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How do perceptions of risk influence the adoption of electric motorcycles? A theory-based investigation considering the multidimensional nature of risk

Duy Quy Nguyen-Phuoc [a,b,*], Diep Ngoc Su [c], Anh Truong [d], Zhi-Chun Li [e], Oscar Oviedo-Trespalacios [f]

[a] Faculty of Road and Bridge Engineering, The University of Danang - University of Science and Technology, Danang City, Vietnam
[b] The University of Danang - Advanced Institute of Science and Technology, Danang City, Vietnam
[c] Bachelor of Hospitality Management at Holmesglen, Melbourne, Australia
[d] Faculty of Business Management, National Economics University, Hanoi, Vietnam
[e] School of Management, Huazhong University of Science and Technology, Wuhan 430074, China
[f] Faculty of Technology, Policy, and Management, Delft University of Technology, Jaffalaan 5, 2628 BX Delft, The Netherlands

A R T I C L E I N F O

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A B S T R A C T

In low- and middle-income countries, electric motorcycles (EMs) are not generally well accepted in the community as many infrastructural, technological, and psychosocial barriers remain unaddressed. A greater understanding of adoption barriers perceived by motorcycle riders can help devise strategies, such as policy and behavioural change interventions, to increase the uptake of EMs. This study aimed to investigate the risk dimensions of EM adoption and integrate them into the Theory of Planned Behaviour to model users' intention to adopt EMs. A multi-group analysis was also conducted to examine the moderating effect of demographic characteristics on the proposed model. The data were collected from two cities in Vietnam, making this one of the region's first theory-based studies on the electrification of the transport system. The outcomes of the structural equation modeling affirmed that the psychosocial variables outlined in the Theory of Planned Behaviour (i.e., attitudes, perceived behavioural control, and social norms) and perceived risk significantly influence the behavioural intention to adopt EMs. These findings hold significance for policymakers and manufacturers as they provide valuable insights into the factors that can be targeted to enhance the adoption of EMs. This represents a crucial step towards advancing sustainability goals in low- and middle-income countries.

1. Introduction

Motorcycles are the preferred mode of travel in many low- and middle-income countries (LMICs). Particularly in Southeast Asia, motorcycles dominate road traffic flow, with more than 235 million vehicles in 2020 (ASEAN Stats) and are recognised as the world's region with the highest per capita motorcycle ownership (CRI, 2023). With the rapid growth of the population, motorcycle ownership continues to rise. Indeed, the motorcycle market is expected to grow by 8 % annually from 2022 to 2026 (Statista, 2022). However, an

* Corresponding author.
E-mail addresses: npqduy@dut.udn.vn (D.Q. Nguyen-Phuoc), lilly.su@holmesglen.edu.au (D.N. Su), anhtt@neu.edu.vn (A. Truong), smzcli@hust.edu.cn (Z.-C. Li), O.OviedoTrespalacios@tudelft.nl (O. Oviedo-Trespalacios).

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increase in the number of fuel-based motorcycles could pose many challenges to sustainability. Fuel combustion engines, such as those used in the most popular motorcycles, are one of the leading causes of air and noise pollution, which results in climate change and health issues (Pucher et al., 2007). As such, there is significant interest in encouraging more environmentally friendly modes of personal transport, such as electric motorcycles (EMs). Like many other Southeast Asian countries, Vietnam is heavily dependent on motorcycles, and motorcycle ownership has increased from 1.2 million to 65 million in the last three decades. Unfortunately, transport accounts for an estimated 18 percent of total greenhouse gas emissions, and the relatively high level of carbon dioxide (CO_2) emissions from the transport sector has been associated with the widespread use of private vehicles (Ngoc et al., 2022). At the 2021 United Nations Climate Change Conference (COP26), Vietnam officially committed to achieving net carbon emissions neutrality by 2050 (PWC, 2022). Many measures aimed at reducing carbon emissions and increasing energy efficiency have been introduced in the country, particularly in the transport sector. In terms of personal mobility, several programs have been implemented to support the adoption of electric motorcycles (EMs) (Fox, 2022). However, despite the numerous benefits, the use of EMs has not grown as anticipated in many LMICs, including Vietnam. The community appears to be hesitant to embrace this new technology due to structural barriers and concerns about the drawbacks of EMs.

To design successful initiatives that effectively change consumer behaviour in choosing a transport mode, it is essential to have a clear understanding of the psychological factors influencing individuals' decisions regarding travel modes (Donald et al., 2014). Most existing studies tend to focus on electric vehicles in high-income jurisdictions, leaving a significant gap in the literature regarding the unique challenges and drivers in low- and middle-income countries (LMICs). In recent years, scholars from LMICs have conducted an increasing number of studies on electric motorcycles (EMs); however, many of them have focused on examining the benefits of EMs, such as emissions and noise reduction (Hernandez et al., 2019; Satiennam et al., 2014). Concerning the adoption of EMs, a review of consumer adoption argues that theory-driven studies are lacking, and only a limited number of factors contributing to EMs' adoption have been considered (Eccarius and Lu, 2020). As such, it is necessary to propose an integrated framework that explores the psychological factors and mechanisms underlying individuals' decisions to adopt EMs.

In current literature, the Theory of Planned Behaviour (TPB) is widely recognised as an effective model for explaining and predicting usage intentions of transport technologies (Zhu et al., 2020; Nguyen-Phuoc et al., 2022b; Fu and Juan, 2017; Javid et al., 2022), even more so than other well-established theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology. The TPB has been extensively applied to transport mode choices, including public transport (Heath and Gifford, 2002; Fu and Juan, 2017), bike-sharing (Zhu et al., 2020; Kaplan et al., 2015), and ride-hailing (Nguyen-Phuoc et al., 2022a; Javid et al., 2022). Although the TPB has been successfully tested in various contexts, Sirakaya and Woodside (2005) state that no single unifying theory has emerged to explain decision-making, and as such, we need to conduct further evaluation to consider contextual factors. Previous scholars have also highlighted the need to incorporate supplementary psychological constructs to improve our understanding of the issues and develop more contextual and culturally-appropriate interventions (Gao et al., 2017; Oviedo-Trespalacios et al., 2021; Nguyen-Phuoc et al., 2024; Nguyen-Phuoc et al., 2023).

In the context of EMs, this mode of transport still presents several disadvantages compared to conventional gasoline vehicles, such as lower speed, limited riding distance, and a scarcity of charging stations or longer charging time requirements (Le et al., 2022). These factors represent different risks for customers. Therefore, the theory of perceived risk is integrated into TPB in this study to explain EMs adoption behaviour and capture the impact of infrastructural, technological, and economic barriers on EMs usage. This is consistent with the call made by Samadzad et al. (2023), who suggested extending widely used theoretical frameworks with perceived risk when studying the intention to adopt innovative technologies like electric scooters. Additionally, the multidimensional nature of risk has not been comprehensively addressed in previous research, neglecting issues such as safety, technical, and financial risk. Poor conceptualisations of risk have been a common issue in transport research (Rod et al., 2023). Importantly, it remains unknown how potential users conceptualise and categorise the various risks associated with EMs. To the best of our knowledge, no study has been conducted to identify the risk dimensions of EM adoption and analyze the combined effect of these dimensions on adoption intention in low- and middle-income countries. This significant research gap motivates the present investigation of critical risks that could act as barriers to adopting EMs.

This study builds upon the foundations laid by Nguyen-Phuoc et al. (2024), who provided an initial exploration into the factors influencing the adoption of electric motorcycles (EMs) in Vietnam. While their studies offered valuable insights, it had limitations that prompted the development of the current research. Specifically, Nguyen-Phuoc et al. (2024) did not incorporate perceived risk as a multidimensional construct, nor did they fully explore the role of socio-demographic factors in shaping behavioural intentions. A lack of understanding on the factors associated with the adoption of EMs can undermine climate action in LMICs. To close this gap, the present study seeks a comprehensive framework to explain the intention to adopt EMs. The specific objectives of this research involve: (1) to investigate the risk dimensions of EM adoption and identify which dimensions are more meaningful in forming perceived risk; (2) to validate the multi-dimensionality of perceived risk and to examine whether perceived risk and original TPB variables (i.e., attitude, perceived behavioural control, and social norms) significantly affect the user's adoption intention of EMs; and (3) to explore whether users' demographic characteristics moderate the links among variables. The findings of this study directly contribute to the body of knowledge of acceptability of EMs, and support policymakers in forming and implementing 'green' transport policy in LMICs. Electric vehicle manufacturers also benefit by the findings since they understand better which risk dimensions are more influential than others. As such, they can focus on reducing these barriers, making EMs more attractive.

