considered key determinants that bridge customers' cognitive evaluations and their subsequent behavioral responses. These emotional responses, formed prior to the actual experience, play a central role in shaping attitudes and behavioral intentions. In the context of hospitality and tourism, a growing body of research has highlighted how both positive anticipated emotions (e.g., pride, satisfaction) and negative anticipated emotions (e.g., guilt, regret) significantly influence customer behavior (Ahn & Back, 2018; Back & Parks, 2003). This is particularly evident in sustainable services, where emotional expectations directly impact how customers perceive and engage with eco-friendly options. Specifically, the study by Han et al. (2011) found that positive anticipated emotion has a direct and positive relationship with revisit intention, whereas negative anticipated emotion exerts a negative effect, making customers less likely to continue using green hotel services. These findings suggest that emotions are not merely peripheral reactions but fundamental drivers that shape decision-making processes in service contexts related to sustainable development.

**H7.** Positive anticipated emotion has a positive impact on attitude.

**H8.** Positive anticipated emotion has a positive impact on the intention to adopt electric motorcycles.

**H9**. Negative anticipated emotion has a negative impact on attitude.

**H10**. Negative anticipated emotion has a negative impact on the intention to adopt electric motorcycles.

Attitude is defined as the overall evaluation an individual makes regarding the performance of a specific behavior (Ajzen, 1991). It is a crucial factor that reflects how a person perceives and assesses a behavior based on the outcomes they expect. According to Sun et al. (2019), attitude is formed through the process of consumers evaluating and conceptualizing a specific behavior, which directly influences their preference and inclination toward a product or service. Yuen and Carter (2006) emphasized that attitude represents the evaluation of behavior based on expected outcomes, while De Groot and Steg (2007) indicated that a positive behavioral attitude is strongly associated with the intention to adopt that behavior. This means that when an individual holds a positive attitude toward a behavior, they are more likely to engage in that behavior.

In the context of research on the adoption of electric motorcycles, several studies have also confirmed that attitude plays a significant role in shaping consumers' intentions. For instance, Dutta and Hwang (2021) found that a positive attitude toward electric motorcycles significantly influences customers' intentions to accept and use this environmentally friendly mode of transportation.

**H11**. Attitude has a positive impact on the intention to adopt electric motorcycles.

#### *2.2.3. Conative*

In the model, intention represents the willingness to perform a behavior. It is defined as the plan or goal that an individual is determined to pursue (Gollwitzer & Oettingen, 2020). Fishbein and Ajzen (1977) also emphasized that intention reflects a person's readiness and commitment to engage in a specific behavior. Once activated, intention functions as an automatic mechanism, driving individuals toward a "must do" or "will do" state (Bagozzi et al., 1992). Currently, the intention to adopt green transportation solutions, particularly electric motorcycles, has attracted significant attention from researchers (Gunawan et al., 2022). Therefore, this study will explore the facilitating and inhibiting factors that influence the intention to use electric motorcycles based on the cognitive–affective–conative framework. With the goal of contributing to this field, the present study will focus on identifying factors that serve as either drivers or barriers to the intention to use electric motorcycles, grounded in the cognitive–affective–conative framework. Fig. 2 illustrates the developed conceptual model.

## 3. Research methodology

### *3.1. Survey design*

To test the proposed theoretical framework, the research team designed a standardized questionnaire consisting of three main sections. The first section provides a brief introduction to the study, including basic information such as the time and location of data collection, which was recorded by the research specialists to ensure transparency and accuracy. The core section focuses on measuring the key theoretical constructs using scales adapted from previous studies. Specifically, economic value was measured using four items referenced from Khurana et al. (2020) and Kim et al. (2018); hedonic value was assessed through three adjusted items from Ashraf et al. (2019); social value was measured using three items proposed by Higueras-Castillo et al. (2019) and Ahn and Kwon (2020); altruistic value was evaluated through three items developed from Ahn and Kwon (2020); and functional value was measured using three items based on Han et al. (2017). Price was assessed with three items referenced from Ahn and Kwon (2020) and (Burnham et al., 2003), effort was measured using three items from (Burnham et al., 2003), and evaluation costs were examined using three items from Hu et al. (2023). Attitude toward behavior was measured using four items, negative anticipated emotion through four items from Passafaro et al. (2014), positive anticipated emotion through four items referenced from Passafaro et al. (2014) and Perugini and Bagozzi

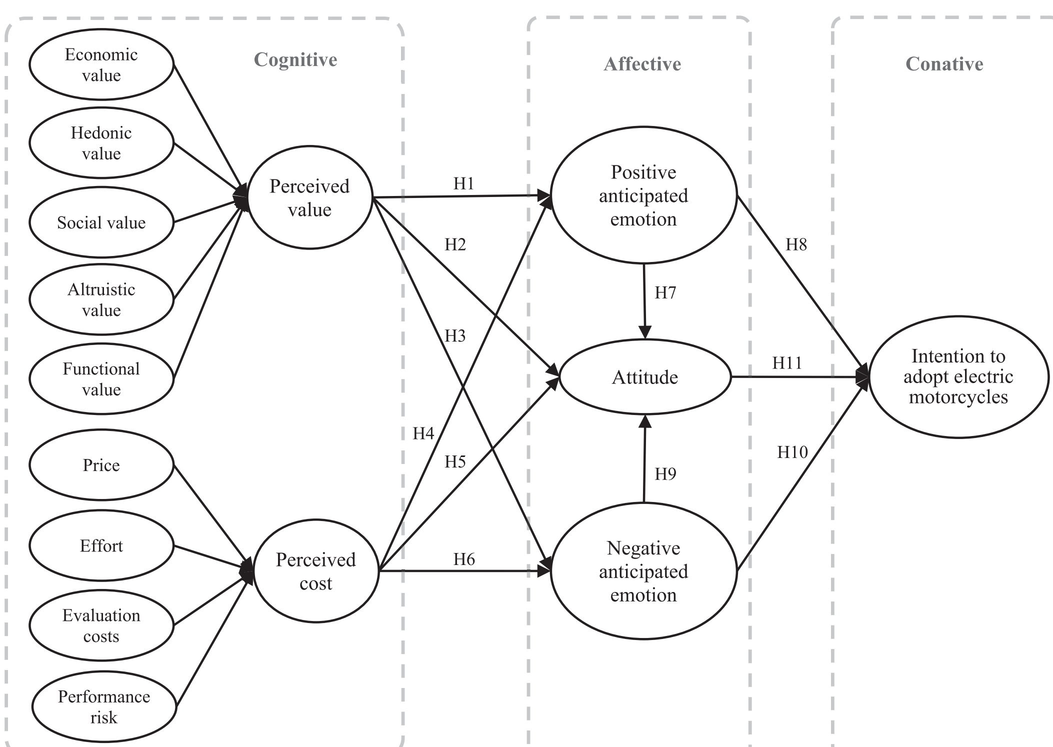


**Fig. 2.** Conceptual framework of the study.

(2001), and intention to use electric motorcycles using four items from Kang et al. (2019). All items were measured using a 7-point Likert scale.

The questionnaire development process was conducted meticulously. The initial English version was reviewed by experts in transportation and consumer behavior research for feedback and revisions. Subsequently, the questionnaire was translated into Vietnamese and tested on a random sample of 30 undergraduate students in Da Nang. Participant feedback primarily focused on wording, prompting the research team to refine the language for clarity and accuracy. After finalizing the revisions, the questionnaire received approval and was officially used for data collection.

### *3.2. Data collection*

The data for this study were collected from residents of Da Nang City, Vietnam. Da Nang was selected because it is one of the Vietnam's leading cities in piloting green transport policies, including incentives for electric motorcycle adoption. The city's high dependency on motorcycles makes it an ideal context to study shifts from conventional to electric two-wheelers. In addition, Da Nang's diverse socio-economic population provides meaningful insights into different adoption patterns. These factors make it a strategic and representative setting to explore electric motorcycle adoption in Vietnam's urban context. In this study, we employed a stratified random sampling approach to ensure the representativeness of the sample. The population was divided into strata based on age and gender, as these characteristics are fundamental demographic variables, widely available, and relatively easy to access. This approach allowed us to maintain proportionality with the population structure while improving the accuracy of the findings.

To maintain scientific rigor and minimize bias, the survey was conducted by a team of well-trained research assistants. Before the data collection process, they received detailed instructions on the research objectives, questionnaire content, and standard interaction protocols with participants. Participants were randomly approached in public locations (e.g., supermarkets, parks), informed about the objectives of the study, and subsequently invited to participate in the survey. Upon agreeing, they received the questionnaire along with supporting materials to record their responses and could request assistance from the research team at any time. To encourage participation and increase response rates, each participant received a small incentive (approximately US $1.30) upon completing the survey. To enhance representativeness, respondents' demographic profiles (i.e., gender and age group) were closely monitored during data collection. The sample distribution was continuously compared against the population proportions for gender and age reported in the 2019 Da Nang census. This procedure allowed real-time adjustments in recruitment, thereby preventing the overrepresentation or underrepresentation of specific demographic groups.

Additionally, research assistants were compensated based on the number of valid responses they collected, ensuring motivation and adherence to the research protocol. The survey targeted specific respondents, excluding individuals who already owned electric motorcycles. Before participating, all respondents were required to provide informed consent after receiving full details about the study. During the data collection period, over 600 responses were recorded, but only 557 were fully completed. Incomplete responses, where participants could not continue due to unforeseen reasons, were excluded. After data collection, a rigorous screening process was conducted to ensure data quality and reliability. This process included checking for completeness, eliminating inconsistent responses, and identifying outliers. Recent advances also highlight the importance of addressing potential data irregularities and outliers to strengthen the robustness of measurement models (Erkuş & Purutçuoğlu, 2021; Yerlikaya-Özkurt & Taylan, 2020). As a result, 21 responses were removed due to missing or inconsistent data, while another 30 were excluded as outliers. After the data cleaning phase, the final dataset consisted of 506 valid responses, which were used for further analysis.

### *3.3. Data analysis*

The covariance-based SEM approach (Jöreskog, 1978) and the variance-based partial least squares approach (Lohmöller & Lohmöller, 1989) are two commonly used methods in research. Understanding the differences between these two approaches is crucial when deciding which method to apply. CB-SEM is primarily used for confirming established hypotheses, meaning it is often applied in studies that build upon previous research models. In contrast, PLS is a prediction-oriented approach to SEM, mainly used for exploratory research but also suitable for confirmatory studies. Moreover, PLS-SEM is highly recommended for research that involves multiple constructs and aims to capture increasing complexity due to theoretical expansion.

This study is developed based on the cognitive–affective–conative framework to analyze the factors influencing consumers' intention to use electric motorcycles. The key factors considered include perceived value, perceived cost, along with customers' positive and negative anticipated emotions.

The PLS-SEM model analysis consists of two evaluation steps: assessing the measurement model and the structural model. To evaluate the measurement model, this study performed Confirmatory Composite Analysis to assess the composite measurement of theoretical constructs (Hair Jr, Hult, Ringle, Sarstedt, Danks, & Ray, 2021). For the structural model assessment, path coefficients were examined to evaluate the relationships between latent constructs. This serves as evidence to confirm or reject the proposed hypotheses. Details of the analytical process are presented in Fig. 3.

## 4. Results

### *4.1. Descriptive statistics*

Table 1 provides a detailed description of the characteristics of survey participants, including gender, occupation, age, marital status, education level, and monthly household income.

The gender distribution in the survey sample is relatively balanced, with 49.60 % male and 50.40 % female. Regarding marital status, 38.54 % of respondents were single, while the remaining participants were married. The age distribution shows that the 25–39 age group accounted for the highest proportion at 36.17 %, followed by the 40–54 age group (29.84 %) and the 16–24 age group (21.94 %). The 55 and above age group had the lowest proportion at only 12.06 %. In terms of education level, the majority of respondents held a university degree (55.39 %), followed by those who completed high school (23.52 %) and those with a college degree (10.47 %). Regarding monthly household income, 24.09 % of participants reported earning over 30 million VND, while 16.80 % had an income between 20 and 30 million VND. The proportion of respondents earning between 10 and 20 million VND was 29.45 %, while the remaining 20.55 % had a monthly income below 10 million VND. This table provides an overview of the demographic and economic profile of the surveyed participants, serving as a basis for further analysis.