The paper is structured as follows: subsequent sections present the theoretical foundation of the study and the formulation of research hypotheses. They are followed by an elucidation of the research methodology employed to substantiate the proposed model and examine the hypotheses. The next section illustrates the research findings through a systematic analysis of the data using Partial Least Squares – Structural Equation Modeling (PLS-SEM). Finally, the paper concludes by discussing the theoretical and managerial implications, acknowledging any constraints, and offering recommendations for future research.

2. Theoretical background

Consumer adoption of new technologies or products can be defined by their behavioural response. Examples of behavioural response include purchasing and using the new technology or product (Huijts et al., 2012; Jansson et al., 2010; Kelly et al., 2023; Oviedo-Trespalacios et al., 2020). Generally, cognitive factors such as intentions can serve as proxy variables for technology adoption, such as purchasing and using electric motorcycles (EMs) (Rezvani et al., 2015; Eccarius and Lu, 2020). Numerous studies in the past have explored consumer behaviour towards new technologies using the theory of reasoned action (TRA), examining intentions to buy electric cars (Nosi et al., 2017) or adopt hybrid electric vehicles (Alzahrani et al., 2019). However, TRA operates on the assumption that a significant portion of human social behaviour falls within the realm of volitional control, enabling predictions based solely on intentions. In 1985, Ajzen introduced the theory of planned behaviour (TPB) to account for behaviours that are not entirely under volitional control. By incorporating the concept of perceived behavioural control as a non-volitional factor, TPB expands on the limitations of TRA (Montano and Kasprzyk, 2015). This theoretical framework aims to provide a comprehensive and adaptable model capable of predicting and explaining behaviour across various behavioural domains.

Prior research on the adoption of EMs has employed a hypothetical choice approach with limited factors, aiming to reduce complexity within state preference surveys (Eccarius and Lu, 2020; Sun and Zhang, 2013; Guerra, 2019; Filippini et al., 2021). However, this choice theory seems inadequate when considering a wider range of psycho-social factors. On the other hand, TPB has emerged as a common theoretical framework in studies on electric vehicle adoption in high-income countries such as Canada (Mohamed et al., 2016), Germany (Degirmenci and Breitner, 2017), and upper middle-income countries such as China (Zhang et al., 2018; Yang et al., 2020). This is problematic as most of the research is needed in countries where motorcycle dependence is higher, specifically in low to low-middle-income countries.

This investigation focuses on the Theory of Planned Behaviour (TPB) and its extension in examining the intention to adopt EMs, which ultimately leads to the purchase and actual use of EMs. It has demonstrated better explanatory power for the intention to adopt new technology among road users compared to other theories, such as the Technology Acceptance Model. Therefore, TPB is considered an appropriate theory to explore the adoption of new technologies in the transport system, such as adopting electric bicycles (Wolf and Seebauer, 2014), shared e-scooters (Mitra and Hess, 2021), Mobility-as-a-Service (Smith et al., 2022), and autonomous vehicles (Wang and Zhao, 2019).

2.1. Theory of planned behaviour

The Theory of Planned Behaviour (TPB), introduced by Ajzen (1991), posits that behavioural intention is shaped by attitude, subjective norms, and perceived behavioural control. This study will assess the acceptance of electric motorcycles (EMs) by examining how these three TPB constructs influence behavioural intention. Higher intention is viewed as a positive outcome since it is closely linked to actual behaviour, such as adopting an EM. The study will explore the impact of attitude, subjective norms, and perceived behavioural control on intention, drawing on the TPB framework, which has been widely validated for its effectiveness in understanding behavioural intentions across various fields, including technology adoption. The selection of these constructs is supported by prior research that highlights their relevance and empirical validation in similar contexts.

Attitude is the psychological emotion, either positive or negative, in response to a behaviour such as adopting EMs (Eagly, 1993, Ajzen, 1991). Taylor and Todd (1995) further expand on this concept suggesting an individual with a positive attitude is more likely to demonstrate positive behavioural intention. While there are various altitudinal factors such as vehicle ownership, comparative economic advantage, government policy, environmental benefits, etc. (Eccarius and Lu, 2020), this study evaluates attitude regarding value, correctness and necessity.

Subjective norms are explained by Ajzen (1991) as the amount of social pressure perceived on an individual engaged in a specific behaviour. In other words, subjective norms can be considered as the social pressure a group can have on an individual, which shapes his/her decisions (Ajzen, 1991). The subjective norms explored in this study include the belief that important groups for an individual (i.e., relatives and friends) support the adoption of EMs.

Perceived behavioural control in the TPB model refers to an individual's perception of the difficulty of engaging in a particular behaviour (Ajzen, 1991). A larger behavioural control can be interpreted as individuals with readily available resources (finance or time), or opportunities are much more likely to conduct a specific behaviour (Chen and Tung, 2014, Madden et al., 1992). This study considers the EM users' financial capacity, usage capability and easiness as factors associated with perceived behavioural control.

TPB has been well-known for its flexibility to include new variables (Kaye et al., 2022; Kelly et al., 2022, 2023; Li et al., 2023; Nguyen-Phuoc et al., 2024; Oviedo-Trespalacios et al., 2021), the present investigation extends the TPB by integrating perceived risk into the model. EMs is considered as an underdeveloped technology product which exists numerous types of risk. In this study, perceived risk is conceptualised based on the well-accepted notion that risk perception is a multidimensional construct. Specifically, the present investigation explores the impact of infrastructural, technological, and economic risks on adopting EMs.

2.2. Perceived risk

Perceived risk, as defined by Bauer (1960) as "a combination of uncertainty plus seriousness of outcome involved," is one of the critical barriers that make consumers reluctant to make purchase decisions (Kim et al., 2008). In the context of transport, travellers' risk perception significantly influences the choice of transport modes/services as well as their travel behaviour (Wang et al., 2019; Nguyen-Phuoc et al., 2020; Rod et al., 2023; Zhang et al., 2019). Perceived risk can be represented by two intertwined components: the possibility of unwanted or undesired outcomes and the severity of said results (Bauer, 1960; Cox and Rich, 1964). According to Wu et al. (2015), there are various dimensions of perceived risk, and the types of risk that users perceive are mostly specific to product characteristics, adopting circumstances, and the availability of information about the attributes of a product.

Compared to internal combustion engine vehicles, there might be some new types of risks associated with electric vehicles. Recently, perceived risk towards electric vehicles has received serious attention from both practitioners and researchers (Wang et al., 2018). Particularly, the role of perceived risk in the adoption of electric vehicles has been widely examined; however, the findings are mixed. One possible reason is that perceived risk is often treated as a unidimensional construct (not a hierarchical construct) in adoption studies, although the authors define perceived risk as comprising different dimensions (Wang et al., 2018; Featherman et al., 2021; Yang et al., 2020). For example, Wang et al. (2018b) defined users' perceived risk towards electric vehicles to include five dimensions: performance risk, physical risk, financial risk, time risk, and psychological risk. Marakanon and Panjakajornsak (2017) suggested a six-dimensional construct of perceived risk, including functional risk, performance risk, physical risk, psychological risk, social risk, and financial risk, and explored the role of this construct in the context of environmentally friendly electronic products in Thailand. McLeay et al. (2018) defined perceived risk associated with hybrid car adoption as a multidimensional concept comprising financial, social, time, psychological, and network externalities.

Similar to electric cars, electric motorcycles (EMs) are emerging technology products that are also associated with underdeveloped technology. In terms of the technical aspect, typical risks such as limited range, malfunctioning products, poor performance, or privacy concerns regarding electronic transactions needed to charge the motorcycle are significant concerns for users (Featherman and Pavlou, 2003). On the operational side, concerns regarding accidents (Phun et al., 2018), maintenance costs, or required riding skills (Ma et al., 2019) can deter riders from adopting this new mode of transport.

The role of perceived risk in EMs adoption intention has been rarely explored. A significant issue in perceived risk research is the neglect of its multidimensional nature (Murtiningrum et al., 2022; Chen et al., 2017; Rod et al., 2023). Therefore, it is necessary to determine the key dimensions of perceived risk for EMs adoption intention and establish it as a hierarchical construct involving different components. By specifying these lower-order components of perceived risk, hierarchical models can encompass specific traits of a more comprehensive conceptual variable of interest (Hair et al., 2016). Building upon previous literature, this study examines nine primary dimensions of perceived risk, which include performance risk, financial risk, privacy risk, time risk, psychological risk, road safety risk, range anxiety risk, explosion and fire risk, and environmental risk.

From a methodological standpoint, perceived risk is considered to be a reflective-reflective second-order construct whose dimensions are closely related and covary. As such, it is anticipated that there is a strong correlation among the dimensions. For instance, users might feel that EMs fail to perform and function as anticipated (performance risk), causing a loss of money (financial risk) and a loss of time (time risk). Additionally, users' concerns regarding explosion and fire safety (explosion & fire risk) as well as concerns about the limited driving range of EMs (range anxiety risk) might result in psychological distress when riding an EM (psychological risk). Higher-order constructs offer several benefits in research (Sarstedt et al., 2019). Firstly, they contribute to model parsimony by reducing the number of relationships in a path model. Instead of establishing connections between multiple independent and dependent constructs, researchers can consolidate the independent constructs into a higher-order construct. Higher-order constructs offer a valuable solution to the bandwidth-fidelity dilemma by striking a balance between the amount of information and the thoroughness of testing, thus leading to more reliable outcomes. There are four types of higher-order constructs: reflective-reflective, reflective-formative, formative-reflective, and formative-formative, with reflective-reflective and reflective-formative constructs being prominently employed in various fields (Becker et al., 2012). Reflective-reflective measurement approaches are prevalent in psychology and management sciences, while reflective-formative approaches are more commonly adopted in disciplines such as economics and sociology. In reflective-reflective models, it is essential that changes in the latent variable precede variations in the indicators. This implies that all indicators within the model share a common underlying concept and can be used interchangeably without affecting the construct's validity, even if certain indicators are included or excluded.

2.2.1. Performance risk

Performance risk pertains to the potential loss incurred when a purchased service or product fails to perform and function as anticipated (Kushwaha and Shankar, 2013). Despite several years of operation, a significant portion of consumers has not yet encountered or experienced EMs within their local vicinity. This lack of familiarity with EMs gives rise to apprehensions regarding the vehicle's reliability, performance, as well as the accessibility and effectiveness of maintenance and charging infrastructure in their respective regions. It is widely acknowledged that electric vehicles exhibit lower performance characteristics, such as engine power, acceleration, and maximum speed, compared to conventional vehicles (Liao et al., 2017, Wicki et al., 2023). In the context of Vietnam, the majority of available EM models typically possess a maximum speed range of 40 km/h to 50 km/h (Le et al., 2022). Furthermore, due to the limited availability of accurate performance profiles for electric vehicles, drivers tend to underestimate their operational capabilities (Rajper and Albrecht, 2020). Research in China on electric vehicle user concerns found that improving technological features in areas like transmission, speed, driving comfort, and overall performance can reduce performance risk (Wang et al., 2018).

2.2.2. Financial risk

Financial risk involves the potential loss of money resulting from an improper buying decision (Kushwaha and Shankar, 2013). EMs are known for their high price tags, and despite offering long-term reliability, they come with significant upfront costs that require financing, insurance, and infrastructure investments. Consumers may also have concerns about future expenses associated with battery or motor replacements in electric vehicles and the financial commitment required for such payments (Rajper and Albrecht, 2020; Zhang et al., 2013). Additionally, the limited utilisation of electric vehicles at present presents challenges in terms of providing associated services such as maintenance and repairs, as they cannot benefit from economies of scale. As a result, offering services at reasonable prices becomes challenging (Kessides, 2013; Mirjat et al., 2018).

2.2.3. Privacy risk

Privacy risk, as conceptualised by Featherman and Pavlou (2003), encompasses the potential loss of control over personal information, which can subsequently be utilized without consent. This includes activities such as fraudulent transactions or the unauthorised disclosure of confidential data. While privacy risks are commonly associated with transport-related services that employ e-payments, such as ride-sharing platforms (Cheng, 2016; Wang et al., 2020), they also assume significance for prospective consumers of EMs. Manufacturers and selling agencies typically request detailed personal information from EM consumers to facilitate enhanced customer services. Moreover, the advanced computerisation and the Global Positioning System (GPS) cloud-connected features of EMs involve the logging of intricate details for each kilometer driven. Within the context of LMICs with limited technological advancements, there is a risk that customer information may be vulnerable to unauthorized access, misuse, or even unauthorised sale without consent (Mohammed and Tejay, 2017).

2.2.4. Time risk

Time risk refers to the belief that customers may lose valuable personal time in the future, particularly in terms of electric vehicle maintenance and unplanned charging. Products that waste customers' time are typically met with the least forgiveness. Scheduled or unscheduled visits to public electric vehicle charging infrastructure stations may be perceived as causing repetitive and unacceptable time delays (Featherman et al., 2021). Unlike the convenient and speedy pit stops at ubiquitous gas stations, charging an electric vehicle often involves searching for and driving to charging stations, waiting in line for a charge, and the actual time required for the recharge process. When inquiring about expectations regarding electric vehicles, prospective users place significant emphasis on the importance of shorter charging times, indicating a desire for electric vehicles that can be quickly recharged to minimise downtime (Donati et al., 2015).

2.2.5. Psychological risk

The adoption of electric vehicles can give rise to psychological risks, which can manifest as frustrations and a loss of ego and peace of mind. When deciding to purchase an electric vehicle, some consumers may experience varying levels of affective and emotional feelings of danger, which disrupt their sense of tranquility. As discussed by Slovic et al. (1980), consumer perceptions of different threats and hazards often translate into concerns about risks. Certain consumers may avoid embracing innovations that require learning, changes in lifestyle, or are perceived as potentially dangerous, leading to avoidance behaviours. Additionally, some individuals may worry about receiving negative opinions from friends or relatives after purchasing electric vehicles (Jiang, 2016).

2.2.6. Road safety risk

Safety risk is a fundamental concern when it comes to adopting new technologies or products. Researchers have consistently emphasised the importance of considering safety risks in various contexts (Hulse et al., 2018; Menon and Alexander, 2020). These risks can encompass a range of factors, including equipment failures, potential hazards, and adverse consequences on individuals' well-being. The unique characteristics of electric vehicles, such as their relatively quiet operation, compared to conventional vehicles, can pose safety challenges, especially in environments with high levels of noise pollution (Hamzah et al., 2013; Poveda-Martínez et al., 2016). Understanding and addressing these safety concerns is crucial to ensure the widespread acceptance and adoption of electric vehicles.

2.2.7. Range anxiety risk

Range anxiety risk arises from concerns about the limited driving range of electric vehicles. In a study examining integration risks of electric vehicles, Capuder et al. (2020) highlighted that range anxiety is among the most significant challenges that potential users can encounter. While one can argue that compared to performance risk, range anxiety risk could be less impactful because of consumers' preference for new technologies that offer a comparable level of driving comfort to their existing options (Yuan et al., 2018, Franke et al., 2016). No study has explicitly considered the latent structure of both risks and their influence on the intention of using an EM.

2.2.8. Explosion & fire risk

Compared to internal combustion engine vehicles, which have been continuously developed and used for the past century, electric vehicles are still in the early stages of their development. Electric vehicles often use lithium-ion batteries, which come with inherent risks and hazards, including fire and explosion. According to Sun et al. (2020), most fire incidents involving electric vehicles are caused by the thermal runaway of lithium-ion batteries. Such fires can occur due to various factors, such as intentional arson, prolonged mistreatment leading to self-ignition in stationary vehicles, charging process-related fires, self-ignition during vehicle operation, and fires resulting from high-speed collisions or other traffic accidents (NTSB, 2018). Furthermore, the pursuit of rapid charging and discharging capabilities, combined with the emphasis on achieving high driving performance in electric vehicles, increases the potential fire risk associated with them. The concern regarding explosion and fire safety, as highlighted by Bisschop et al. (2020), acts as a hindrance to the widespread adoption of electric vehicles as the dominant mode of transport.