### *4.2. Measurement model evaluation*

#### *4.2.1. First-order measurement model evaluation*

The measurement model was evaluated based on key criteria, including indicator loadings, internal reliability, convergent validity, and discriminant validity (see Table 2), following the guidelines of Hair Jr, Hult, Ringle, and Sarstedt (2021). The results indicate that most indicators had loadings exceeding the threshold of 0.708, ensuring reliability in measuring the latent variables. Additionally, the Cronbach's alpha (CA), rho_A, and composite reliability (CR or rho_C) values for all seven latent variables were above 0.7, confirming the internal

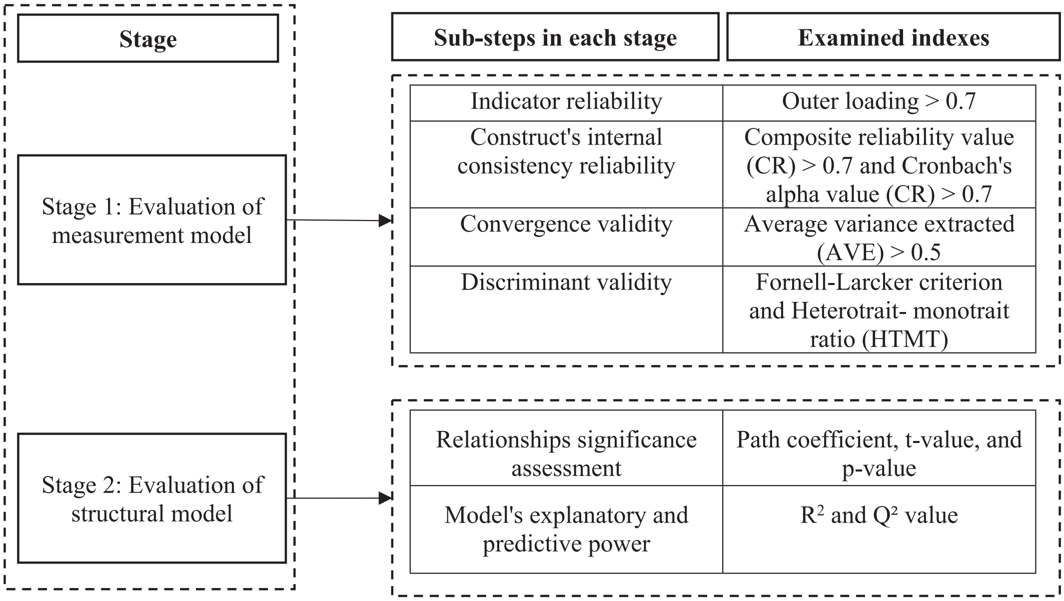


**Fig. 3.** Primary data analysis techniques and procedure.

**Table 1**
Survey respondent characteristics.

| Characteristics | n | % | Characteristics | n | % |
|---|---|---|---|---|---|
| *Gender* | | | *Occupation* | | |
| Male | 251 | 49.60 | Student | 91 | 17.98 |
| Female | 255 | 50.40 | Professionals | 33 | 6.52 |
| *Age* | | | Business and Self-Employment | 93 | 18.38 |
| 16–24 | 111 | 21.94 | Service staff | 66 | 13.04 |
| 25–39 | 183 | 36.17 | Office worker | 72 | 14.23 |
| 40–54 | 151 | 29.84 | State (government) official | 63 | 12.45 |
| 55+ | 61 | 12.06 | Homemaker | 29 | 5.73 |
| *Marital status* | | | Retire | 50 | 9.88 |
| Single | 195 | 38.54 | Unemployment | 3 | 0.59 |
| Married | 311 | 61.46 | Others | 6 | 1.19 |
| | | | *Monthly family income (VND)* | | |
| *Degree of education* | | | | | |
| Lower high school | 23 | 4.55 | No income | 42 | 8.30 |
| High school | 119 | 23.52 | ≤ 10 million | 104 | 20.55 |
| College | 53 | 10.47 | > 10–20 million | 149 | 29.45 |
| University | 283 | 55.93 | > 20–30 million | 85 | 16.80 |
| Above university | 22 | 4.35 | > 30 million | 126 | 24.90 |
| Others | 6 | 1,19 | | | |

consistency of the measurement items. Furthermore, the average variance extracted (AVE) values for all constructs exceeded the 0.5 threshold, as per Fornell and Larcker (1981), indicating a high degree of shared variance among indicators within each construct and strong convergent validity. To assess discriminant validity, the study employed the HTMT ratio, a modern approach proposed by Henseler et al. (2015) Based on the data presented in Table 3, all HTMT values were below the 0.85 threshold, demonstrating clear differentiation between constructs.

These results confirm that the measurement model meets all evaluation criteria, ensuring reliability and convergent validity while providing a solid foundation for analyzing the relationships between constructs in the structural model.

#### 4.2.2. *Second-order measurement model evaluation*

Table 4 presents the second-order measurement structure of the two variables: perceived value (PVA) and perceived cost (PCO). During the analysis, the factors social value and performance risk were removed from the model due to their outer loadings falling below the 0.6 threshold (Hair et al., 1998). After excluding these factors, the analysis results indicated no signs of multicollinearity among the remaining components, as the variance inflation factor (VIF) values for all components were below the cutoff threshold of 5 (Hair et al., 1998).

### 4.3. *Structural model evaluation*

This section presents the results of direct, indirect, and total effects. The rationale for including both indirect and total effects analyses, alongside direct effects, is to provide a more comprehensive understanding of the model's structural relationships. Specifically, indirect effects analysis reveals the mediating mechanisms through which cognitive constructs influence behavioral intention, while total effects analysis captures the overall magnitude of influence by combining both direct and mediated pathways.

In this study, the Consistent Partial Least Squares (PLSc) algorithm, as proposed by Dijkstra and Henseler (2015), was employed rather than traditional PLS-SEM. The choice of PLSc is justified on two grounds. First, all constructs in our model are operationalized as reflective measurement models, for which PLSc provides consistent estimates of loadings, correlations, and structural path coefficients by correcting the attenuation bias inherent in traditional PLS. Second, our research is primarily theory-testing in nature, drawing on a Cognitive–Affective–Conative framework, where assessing the structural relationships among reflective constructs is of central importance. Under PLSc, the application of global model fit indices (e.g., SRMR) is appropriate and aligns with recommendations by Henseler et al. (2016). Accordingly, our evaluation integrates both the established PLS-SEM assessment criteria (reliability, convergent and discriminant validity, $R^2$, $Q^2$) and the model fit measures enabled by PLSc, thereby strengthening the robustness and theoretical validity of our findings. The SRMR statistic is calculated as:

$$SRMR = \sqrt{\frac{\sum_{i=1}^{k}\sum_{j=1}^{k}\left(s_{ij} - \widehat{\sigma}_{ij}\right)^2}{k(k+1)/2}} \quad (1)$$

where:

- $s_{ij}$ = empirical correlation between indicators iii and jjj,
- $\widehat{\sigma}_{ij}$ = model-implied correlation,