2.2.9. Environment risk

While electric vehicles are generally recognised for their minimal pollution emissions, it is crucial not to overlook the end-of-life challenges associated with lithium-ion batteries due to their environmental hazards (Hua et al., 2021). On the other hand, it is important to note that electric vehicles can produce a significant amount of pollutants during the manufacturing process (Emilsson and Dahllöf, 2019; Melin, 2019). The production of large lithium-ion batteries is a major source of emissions throughout the lifecycle of electric vehicles. The extraction and processing of minerals such as lithium, cobalt, and nickel, which are essential components of modern electric vehicle batteries, often require the use of fossil fuels and high-temperature heating processes. This intensive battery production is estimated to contribute to electric vehicles generating approximately 80 % more emissions during manufacturing compared to the production of a similar gas-powered vehicle (Climate Port, 2022).

3. Hypothesis development

Previous behavioural studies following the TPB have hypothesised that subjective norms, attitude towards the behaviour and perceived behavioural control are the antecedents of intention to use and intention is the antecedent of behaviour (Eccarius and Lu, 2020, Ajzen, 1991). It has been well-demonstrated that users with high intentions are likelier to engage in a particular behaviour than those with lower intentions. In the context of transport, subjective norms such as the influence of family and acquaintances are the relevant factors contributing to the adoption of new technology such as EMs (Rezvani et al., 2015). Similarly, the positive attitude of users contributes to the intention to use and, consequently, the adoption of electric vehicles (Shalender and Sharma, 2021). In contrast, a negative attitude towards a product or a service leads to the intention to abandon or discontinue usage (Ma et al., 2019). Regarding EMs, consumer attitudinal factors towards the vehicles' technical attributes like range and speed or pro-environmental attributes are connected to the adoption of EMs (Eccarius and Lu, 2020). Likewise, perceived behavioural control and subjective norms and attitudes predict customers' intention to purchase and operate battery electric vehicles (Simsekoglu et al., 2019). According to Ajzen (1991), perceived behavioural control, specifically ease of use, positively affects the intention to use. This connection holds across many transport-related behaviours such as impaired walking (Oviedo-Trespalacios et al., 2021, Lennon et al., 2017), airline tickets (Suki and Suki, 2017) and ride-hailing (Nguyen et al., 2021, Nguyen-Phuoc et al., 2022b). Additionally, according to the TPB, perceived behavioural control is positively related to the adoption intention and usage of EMs (Simsekoglu et al., 2019). Therefore, the following hypothesises are proposed as follows:

H_1: Subjective norms has a positive direct effect on the adoption of EMs.
H_2: Attitude has a positive direct effect on the adoption of EMs.
H_3: Perceived behavioural control has a positive direct effect on the adoption of EMs.

Given the inherent difficulty in objectively measuring risk, the existing literature predominantly defines perceived risk as an individual's subjective perception of the potential loss incurred while striving for a desired outcome (Stone and Grønhaug, 1993). Building on the expectancy-value model of attitude developed by Fishbein and Ajzen (1977), attitudes towards an object are believed to originate from individuals' beliefs about the object. In the context of attitudes towards a specific behaviour, each belief associates the behaviour with specific outcomes or attributes that are already regarded positively or negatively (Ajzen, 1991). As a result, "unfavorable attitudes are formed towards behaviours that are linked to predominantly undesirable consequences" (Ajzen, 1991, p. 191). Thus, given the uncertainties and potential negative repercussions associated with the adoption of EMs, it is reasonable to anticipate that perceived risk will contribute to unfavorable attitudes towards their adoption.

In the context of transport, perceived risks when accessing transport are found to negatively impact their attitude and, therefore, their intention to use the service (Zhang et al., 2019). Also, Ma et al. (2019) concluded in their study on Chinese ride-hailing service usage that various perceived risks (e.g., time risk, physical risk) can negatively affect customers' attitudes towards the ride-booking application and the service. Similarly, Zhang et al. (2019) and Oviedo-Trespalacios et al. (2019) confirmed that perceived risk had an effect on initial customer trust and attitude towards using autonomous vehicles and other forms of driver support systems. Also, when adopting new technology, users might be exposed to risks linked with poor integration of the technology and can result in a penalty. For example, the lack of critical infrastructure such as charging facilities, results in the risk of the driver not being able to reach their destination (Zhang et al., 2017). According to She et al. (2017), electric vehicle users face the risk of inaccessible charging stations, limited driving range, short battery life and long charging time, which were prospective barriers to users' reluctance to adopt the vehicles. In addition, Wolf et al. (2014) indicate relationships between the perceived financial, time, physical and social risks and customers' attitudes towards electric vehicles. Therefore, the following hypothesises are proposed for testing. Please note that as part of this research, we will consider a wide range of risks to measure perceived risk considering its multidimensional nature.

H_4: Perceived risk has a negative direct effect on the adoption of EMs.
H_5: Perceived risk has a negative direct effect on attitude.

Demographic factors such as gender, age, educational level or income have been evaluated by various studies in the context of the adoption of technology (Eccarius and Lu, 2020, Kaye et al., 2022). Specifically, there has not been a consistent consensus regarding the effect and importance of gender factors in forming attitude towards motorcycles and EMs (Eccarius and Lu, 2020). At the same time, some studies suggest that gender is more important when evaluating motorcycle attributes than four-wheeled vehicles (Chen, 2015). Other studies attribute the differences to cultural circumstances instead (Guerra, 2019; Jones et al., 2013). Similar to gender, there are also debates on the relevance of age when investigating adoption behaviour. Wolf et al. (2014) found that early electric bicycle adopters were 60 years old and older, thus suggesting there are differences in the willingness to use EMs by age. Madigan et al. (2016)

determined that age does not moderate the relationships related to adopting automated vehicles.

Concerning the effect of income, Vassileva and Campillo (2017) and Zubaryeva et al. (2012) determined that higher-income populations in Europe are more likely to adopt electric vehicles compared to lower-income families. There have been limited studies exploring the moderate effect of demographic factors on the formation of EM adopting intention, particularly in a motorcycle-dependent country. Hence, this study combines these demographic factors in its investigation to determine their moderating effects on the proposed relationships. Thus, the following hypotheses are established in this study as follows:

H_6: Gender, age, educational level, income and location have moderating roles in the relationship between subjective norms and the adoption of EMs

H_7: Gender, age, educational level, income and location have moderating roles in the relationship between attitude and the adoption of EMs

H_8: Gender, age, educational level, income and location have moderating roles in the relationship between perceived behavioural control and the adoption of EMs

H_9: Gender, age, educational level, income and location have moderating roles in the relationship between perceived risk and the adoption of EMs

In summary, Fig. 1 illustrates the developed model, including first- and second-order constructs.

4. Methodology

4.1. Questionnaire development

Data was collected using a face-to-face questionnaire survey to validate the proposed conceptual model and research hypotheses. The questionnaire survey had three parts. In the first part, information about the research aim, research objectives as well as the rights of survey participants were presented. The second part, the main part of the questionnaire, consisted of items measuring constructs in the conceptual model. Most of the measurement items were developed based on the review of pre-validated literature and modified to be suitable in the research context. The authors also developed several items related to the risk of adopting EMs based on previous related studies, as shown in Appendix A1. All questionnaire items were scored on a seven-point Likert-type scale in which 1 = 'Strongly Disagree' and 7 = 'Strongly Agree'. In the last part of the questionnaire, demographic details of the participants were collected, such as gender, age, and education level. A panel of five transport experts pretested the initial questionnaire. The revised version was then tested with 30 undergraduate students in the University of Danang before the full-scale survey was carried out.

4.2. Data collection and descriptive statistics of participants

In this study, the survey's target population was individuals who had not owned an electric motorcycle. As such, the convenience sampling method was used to collect data since this method was particularly effective in the case the survey population was substantial (Song et al., 2012). The field survey was conducted in two large cities in Vietnam (i.e., Hochiminh and Danang) from 4th April 2022 to 19th May 2022. Hochiminh city, not only the largest city in Vietnam but also serves as the country's economic hub, is situated in the

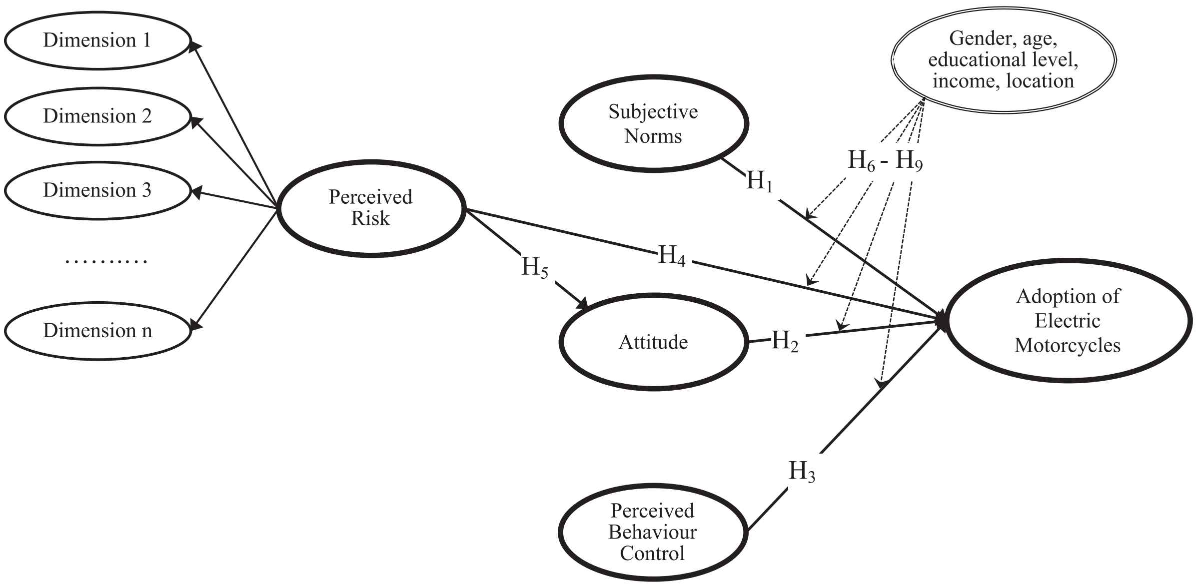
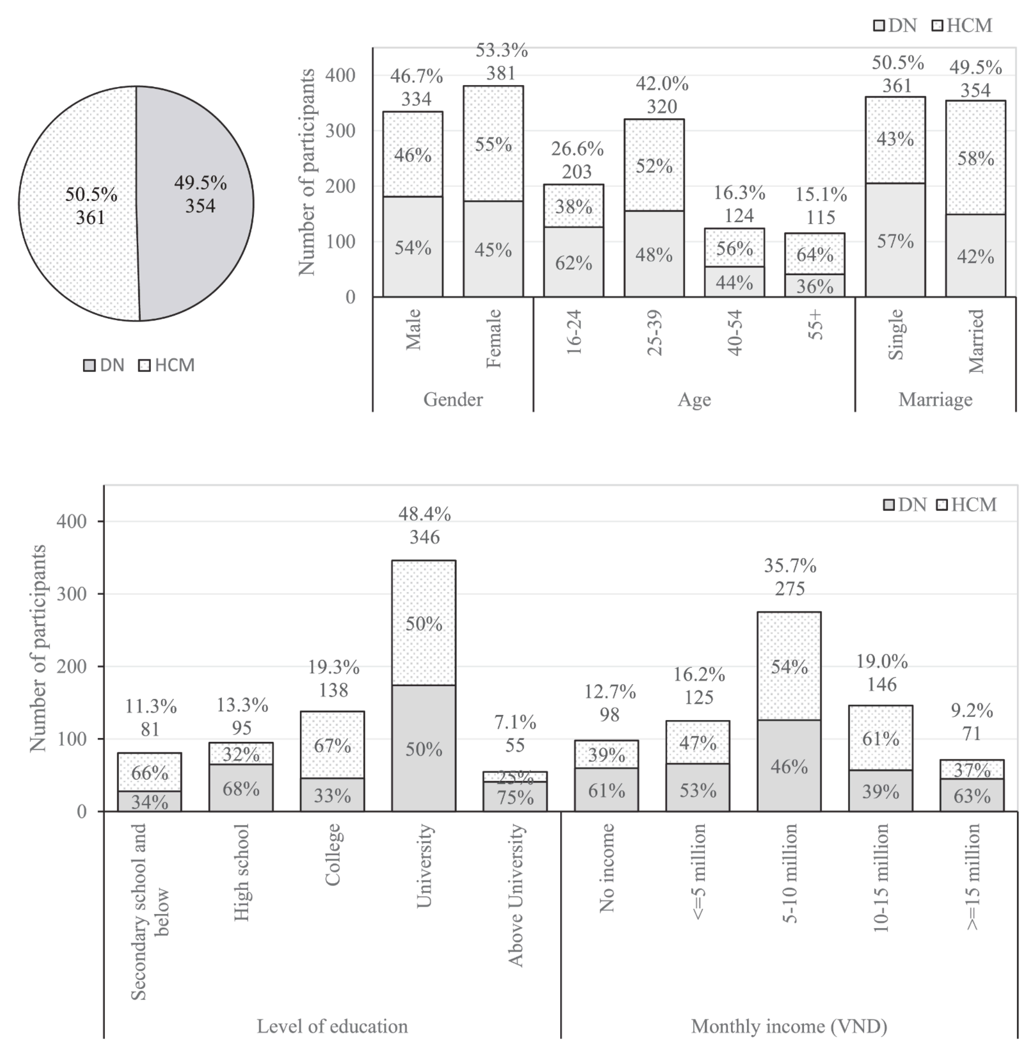


Fig. 1. Proposed conceptual model.

south-eastern region. It covers an area of 2,095 square kilometers and is home to a population of 8,993,082 residents (General Statistics Office, 2020). On the other hand, Danang city, located in the central region of Vietnam, holds the distinction of being the country's third-largest city. It is widely recognized as a popular tourist destination. Danang spans an area of 1,285 square kilometers and has a population of 1,046,252 inhabitants (General Statistics Office, 2020). Both cities are exceptionally proactive in their development endeavors and are steadfast in their commitment to achieving sustainable development objectives (Nguyen et al., 2023; Pham et al., 2022).

A total of five well-trained research assistants in each city approached public areas such as malls, public transport stations, coffee shops, parks and invited people to participate in the survey. Only participants willing to participate in the survey and answer 'No' to the screening question ('have you ever owned a electric motorcycle') were recruited. To increase the response rate, a small amount of money (around $1) was paid to participants when they completed the questionnaire. Out of 800 questionnaires distributed by the research assistants, a total of 769 were returned. However, after discarding responses with missing values and outliers, 715 questionnaires were used for further analysis, representing an 89.38 % response rate. Fig. 2 illustrates the profiles of survey participants. Of the participants, 50.5 % was from Hochiminh and 49.5 % was from Danang. Male accounted for 43.8 % of the sample, while 53.3 % was female. The group aged 25–29 accounted for the highest parentage with 42.0 %, followed by the 16–24 group with 26.6 %. Regarding marital status, 50.5 % were single and 49.5 % were married. Around half of the participants received a university education, and 35.7 % had a monthly income between 5 and 10 million VND (1USD = 23,000 VND).

To examine common method bias, a non-response bias test was conducted by comparing the responses of early and late survey participants. Since no difference between early and late participants' responses (at 0.01 significant level) was found, non-response bias



Notes: DN: Danang city, HCM: Hochiminh city, 1USD=23,000 VND

Fig. 2. Descriptive statistics of participants.

was not a concern. Additionally, a bivariate correlation analysis was performed. All correlations among the proposed model's latent constructs were lower than 0.9. As such, no common method bias was confirmed in this study.

5. Data analysis and findings

Partial Least Squares Structural Equation Modelling (PLS-SEM) was implemented to test the hypotheses in the proposed model and to examine how well the model fitted with the obtained data. PLS-SEM was also used to evaluate the measurement models and the relationships between observed indicators and latent constructs. Compared to Covariance-Based Structural Equation Modelling (CB-SEM), PLS-SEM had several advantages, such as reducing parameter estimation bias, being appropriate with a small sample size or not effecting by the distribution of data. In this study, SmartPLS 3 was used to test the theoretical model. The PLS algorithm and bootstrapping with 5,000 subsamples were applied to examine path coefficients' significance, as Hair et al. (2016) suggested. Since the proposed model include a higher-order construct, the disjoint two-stage approach was applied to specify and estimate higher-order constructs in PLS-SEM (Sarstedt et al., 2019). In the stage one, the disjoint two-stage approach considered only the lower-order components of the higher-order construct in the path model. These were directly linked to all other constructs that the higher-order construct is theoretically related to. The model assessment at this stage focused on the measurement models of lower-order components, which satisfied all relevant criteria (e.g., internal consistency, convergent validity, and discriminant validity). In stage two, we used the latent variable scores of the lower-order components obtained from stage one to create and estimate the stage two model. The evaluation of stage two focused on the measurement model of the higher-order component.