**Table 2**
First-order measurement model evaluation.

| Constructs | | Code | Loadings | CA | Composite reliability (rho_a) | CR | AVE |
|---|---|---|---|---|---|---|---|
| Perceived value (PVA) | Economic value (EVA) | EVA1 | 0.790 | 0.847 | 0.851 | 0.897 | 0.686 |
| | | EVA2 | 0.881 | | | | |
| | | EVA3 | 0.833 | | | | |
| | | EVA4 | 0.806 | | | | |
| | Hedonic value (HVA) | HVA1 | 0.771 | 0.780 | 0.783 | 0.872 | 0.696 |
| | | HVA2 | 0.854 | | | | |
| | | HVA3 | 0.874 | | | | |
| | Social value (SVA) | SVA1 | 0.868 | 0.827 | 0.832 | 0.897 | 0.743 |
| | | SVA2 | 0.881 | | | | |
| | | SVA3 | 0.837 | | | | |
| | Altruistic value (AVA) | AVA1 | 0.869 | 0.861 | 0.863 | 0.915 | 0.783 |
| | | AVA2 | 0.905 | | | | |
| | | AVA3 | 0.880 | | | | |
| | Functional value (FVA) | FVA1 | 0.815 | 0.709 | 0.724 | 0.836 | 0.631 |
| | | FVA2 | 0.844 | | | | |
| | | FVA3 | 0.719 | | | | |
| Perceived cost (PCO) | Price (PRI) | PRI1 | 0.770 | 0.793 | 0.85 | 0.875 | 0.702 |
| | | PRI2 | 0.853 | | | | |
| | | PRI3 | 0.885 | | | | |
| | Effort (EFF) | EFF1 | 0.840 | 0.828 | 0.853 | 0.896 | 0.742 |
| | | EFF2 | 0.882 | | | | |
| | | EFF3 | 0.861 | | | | |
| | Evaluation costs (ECO) | ECO1 | 0.778 | 0.851 | 0.853 | 0.899 | 0.691 |
| | | ECO2 | 0.857 | | | | |
| | | ECO3 | 0.853 | | | | |
| | | ECO4 | 0.835 | | | | |
| | Performance risk (PRI) | PRI1 | 0.882 | 0.841 | 0.911 | 0.901 | 0.753 |
| | | PRI2 | 0.920 | | | | |
| | | PRI3 | 0.797 | | | | |
| Attitude (ATT) | | ATT1 | 0.759 | 0.821 | 0.832 | 0.882 | 0.653 |
| | | ATT2 | 0.864 | | | | |
| | | ATT3 | 0.871 | | | | |
| | | ATT4 | 0.729 | | | | |
| Negative anticipated emotion (NAE) | | NAE1 | 0.886 | 0.913 | 0.915 | 0.939 | 0.793 |
| | | NAE2 | 0.917 | | | | |
| | | NAE3 | 0.905 | | | | |
| | | NAE4 | 0.853 | | | | |
| Positive anticipated emotion (PAE) | | PAE1 | 0.839 | 0.865 | 0.87 | 0.908 | 0.712 |
| | | PAE2 | 0.879 | | | | |
| | | PAE3 | 0.868 | | | | |
| | | PAE4 | 0.785 | | | | |
| Intention to adopt electric motorcycles (IAD) | | IAD1 | 0.850 | 0.809 | 0.817 | 0.887 | 0.724 |
| | | IAD2 | 0.895 | | | | |
| | | IAD3 | 0.806 | | | | |

Note: M = Mean; SD = Standard Deviation; CR = Composite Reliability; AVE = Average Variance Extracted.

**Table 3**
Heterotrait-Monotrait Ratio (HTMT) of the first-order factor model.

| Constructs | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. AVA | | | | | | | | | | | | | |
| 2. ATT | 0.488 | | | | | | | | | | | | |
| 3. EVA | 0.362 | 0.462 | | | | | | | | | | | |
| 4. EFF | 0.032 | 0.083 | 0.102 | | | | | | | | | | |
| 5. ECO | 0.061 | 0.056 | 0.064 | 0.590 | | | | | | | | | |
| 6. FVA | 0.670 | 0.535 | 0.403 | 0.069 | 0.065 | | | | | | | | |
| 7. HVA | 0.489 | 0.626 | 0.536 | 0.125 | 0.133 | 0.576 | | | | | | | |
| 8. IAD | 0.309 | 0.441 | 0.526 | 0.092 | 0.162 | 0.349 | 0.574 | | | | | | |
| 9. NAE | 0.127 | 0.194 | 0.272 | 0.453 | 0.380 | 0.152 | 0.277 | 0.214 | | | | | |
| 10. PRI | 0.032 | 0.051 | 0.101 | 0.580 | 0.621 | 0.066 | 0.193 | 0.155 | 0.234 | | | | |
| 11. PAE | 0.364 | 0.535 | 0.469 | 0.109 | 0.100 | 0.523 | 0.657 | 0.446 | 0.406 | 0.044 | | | |
| 12. PRI | 0.158 | 0.100 | 0.230 | 0.496 | 0.550 | 0.093 | 0.076 | 0.194 | 0.429 | 0.395 | 0.172 | | |
| 13. SVA | 0.706 | 0.503 | 0.405 | 0.065 | 0.066 | 0.611 | 0.586 | 0.394 | 0.080 | 0.055 | 0.413 | 0.069 | |

- $k$ = number of observed indicators.

$R^2$ measures the proportion of variance in the dependent construct explained by its predictors. In PLS-SEM, higher $R^2$ values indicate stronger explanatory power of the structural model. The $R^2$ statistic is calculated as:

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{2}$$

where:

- $y_i$ are observed values,

**Table 4**
Second-order measurement model evaluation.

| Second-order/first-order constructs | Outer weights | Standard deviation | t-values | p-values | Outer loadings | VIF |
|---|---|---|---|---|---|---|
| Perceived value (PVA) | | | | | | |
| Economic value | 0.315*** | 0.062 | 5.087 | 0.000 | 0.696 | 1.284 |
| Hedonic value | 0.588*** | 0.053 | 11.101 | 0.000 | 0.891 | 1.451 |
| Altruistic value | 0.127** | 0.062 | 2.052 | 0.040 | 0.601 | 1.485 |
| Functional Value | 0.263*** | 0.061 | 4.295 | 0.000 | 0.685 | 1.530 |
| Perceived cost (PCO) | | | | | | |
| Price | 0.529*** | 0.120 | 4.417 | 0.000 | 0.835 | 1.341 |
| Effort | 0.486*** | 0.140 | 3.481 | 0.001 | 0.820 | 1.412 |
| Evaluation costs | 0.227** | 0.112 | 2.024 | 0.043 | 0.704 | 1.458 |

Notes: ns = not significant, *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- $\hat{y}_i$ are predicted values,
- $\bar{y}$ is the mean of observed values.

In PLS-SEM, predictive relevance of the model is commonly assessed through the Stone–Geisser $Q^2$ value, obtained via the blindfolding procedure. Blindfolding systematically omits part of the data and predicts the omitted portion using the estimated model. The $Q^2$ statistic is calculated as:

$$Q^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \quad (3)$$

where:

- $y_i$ are actual values,
- $\hat{y}_i$ are model-predicted values,
- $\bar{y}$ is the mean of the observed values.

#### 4.3.1. *The tests of model fit*

The study employs the Standardized Root Mean Square Residual (SRMR) index along with the bootstrap procedure to assess the model fit, following the approach of Henseler et al. (2016). The analysis results indicate that the SRMR value is 0.049, which is below the recommended threshold of 0.08 suggested by Hu and Bentler (1999). This demonstrates that the model exhibits a good fit with the actual data.

#### 4.3.2. *Direct effects*

The results of the direct effects in the structural model are presented in Table 5 and Fig. 4. First, perceived value has a significant positive impact on attitude ($\beta = 0.484$, $p < 0.001$) and positive anticipated emotion ($\beta = 0.082$, $p = 0.064$), confirming H1 and H2. Additionally, perceived value has a significant negative impact on negative anticipated emotion ($\beta = -0.244$, $p < 0.001$), supporting H3. Next, perceived cost exhibits a positive effect on negative anticipated emotion ($\beta = 0.463$, $p < 0.001$) and a negative effect on positive anticipated emotion ($\beta = -0.114$, $p = 0.007$), supporting H4 and H6. Furthermore, positive anticipated emotion has a positive impact on attitude ($\beta = 0.171$, $p = 0.015$), supporting H7. Finally, both positive anticipated emotion and attitude have positive effects on Intention to adopt electric motorcycles, supporting H8 and H11, with path coefficients of ($\beta = 0.246$, $p < 0.001$) and ($\beta = 0.240$, $p < 0.001$), respectively.

**Table 5**
Direct effects.

| Path relation | Coefficient | Standard deviation | t-values | p-values | Hypothesis |
|---|---|---|---|---|---|
| Perceived value - > Positive anticipated emotion | 0.591*** | 0.034 | 17.571 | <0.001 | H1 |
| Perceived value - > Attitude | 0.484*** | 0.063 | 7.699 | <0.001 | H2 |
| Perceived value - > Negative anticipated emotion | −0.244*** | 0.041 | 5.991 | <0.001 | H3 |
| Perceived cost - > Positive anticipated emotion | −0.114*** | 0.042 | 2.716 | 0.007 | H4 |
| Perceived cost - > Attitude | −0.013^ns | 0.053 | 0.236 | 0.813 | H5 |
| Perceived cost - > Negative anticipated emotion | 0.463*** | 0.043 | 10.770 | <0.001 | H6 |
| Positive anticipated emotion - > Attitude | 0.171** | 0.070 | 2.438 | 0.015 | H7 |
| Positive anticipated emotion - > Intention to adopt electric motorcycles | 0.246*** | 0.054 | 4.590 | <0.001 | H8 |
| Negative anticipated emotion - > Attitude | 0.023^ns | 0.050 | 0.466 | 0.641 | H9 |
| Negative anticipated emotion - > Intention to adopt electric motorcycles | −0.054^ns | 0.049 | 1.106 | 0.269 | H10 |
| Attitude - > Intention to adopt electric motorcycles | 0.240*** | 0.055 | 4.363 | <0.001 | H11 |

Notes: ns = not significant, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

#### 4.3.3. *Indirect effects*

This study analyzed the mediating role of the variables ATT, NAE, and PAE in the relationships among the latent variables under consideration. The results in Table 6 present the direct path coefficients of the five key constructs (PVA, PCO, ATT, NAE, PAE, and IDA), including path coefficients, standard deviation (SD), *t*-values, and *p*-values. All indirect relationships are convincingly supported at the 1 % significance level (Zhao et al., 2010).

Specifically, ATT is identified as a crucial mediator, bridging the relationship between PVA and IDA ($\beta_{PVA \to ATT \to IDA} = 0.116$, $t = 3.306$, $p = 0.001$) as well as between PAE and IDA ($\beta_{PAE \to ATT \to IDA} = 0.041$, $t = 2.300$, $p = 0.021$). Additionally, PAE also mediates the relationships between PVA, PCO, and IDA, with path coefficients of ($\beta_{PVA \to PAE \to IDA} = 0.145$, $t = 4.128$, $p \leq 0.001$) and ($\beta_{PCO \to PAE \to IDA} = -0.028$, $t = 2.304$, $p = 0.021$). Notably, the study also highlights the mediating role of PAE in the relationships between PVA, PCO, and ATT, with path coefficients of ($\beta_{PCO \to PAE \to ATT} = 0.020$, $t = 1.736$, $p = 0.083$) and ($\beta_{PVA \to PAE \to ATT} = 0.101$, $t = 2.434$, $p = 0.015$). These findings provide deeper insights into the complex relationships among the variables in the research model.

#### 4.3.4. *Total effects*

Table 7 presents the total effects of the latent variables on IDA in the research model. The results indicate that perceived value (PVA) has the