5.1. Dimensions forming perceived risk construct

In this study, the perceived risk construct was structured as a reflective-reflective second-order construct. Measurement items were built from an extensive literature review and author development. As such, it was necessary to investigate its underlying relationships and its appropriateness in describing the content of construct through Exploratory Factor Analysis (EFA). EFA process includes several steps:

Firstly, the Kaiser–Mayer–Olkin (KMO) test and Bartlett's test of sphericity were used to confirm the suitability of the collected data. Table 1 shows that the value of KMO was 0.873, which was higher than the threshold of 0.6 suggested by (Pallant, 2011). The

Table 1
Factor analysis of perceived risk dimensions.

Component	C1	C2	C3	C4	C5	C6	C7	C8	C9	Label
Eigen-values	8.918	2.523	2.346	1.925	1.397	1.256	1.158	1.107	0.940	
Cronbach's Alpha	0.940	0.865	0.852	0.855	0.830	0.757	0.725	0.759	0.857	
Explained variance %	30.752	8.698	8.089	6.637	4.819	4.330	3.992	3.817	3.240	
Cumulative %	30.752	39.451	47.539	54.176	58.995	63.325	67.317	71.134	74.374	
Q1								0.830		Road Safety Risk
Q2								0.803		
Q3								0.733		
Q4					0.813					Range Anxiety Risk
Q5					0.832					
Q6					0.843					
Q7		0.815								Explosion & Fire Risk
Q8		0.910								
Q9		0.865								
Q10			0.961							Financial Risk
Q11			0.772							
Q12			0.657							
Q13			0.640							
Q14						0.788				Time Risk
Q15						0.884				
Q16						0.656				
Q17						0.597				
Q18	0.880									Privacy Risk
Q19	0.989									
Q20	0.965									
Q21							0.728			Performance Risk
Q22							0.792			
Q23							0.649			
Q24							0.665			
Q25				0.699						Psychological Risk
Q26				0.961						
Q27				0.947						
Q28									0.895	
Q29									0.911	

Kaiser–Mayer–Olkin (KMO) = 0.873, χ^2 = 12,114.752, $p < 0.001$.

result of the Bartlett test was $\chi 2 = 12,114.752$, $p < 0.001$, which was meaningful at the 0.01 significance level. The preliminary analysis confirmed the data's suitability for the EFA. Secondly, Principal Component Analysis (PCA) revealed the underlying relationships among measurement items in which high correlations items were grouped together to form dimensions of a construct. The results showed that 29 measurement items resulted in nine dimensions, explaining 74.37 percent of the total variance; however, there was a dimension, forming from two item Q28 and Q29, having the Eigen values lower than 1. Hence, these two items were omitted and other 27 measurement items were kept to be rotated at the next step in EFA process. Factor rotations were conducted with promax rotation method which belonged to oblique rotation methods. The results of EFA analysis indicated that eight retained dimensions were extracted and explained 71.13% of the cumulative variance which was suitable for the social science research (Hair et al., 2010). These dimensions were also labeled according to the appropriateness of included individual items. They were Road Safety Risk (RSR), Range Anxiety Risk (RAR), Explosion & Fire Risk (EFR), Financial Risk (FIR), Time Risk (TIR), Privacy Risk (PRR), Performance Risk (PER) and Psychological Risk (PYR). Out of eight dimensions, Privacy Risk, including three items explained 30.75% of the total variance (the highest percentage), followed by Explosion & Fire Risk (8.69%) and Financial Risk (8.08%). The factor loadings of all the items ranged from 0.597 to 0.989, indicating the high loaded values of each item onto relevant dimensions. The Cronbach's alpha value, which reflected the internal consistency among measurement items in one perceived risk's dimension, was also checked to

Table 2
First-order measurement model evaluation.

Constructs	Items	Factor Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
Privacy Risk (PRR)			0.961	0.892
	PRR1	0.930		
	PRR2	0.946		
	PRR3	0.959		
Explosion & Fire Risk (EFR)			0.903	0.758
	EFR1	0.727		
	EFR2	0.944		
	EFR3	0.923		
Financial Risk (FIR)			0.912	0.776
	FIR1	–		
	FIR2	0.855		
	FIR3	0.928		
	FIR4	0.858		
Psychological Risk (PYR)			0.955	0.913
	PER1	–		
	PER2	0.941		
	PER3	0.970		
Range Anxiety Risk (RAR)			0.898	0.746
	RAR1	0.848		
	RAR2	0.868		
	RAR3	0.874		
Time Risk (TIR)			0.844	0.734
	TIR1	–		
	TIR2	0.728		
	TIR3	0.968		
	TIR4	–		
Performance Risk (PER)			0.872	0.774
	PER1	–		
	PER2	0.833		
	PER3	0.924		
	PER4	–		
Road Safety Risk (RSR)			0.937	0.881
	ACR1	–		
	ACR2	0.930		
	ACR3	0.947		
Subjective Norms (SUN)			0.955	0.877
	SUN1	0.940		
	SUN2	0.949		
	SUN3	0.920		
Attitude (ATT)			0.900	0.751
	ATT1	0.847		
	ATT2	0.875		
	ATT3	0.877		
Perceived Behaviour Control (PBC)			0.896	0.742
	PBC1	0.830		
	PBC2	0.869		
	PBC3	0.885		
Adoption of Electric Motorcycles (AEM)			0.966	0.905
	AEM1	0.947		
	AEM2	0.953		
	AEM3	0.955		

confirm the reliability of each dimension. Table 1 showed that all of the Cronbach's values of eight dimensions overcome the threshold of 0.7, which confirmed that all explored dimensions were reliable.

Consequently, EFA process showed that perceived risk was a second-order construct that included eight main dimensions formed from 27 measurement items. This second-order construct was then included in the proposed theoretical model to analyse the effect of perceived risk on attitude as well as on the adoption of electric motorcycles.

5.2. First-order measurement model evaluation

Confirmatory Factor Analysis (CFA) was used to assess the measurement models, including the first- and second-order measurement models. According to Hair et al. (2016), a measurement model could be assessed through internal consistency reliability, convergent validity and discriminant validity. Table 2 revealed that composite reliability (CR) values of all latent constructs, a criteria used to check the internal consistency reliability of constructs, was between 0.844 and 0.961, exceeding the 0.7 benchmark suggested by Fornell and Larcker (1981). Besides, the convergent validity of constructs was assessed based on factor loadings and average variance extracted (AVE). The value of factor loadings of measurement items ranged from 0.728 to 0.970, overcome 0.7 benchmark recommended by Hair et al. (2010). It is noted that seven measurement items of perceived risks' dimensions were omitted for further analysis since their loading values were below 0.7. Also, the values of AVE of all constructs were between 0.734 and 0.913, surpassing the threshold of 0.5 (Hair et al., 2010). In this study, Heterotrait-Monotrait Ratio (HTMT) was used to assess the discriminant validity of latent constructs. Table 3 showed that the HTMT value of each latent construct was below the cut-off value of 0.85 (Henseler et al., 2016). Hence, the proposed theoretical model was confirmed to have good reliability, convergent validity, and discriminant validity for all first-order constructs.

5.3. Second-order measurement model evaluation

The assessment of second-order constructs was carried out based on a number of criteria, including the significance and relevance of the outer loading, the indicator collinearity and average variance extracted (Hair et al., 2017a). The results of the evaluation are presented in Table 4.

Variance inflation factor (VIF) was used to test the collinearity of the reflective indicators (Hair et al., 2017a). Table 4 showed that all of VIF values were less than 5, the cut-off value, which indicated no multi-collinearity among the dimensions of the second-order construct. The result of the second-order measurement model showed that when perceived risk construct included eight dimensions (Model1), the AVE value of perceived risk was 0.420, lower than the threshold of 0.5. Additionally, there were five dimensions having outer loadings below 0.7. Retaining an indicator of a construct was based on the value of outer loading where it is suggested that this value should be greater than 0.7 (Hair et al., 2011). As such, three dimensions (i.e., PYR, RAR and RSR), which had low loading factors, were eliminated. In Model 2, only five dimensions were retained, including PRR, EFR, FIR, TIR, PER. The AVE value of the second-order construct increased to 0.548 (> 0.5, the cut-off value) and the outer loadings of all the dimensions (first-order constructs) varied from 0.702 to 0.784, which were higher than the 0.7 threshold. As such, the perceived risk formed by five dimensions was used to assess the structural model.