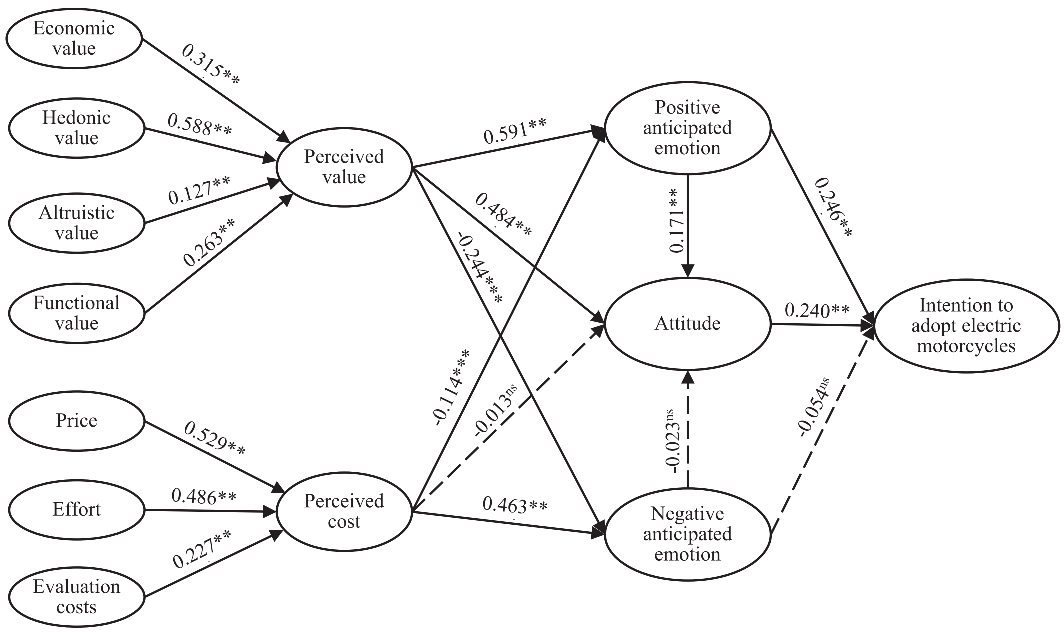


**Fig. 4.** Results of PLS-SEM.

strongest impact on IDA, with a coefficient of ($\beta_{PVA \rightarrow IDA} = 0.298$, $t = 7.480$, $p < 0.001$). Following this, positive anticipated emotion (PAE) also exhibits a significant effect, with a coefficient of ($\beta_{PAE \rightarrow IDA} = 0.287$, $t = 5.799$, $p < 0.001$).

Conversely, attitude (ATT) has the smallest impact on IDA, though it remains statistically significant, with $\beta_{ATT \rightarrow IDA} = 0.240$, $t = 4.363$, $p < 0.001$). Finally, perceived cost (PCO) exerts a negative effect on IDA, as reflected in the coefficient $\beta_{PCO \rightarrow IDA} = -0.058$, $t = 2.298$, $p = 0.022$). These findings emphasize the crucial role of perceived value and positive emotions in driving adoption intention, while also highlighting the hindering effect of perceived cost.

#### 4.3.5. *Predictive relevance assessment*

The structural model evaluation includes the coefficient of determination ($R^2$) and the predictive relevance ($Q^2$), two key measures for assessing the predictive capability and accuracy of the model (Hair et al., 2016) (see Table 8). The $R^2$ coefficient reflects the proportion of variance in the endogenous constructs explained by the independent variables in the model. The $R^2$ value for behavioral intention is 0.184, indicating that the model explains approximately 18.4 % of the variance in consumers' intention to adopt electric motorcycles. While this figure may appear modest, it is within the acceptable range for early-stage behavioral studies, particularly in contexts involving emerging technologies and evolving markets like Vietnam. Therefore, the relatively low $R^2$ for intention may reflect the complexity and multi-dimensionality of real-world decision-making in sustainable transport. It also highlights the need for future research to incorporate broader socio-environmental constructs or contextual enablers. Importantly, the model demonstrates stronger explanatory power for affective components ($R^2 = 0.350$ for attitude; $R^2 = 0.280$ for negative anticipated emotions; $R^2 = 0.365$ for positive anticipated emotions), reinforcing the central role of affective mechanisms in shaping behavioral outcomes.

Additionally, the $Q^2$ index, a cross-validated redundancy measure obtained via blindfolding to test the model's predictive accuracy, requires a value greater than 0 to confirm the model's predictive relevance. The findings indicate that the $Q^2$ for the intention to adopt electric motorcycles is 0.131, reflecting satisfactory predictive relevance and suggesting that the model possesses adequate capability to predict consumers' adoption intentions in this context (Hair et al., 2016).

## 5. Discussion

Electric motorcycles are gaining increasing global attention as a sustainable mobility solution with both environmental and personal benefits. While previous research has primarily examined adoption through performance, cost, and environmental factors, often relying on established models like the Technology Acceptance Model and the Theory of Planned Behavior, this study introduces a novel application of the Cognitive–Affective–Conative (CAC) framework to the electric motorcycle adoption context. This approach offers a more comprehensive understanding by integrating cognitive evaluations (perceived value and cost) with emotional responses (positive and negative anticipated emotions) that shape consumer attitudes and intentions. Specifically, the study investigates how perceived value and cost influence adoption intention, with anticipated emotions acting as mediators. Using second-order structural equation modeling on survey data from Vietnam, a country with one of the world's highest motorbike usage rates and a largely low-to-middle income population, this research provides both theoretical contributions and practical insights for promoting electric motorcycle adoption in emerging economies.

The findings of this study reveal that positive anticipated emotion significantly influences consumers' intention to adopt electric motorcycles. This supports previous research in the green hospitality sector, where positive anticipated emotions have been recognized as major drivers of customers' adoption intentions (Han et al., 2011). Consistent with these earlier findings, the present study demonstrates that when consumers anticipate positive emotional outcomes from using electric motorcycles, such as feeling environmentally responsible or socially admired, their intention to adopt these vehicles increases substantially. Moreover, positive anticipated emotion serves as a mediating factor between perceived value and adoption intention. This suggests that when consumers perceive electric motorcycles as valuable, whether economically, hedonically, altruistically, or functionally, their positive emotional expectations intensify, which in turn fosters a stronger Intention to adopt electric motorcycles. This mediating role highlights the importance of addressing emotional aspects in conjunction with perceived value when promoting electric motorcycles.

Conversely, negative anticipated emotion, such as fear of inconvenience or dissatisfaction, was found to be statistically insignificant in predicting adoption intention in this study. This finding is noteworthy as

**Table 6**
Indirect effects.

| Path relation | Coefficient | Standard deviation | t-values | p-values |
|---|---|---|---|---|
| Perceived Cost - > Negative anticipated emotion - > Attitude | 0.010$^{ns}$ | 0.024 | 0.459 | 0.646 |
| Perceived cost - > Negative anticipated emotion - > Intention to adopt electric motorcycles | −0.025$^{ns}$ | 0.023 | 1.086 | 0.278 |
| Perceived value - > Negative anticipated emotion- > Attitude | −0.006$^{ns}$ | 0.013 | 0.442 | 0.659 |
| Negative anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | 0.006$^{ns}$ | 0.012 | 0.458 | 0.647 |
| Perceived value - > Negative anticipated emotion - > Intention to adopt electric motorcycles | 0.013$^{ns}$ | 0.013 | 1.021 | 0.307 |
| Perceived cost - > Attitude - > Intention to adopt electric motorcycles | −0.003$^{ns}$ | 0.013 | 0.232 | 0.817 |
| Perceived value - > Attitude - > Intention to adopt electric motorcycles | 0.116*** | 0.035 | 3.306 | 0.001 |
| Positive anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | 0.041** | 0.018 | 2.300 | 0.021 |
| Perceived cost - > Positive anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | −0.005* | 0.003 | 1.686 | 0.092 |
| Perceived value - > Positive anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | 0.024** | 0.011 | 2.303 | 0.021 |
| Perceived cost - > Negative anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | 0.003$^{ns}$ | 0.006 | 0.449 | 0.653 |
| Perceived value - > Negative anticipated emotion - > Attitude - > Intention to adopt electric motorcycles | −0.001$^{ns}$ | 0.003 | 0.441 | 0.659 |
| Perceived cost - > Positive anticipated emotion - > Attitude | −0.020* | 0.011 | 1.736 | 0.083 |
| Perceived cost - > Positive anticipated emotion - > Intention to adopt electric motorcycles | −0.028** | 0.012 | 2.304 | 0.021 |
| Perceived value - > Positive anticipated emotion - > Attitude | 0.101** | 0.042 | 2.434 | 0.015 |
| Perceived value - > Positive anticipated emotion - > Intention to adopt electric motorcycles | 0.145*** | 0.035 | 4.138 | <0.001 |

Notes: ns = not significant, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

it contradicts prior research in the green hospitality context, where negative anticipated emotions have typically been linked to decreased service adoption due to concerns over negative experiences (Bagozzi et al., 2003). The insignificance of negative emotion in this study may suggest that when it comes to electric motorcycle adoption, positive motivators outweigh negative deterrents, or that negative concerns are less salient to consumers in the current context. Furthermore, the study finds that attitude toward electric motorcycles significantly positively affects the intention to adopt, corroborating the findings of prior studies (Chen et al., 2012; Dutta & Hwang, 2021; Jayasingh et al., 2021). Importantly, attitude also acts as a mediator between perceived value and adoption intention. This suggests that perceived benefits of electric motorcycles influence consumers' overall attitude, which subsequently shapes their behavioral intentions. Therefore, enhancing consumer attitudes by reinforcing both the practical and emotional value of electric motorcycles could be an effective strategy for encouraging environmentally friendly behavior and promoting the broader adoption of sustainable transport solutions.

**Table 7**
Total effects.

| Path relation | Coefficient | Standard deviation | t-values | p-values |
|---|---|---|---|---|
| Perceived value - > Intention to adopt electric motorcycles | 0.298*** | 0.040 | 7.480 | 0.000 |
| Perceived cost - > Intention to adopt electric motorcycles | −0.058* | 0.025 | 2.298 | 0.022 |
| Positive anticipated emotion - > Intention to adopt electric motorcycles | 0.287*** | 0.049 | 5.799 | 0.000 |
| Negative anticipated emotion - > Intention to adopt electric motorcycles | −0.049$^{ns}$ | 0.047 | 1.033 | 0.302 |
| Attitude - > Intention to adopt electric motorcycles | 0.240*** | 0.055 | 4.363 | 0.000 |

Notes: ns = not significant, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 8**
Predictive accuracy and predictive relevance results.

| Latent constructs | $R^2$ | $Q^2$ |
|---|---|---|
| Attitude | 0.350 | 0.225 |
| Intention to adopt electric motorcycles | 0.184 | 0.131 |
| Negative anticipated emotion | 0.280 | 0.217 |
| Positive anticipated emotion | 0.365 | 0.258 |

The research findings further confirm that perceived value, conceptualized as a second-order construct comprising economic, hedonic, altruistic, and functional value, exerts a significant influence on both attitude and positive anticipated emotion. This result aligns with prior studies demonstrating that consumer attitudes toward electric motorcycles are strongly shaped by the extent to which they perceive these vehicles to deliver multiple types of value. Furthermore, perceived value not only enhances positive anticipated emotions (e.g., pride, satisfaction), but also plays a role in diminishing negative anticipated emotions (e.g., anxiety, regret). This is consistent with Bettiga and Lamberti (2018) argument that anticipated emotions are directly influenced by perceived value, which subsequently guides consumers' decision-making processes in product adoption. In contrast, perceived cost, a second-order construct formed by monetary price, effort, and evaluation costs, has an adverse effect on emotional responses. Specifically, it negatively impacts positive anticipated emotion while increasing negative anticipated emotion. This finding corroborates evidence from the green hospitality sector, where high perceived costs are often associated with diminished enthusiasm and heightened apprehension regarding sustainable consumption choices (Ahn & Kwon, 2020). Together, these findings underscore the dual emotional pathway through which perceived value and perceived cost shape consumer intention, offering critical insights for marketers and policymakers aiming to influence behavior through both rational and affective appeals. These findings are consistent with broader decision science perspectives, which emphasize that consumer adoption in market economies is a complex decision-making process shaped by uncertainty, trade-offs, and strategic considerations (Savku & Weber, 2022). From this standpoint, game-theoretic and stochastic modeling approaches provide useful insights into how individuals balance risks and benefits in forming behavioral intentions (Ergün et al., 2023).

In terms of the total effect, perceived value emerged as the strongest predictor of adoption intention, indicating that consumers' willingness to adopt electric motorcycles is primarily driven by the perceived benefits they associate with the product, such as functionality, cost efficiency, emotional satisfaction, and environmental contribution. In contrast, perceived cost exhibited a negative but relatively weak impact, suggesting that although financial and effort-related considerations may discourage adoption to some extent, their influence is overshadowed by the perceived overall value gained. This finding implies that when consumers recognize substantial benefits, they tend to tolerate or discount associated costs. It also reinforces the notion that enhancing perceived value, through pricing strategies, improved product performance, and stronger emotional or social appeal, may be more effective in promoting adoption than solely focusing on reducing perceived costs. This result is consistent with previous research in the health behavior domain, where perceived values such as health, safety, and well-being were found to strongly influence individuals' compliance with recommended health behaviors (Yilmaz & Çağlayan, 2016).

The results provide valuable insights that support both the government and electric motorcycle manufacturers in developing appropriate growth strategies. Based on key findings, optimal strategies aligned with existing resources can be proposed to enhance the adoption and usage of electric motorcycles as desired. These results are not only useful for efficient resource allocation but also help in optimizing proposed strategies, ensuring practical feasibility and high effectiveness. Through analysis, key factors influencing the intention to adopt electric motorcycles have been identified, forming a solid foundation for practical solutions to strengthen consumer acceptance of this mode of transportation.