5.4. Structural model results

The structure model was assessed through a number of criteria, including model fit, coefficient of determination (R^2), predictive relevance (Q^2) and path coefficient (β). The standardised root mean residual (SRMR) was 0.058 which was smaller than the 0.08 threshold and NFI which was higher than the 0.858 threshold, indicating a good model fit. While R^2 value revealed the accuracy, Q^2 value showed the relevance in the prediction capability of the proposed model. The results showed that the R^2 value of AEM was 0.401, indicating a moderate level of predictive accuracy since R^2 was greater than the cut-off value of 0.333 suggested by Henseler et al. (2009). On the other hand, the Q^2 value of AEM was 0.341. According to Hair et al. (2016), a positive Q^2 value indicated that the

Table 3
Heterotrait-Monotrait Ratio of the first-order factor model.

Constructs	ATT	AEM	EFR	FIR	TIR	PBC	PER	PRR	PYR	RAR	SAR	SUN
ATT												
AEM	0.598											
EFR	0.047	0.169										
FIR	0.131	0.134	0.466									
TIR	0.028	0.136	0.621	0.732								
PBC	0.607	0.478	0.054	0.210	0.065							
PER	0.104	0.168	0.584	0.477	0.589	0.101						
PRR	0.102	0.078	0.472	0.554	0.626	0.185	0.429					
PYR	0.081	0.043	0.217	0.323	0.316	0.077	0.446	0.341				
RAR	0.109	0.115	0.415	0.373	0.497	0.079	0.351	0.206	0.113			
SAR	0.065	0.146	0.551	0.346	0.468	0.090	0.432	0.473	0.201	0.313		
SUN	0.615	0.528	0.075	0.036	0.109	0.403	0.056	0.076	0.029	0.107	0.097	

Table 4
Second-order measurement model evaluation.

Model	Second-order/ First-order constructs	AVE	VIF	Outer Loadings	SD	t-value	p-value
Model 1	**Perceived Risk (PRI)**	0.420					
	Privacy Risk (PRR)		1.696	0.683	0.073	9.406	<0.001
	Explosion & Fire Risk (EFR)		1.664	0.791	0.042	19.035	<0.001
	Financial Risk (FIR)		1.631	0.715	0.060	11.837	<0.001
	Psychological Risk (PYR)		1.234	0.327	0.107	3.068	0.002
	Range Anxiety Risk (RAR)		1.251	0.498	0.086	5.811	<0.001
	Time Risk (TIR)		1.711	0.732	0.046	15.936	<0.001
	Performance Risk (PER)		1.532	0.699	0.061	11.489	<0.001
	Road Safety Risk (RSR)		1.433	0.652	0.060	10.894	<0.001
Model 2	**Perceived Risk (PRI)**	0.548					
	Privacy Risk (PRR)		1.552	0.702	0.057	12.309	<0.001
	Explosion & Fire Risk (EFR)		1.497	0.784	0.037	21.309	<0.001
	Financial Risk (FIR)		1.585	0.750	0.041	18.360	<0.001
	Time Risk (TIR)		1.659	0.740	0.043	17.377	<0.001
	Performance Risk (PER)		1.390	0.723	0.045	15.939	<0.001

Notes: AVE: Average Variance Extracted, VIF: Variance Inflation Factor, SD: Standard Deviation

developed model had a good predictive ability. Q^2 value was obtained by performing a blindfolding procedure.

Fig. 3 and Table 5 presented the direct and indirect effects among the latent constructs of the proposed model. While three original TRB constructs (i.e., SUN, ATT and PBC) significantly and positively affected AEM, PRI was found to have negative impact on AEM ($\beta = -0.144^{***}$, t = 4.268). Additionally, the negative effect between PRI on ATT was confirmed in this study ($\beta = -0.096^{**}$, t = 2.345). ATT was also found to mediate the relationship between PRI and AEM; however, the coefficient of this indirect effect was relatively low ($\beta' = -0.027^{**}$, t = 2.203). Consequently, all hypotheses H_1, H_2, H_3, H_4 and H_5 were supported in this study.

5.5. Multigroup analysis

The Henseler's multigroup analysis (MGA) was applied to examine the influence path of the intention to adopt EMs among groups with different demographic, including gender, age, educational level, income and location (Henseler et al., 2016). Prior to performing MGA, an evaluation of measurement invariance of composite models (MICOM) was conducted using the three-step procedure, as outlined by (Sinkovics et al., 2016). According to Henseler et al. (2016), the assessment of measurement invariance aims to ascertain whether, when observing and studying phenomena under varying conditions, measurement models produce consistent measures of the same underlying attribute. Table A2a and Table A2b showed the results of the MICOM three-step procedure. The findings showed that measurement invariance had been partially established when comparing groups which met the minimum criteria necessary for evaluating significant differences between the two groups using MGA.

In Henseler's MGA method, the non-parametric method, a significant difference between specific path coefficients between two groups at a significance level of 10% was confirmed when a p-value was higher than 0.9 or lower than 0.1. Before performing the MGA, 715 valid samples were classified into two groups based on the above demographic factors. In terms of gender, there were 334 male and 381 female participants. The cut-off of 30 years old was chosen to divide the sample into two groups: young group and middle & older group. There were 346 participants aged under 30 and 369 participants aged 30 and older. Regarding income, two groups were

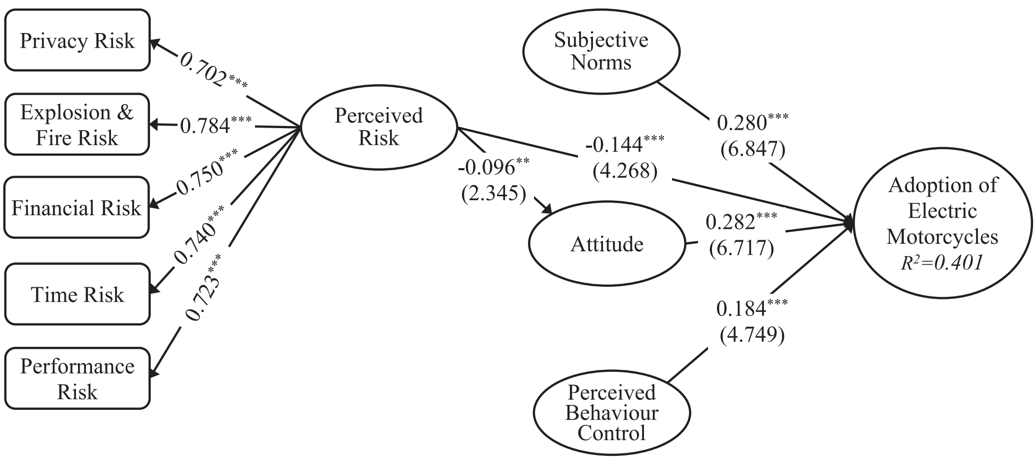


Fig. 3. Findings of structural equation model.

Table 5
Direct, indirect and total effect.

Path	Effect	Coefficient	SD	t-value	p-value
PRI → AEM	Direct effect	−0.144***	0.034	4.268	<0.001
	Indirect effect	−0.027**	0.012	2.203	0.028
	Total effect	−0.171	0.032	5.390	<0.001

Notes: ***p < 0.01, **p < 0.05, *p < 0.1, ns non-significant.

created, including low-income group (223 participants who earned less than 5 million VND per month) and middle- and high-income group (492 participants who earned 5 million VND and over). Based on the education level, no university degree group (314 participants) and have university degree group (401 participants) were divided.

The MGA results (Table 6) showed that there was no significant difference in the direct impact of all influencing factors on EMs adoption intention in terms of gender. The impact of perceived risk on the adoption intention was found to be significantly different between age groups as well as education level groups. The effect was higher in middle & older group (−0.226***) compared to young group (−0.114*). The effect of perceived risk on the intention was found to be significant and negative in group having no university degree (−0.251***), while in the group with a university degree the link was not found to be significant (−0.110ns). The results also revealed that income significantly moderated the link between subjective norms and the EMs adoption intention. The effect of subjective norms was significant and higher in the midder & older group (0.334***) compared to the young group (0.190**). Regarding location, significant differences were found in the link between perceived behaviour control and the adoption intention and the link between perceived risk and the intention. For participants from HCM, the effect of perceived risk on the intention was significant and negative (−0.360***), while the effect was not significant and positive for DN participants (0.163ns).