First, positive anticipated emotion is identified as a key factor directly influencing the intention to use electric motorcycles. Therefore, enhancing customers' positive emotional experiences plays a crucial role in promoting product adoption. Manufacturers should develop practical strategies, such as designing high-performance models that offer superior user experiences, from sleek designs and advanced technology to comfort and safety in operation. In addition, social media campaigns, advertising messages, promotional content, and educational interventions aimed at raising awareness about the features and benefits of electric motorcycles can be highly effective. Simplifying electric motorcycle usage through user-friendly designs is also essential (Shaikh et al., 2023). Next, customer attitude is recognized as a crucial determinant of electric motorcycle adoption intention. A positive attitude toward electric motorcycles often stems from perceived benefits, such as environmental protection, cost savings, and modern technology. To strengthen this attitude, especially in the Vietnamese context, targeted campaigns should be implemented. In rural areas, campaigns can focus on economic benefits, while in urban regions, they should emphasize reducing air pollution and traffic congestion (Nguyen-Phuoc, Su, et al., 2025).

Second, to encourage customers to adopt electric motorcycles, focusing on personal experience and perceived value is crucial. Customers tend to share their positive experiences on social media, creating a strong ripple effect. One of the key factors influencing electric motorcycle adoption intention is emotional value. When customers perceive enjoyment, comfort, and satisfaction while using electric motorcycles, their purchase and usage intention increases significantly. Therefore, manufacturers should organize events that allow urban residents to directly experience electric motorcycles. These initiatives may include test rides, vehicle-sharing activities, and visits to electric motorcycle experience centers (Li et al., 2017). Additionally, economic value is another crucial factor. Customers often prioritize products with clear financial benefits, such as low operating costs or maintenance incentives. From a consumer perspective, financial measures such as subsidies and tax reductions can stimulate customer interest in using electric motorcycles for daily transportation (Nguyen-Phuoc, Truong, et al., 2025). Moreover, social and humanitarian values also play a significant role. Electric motorcycles are not just vehicles but also symbols of a sustainable lifestyle, environmental awareness, and social responsibility. In the Vietnamese context, the government can launch initiatives to raise public awareness about the environmental benefits of electric motorcycles, thereby improving public perception and acceptance (Jayasingh et al., 2021).

Finally, perceived cost is a crucial factor influencing the intention to use electric motorcycles, primarily by shaping positive anticipated emotions. There are two key aspects of perceived cost: price and effort. Price is directly related to the financial expenditure required to own and use the product. Therefore, manufacturers should offer competitive pricing that aligns with consumers' income levels, especially in markets like Vietnam. Additionally, the government should introduce more financial incentives to accelerate electric motorcycle adoption (Jayasingh et al., 2021). Meanwhile, effort refers to the time and energy customers need to invest in learning about and adapting to the product. To minimize this barrier, manufacturers should organize test-ride events in high-density areas, shopping malls, or technology fairs. Establishing easily accessible product display points will also allow customers to interact directly with electric motorcycles. Furthermore, sales teams should be well-trained to provide dedicated support and address customer concerns effectively. Additionally, comprehensive marketing strategies should be designed to enhance customer awareness and facilitate recognition of the benefits of electric motorcycles. Promoting user-generated content, such as reviews and personal experiences shared on online platforms, can generate a ripple effect that strengthens brand image and fosters broader community adoption.

## 6. Conclusion

While prior work by leading scholars in mobility, behavioral intention, and PLS-SEM modeling has advanced methodological and theoretical knowledge, our study extends this by focusing on Vietnam as both an extreme and critical case for testing adoption pathways. Few studies have empirically explored how urban contexts characterized by extreme motorcycle dependency, worsening air quality, and ambitious policy commitments (e.g., net-zero by 2050, restrictions on conventional motorcycles in major CBDs) shape adoption intentions toward electric mobility. By filling this gap, our research contributes original evidence that is not only timely for Vietnam but also transferable to other low- and middle-income countries facing similar urban mobility challenges.

Specifically, this study advances the understanding of electric motorcycle adoption by applying the cognitive–affective–conative (CAC) framework, highlighting the interplay between perceived value, perceived cost, emotional responses, and behavioral intention. The findings reveal that positive anticipated emotion and consumer attitude significantly drive the adoption intention, with perceived value enhancing both dimensions. In contrast, perceived cost undermines positive emotional responses and reinforces negative ones. Notably, negative anticipated emotion does not directly influence adoption intention in this context, suggesting that positive motivators may outweigh deterrents. These insights offer valuable guidance for policymakers and manufacturers, particularly in emerging markets like Vietnam, by emphasizing the importance of promoting emotional and experiential value, reducing perceived cost barriers, and fostering positive public attitudes through targeted campaigns, financial incentives, and user-centered design strategies. Additionally, the current study also provides insights for emerging applications in contexts of rapid electrification and digitalization. Lessons from Vietnam are relevant to electric cars, renewable energy, smart mobility, and digital platforms where perceptions of value, cost, and attitute influence behavioral intention. These findings underscore cross-sector learning, with methods from sustainable transport informing challenges such as climate action or sustainable consumption.

While this study offers valuable insights into electric motorcycle adoption in Vietnam, several limitations must be acknowledged. First, the use of a convenience sample from a single city (Da Nang) limits generalizability; future studies should include multiple regions or national samples for broader applicability. Second, the cross-sectional design restricts causal interpretation, highlighting the need for longitudinal or experimental approaches to track changes over time. Third, a potential limitation of this study is the reliance on self-reported survey data, which may introduce common method variance (CMV) and inflate the observed relationships among constructs. Although procedural remedies were applied in the design stage, future research should incorporate statistical controls or multi-source data to further mitigate CMV concerns. Finally, while structural equation modeling (SEM) provided valuable insights into the causal relationships within our framework, it also has certain drawbacks. Specifically, SEM assumes relative homogeneity across respondents and does not fully capture the presence of distinct subgroups with divergent behavioral patterns. In addition, our model emphasizes explanatory power but offers limited capacity for predictive validation, which constrains its practical generalizability. To address these limitations, future research could adopt heterogeneity-aware approaches (e.g., FIMIX-PLS or latent class SEM) to uncover user segments with unique adoption pathways, and apply predictive validity assessments (e.g., PLSpredict, cross-validation) to strengthen out-of-sample robustness. By integrating multiple methodological approaches, future studies can address the shortcomings of SEM and expand the generalizability of sustainable mobility research across diverse settings (Hair et al., 2016; Shmueli et al., 2019).

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## CRediT authorship contribution statement

**Bien Van Nguyen:** Writing – original draft, Data curation, Conceptualization. **Duy Quy Nguyen-Phuoc:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Nhat Dinh Quang Vo:** Writing – review & editing, Writing – original draft, Conceptualization. **Diep Ngoc Su:** Writing – review & editing, Writing – original draft, Conceptualization. **Oscar Oviedo-Trespalacios:** Writing – review & editing, Writing – original draft, Conceptualization.

## Declaration of competing interest

None.

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## Data availability

Data will be made available on request.

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