6. Discussion

6.1. Theoretical implications

Electric motorcycles (EMs) have the potential to contribute to sustainable mobility and the achievement of sustainable development goals, especially in countries with high motorcycle usage. While extensive research has focused on the adoption intention of electric cars, primarily in high-income countries, there is still a lack of understanding regarding the adoption intention of EMs in LMICs. It is crucial to address this knowledge gap by conducting research specifically on the acceptance of EMs. Given that climate change is an existential and global threat, it is essential to generate evidence-based knowledge on the electrification of the transport system that is useful for both high-income countries and LMICs. To achieve this, the present paper proposes a theoretical framework based on the Theory of Planned Behaviour (TPB) to explain the adoption of EMs. The framework results showed that all three original TPB constructs (i.e., attitude towards EMs, subjective norms, and perceived behavioural control) were confirmed to have significant and positive effects on the adoption intention of electric motorcycles (EMs) in the context of a middle-income country. Naturally, this is

Table 6
Multigroup analysis results.

Group	Relationship	Effect	Coefficient Group 1	Coefficient Group 2	Coefficient Difference	*p*-value Difference (One-Tailed)	Supported
Male (1) vs Female (2)	SUN → AEM	Total	0.245***	0.307***	0.062	0.779	No/No
	ATT → AEM	Total	0.336***	0.232***	0.105	0.102	No/No
	PBC → AEM	Total	0.171***	0.200***	0.030	0.651	No/No
	PRI → AEM	Total	−0.177***	−0.180***	0.003	0.466	No/No
Young (1) vs Middle & Older (2)	SUN → AEM	Total	0.302***	0.246***	0.056	0.242	No/No
	ATT → AEM	Total	0.286***	0.275***	0.011	0.447	No/No
	PBC → AEM	Total	0.172***	0.212***	0.039	0.699	No/No
	PRI → AEM	Total	−0.114*	−0.226***	0.112	0.056	***Yes/Yes***
Low income (1) vs Middle & High income (2)	SUN → AEM	Total	0.190**	0.334***	0.144	0.946	***Yes/Yes***
	ATT → AEM	Total	0.292***	0.292***	0.000	0.500	No/No
	PBC → AEM	Total	0.218***	0.136***	0.083	0.168	No/No
	PRI → AEM	Total	−0.180ns	−0.206***	0.026	0.545	No/No
No university degree (1) vs Have a university degree (2)	SUN → AEM	Total	0.284***	0.273***	0.011	0.451	No/No
	ATT → AEM	Total	0.241***	0.318***	0.077	0.828	No/No
	PBC → AEM	Total	0.231***	0.133**	0.098	0.104	No/No
	PRI → AEM	Total	−0.251***	−0.110ns	0.141	0.977	***Yes/Yes***
DN (1) vs HCM (2)	SUN → AEM	Total	0.324***	0.275***	0.048	0.268	No/No
	ATT → AEM	Total	0.228***	0.279***	0.052	0.748	No/No
	PBC → AEM	Total	0.125**	0.268***	0.143	0.977	***Yes/Yes***
	PRI → AEM	Total	0.163ns	−0.360***	0.523	0.000	***Yes/Yes***

Note: For coefficient: ** significant at 95%, *** significant at 99%.
For coefficient difference: * significant at 90%.

consistent with previous studies on the behavioural intention to use electric vehicles, which found significant and positive effects of TPB constructs on behavioural intention (Shalender and Sharma, 2021; Gunawan et al., 2022).

Another important finding is that subjective norms and attitudes were found to have an equal impact on the intention to adopt EMs, while perceived behavioural control had a lesser influence. Previous research has shown inconsistent relationships between attitude, subjective norms, perceived behavioural control, and behavioural intention. For example, studies conducted in individualistic cultures in the United States and Western countries have shown weak or no link between subjective norms and intention (Sparks, 2007). In contrast, this study was conducted in an Asian country with a more collectivist culture (Awanis et al., 2017), where people are more influenced by social norms. This explains the high impact of subjective norms on the adoption intention in this study. Consistent with previous research (Oviedo-Trespalacios et al., 2021), the findings highlight differences between Western and non-Western countries in terms of TPB and the relative importance of its predictors.

The TPB often generates mid-to-low predictive power, particularly when applied to actual choices in the field of transport, as it places heavy emphasis on attitude, subjective norms, and perceived behavioural control rather than objective contextual factors like risk or cost. This focus can lead to discrepancies between stated intentions and real-world decisions. To address the flaws of this theory, additional factors have often been incorporated to enhance its predictive accuracy (Hai et al., 2024, Dixit et al., 2022). In this study, perceived risk towards EMs, a factor that has garnered significant attention from both practitioners and researchers (Wang et al., 2018), has been integrated into the TPB framework. The present study also aimed to investigate the dimensions that constitute the perceived risk of using EMs. Through exploratory factor analysis (EFA), eight dimensions of risk were identified: road safety risk, range anxiety risk, explosion & fire risk, financial risk, time risk, privacy risk, performance risk, and psychological risk. These dimensions align with Bauer's (1960) theory of perceived risk and are consistent with findings from previous related studies (Eccarius and Lu, 2020; Chen et al., 2012; Featherman and Pavlou, 2003; Phun et al., 2018). Additionally, privacy risk is found to account for over 30 % of the total variance in perceived risk towards EM adoption intention is particularly noteworthy. This substantial percentage suggests that concerns related to privacy such as data security, unauthorised tracking, and potential misuse of personal information, are significant factors influencing consumers' apprehension about adopting EMs. The high variance explained by privacy risk underscores the need for EM manufacturers and policymakers to address these issues explicitly.

When extending the TPB model with perceived risk, the results of structural equation modeling (SEM) revealed that perceived risk was a second-order reflective construct comprising five first-order constructs: privacy risk, explosion & fire risk, financial risk, time risk, and performance risk. Furthermore, the results from the structural model highlighted the significant negative relationship between perceived risk and the intention to adopt EMs, although its magnitude was not as high as that of other TPB constructs. This finding is consistent with previous studies conducted in Vietnam, which suggested that the impact of perceived risk on intention was lower compared to TPB constructs (Nguyen-Phuoc et al., 2022b; Nguyen et al., 2019). One possible explanation is that EMs are still a relatively new mode of transport in Vietnam, and people may have limited knowledge about the potential risks associated with them and the magnitude of their impact. This demonstrates that it is crucial for stakeholders in the transport system to address any misinformation related to EMs, as it can influence the intention to adopt them.

The present manuscript not only provides good insights into the role of perceived risks on motorcycle riders' intention to get an EM but also introduces carefully validated instruments for measuring the different dimensions of risk associated with EM adoption. Focusing solely on one aspect of risk, such as range anxiety or performance risk, while neglecting others, could prove to be an ineffective approach. By failing to adequately address other important dimensions of risk, awareness-raising initiatives may fall short of their intended effectiveness. Therefore, this research highlights the necessity for governments and stakeholders to adopt a holistic perspective on risk, encompassing all relevant dimensions, to ensure the success of EM adoption efforts and create a safer and more sustainable transport landscape. This contribution is pivotal in the realm of electric vehicle adoption, as it equips electric vehicle manufacturers, policymakers, and regulatory authorities with the necessary tools to navigate the complex landscape of EM promotion.

The present study confirmed the moderating effects of several demographic factors on the paths of the proposed model. Specifically, the negative association of perceived risk with EMs adoption intention was more pronounced among participants in the middle and older age groups, those with lower education levels, and those residing in Hochiminh (HCM) City. One possible explanation for the greater importance of perceived risk in the middle and older age groups is that older individuals tend to be more cautious in decision-making and seek greater certainty before making a choice (Lumpkin et al., 1989). Furthermore, the positive association of subjective norms with intention was more evident among individuals in the middle and high-income brackets. This could be because middle and high-income individuals might be more influenced by social expectations, peer pressure, and societal norms, especially when it came to adopting newer, more advanced technologies like EMs. They were likely to be surrounded by social circles that valued sustainability, status, and innovation, making subjective norms a stronger determinant of their intention to adopt EMs. Besides, individuals in higher income brackets generally had greater financial capacity to act on social influences and recommendations. When subjective norms encouraged EM adoption, wealthier individuals might feel more pressure to conform, as they could afford the costs associated with electric vehicles. The finding of MGA also showed that the positive relationship between perceived behavioural control and adoption intention was stronger among individuals living in HCM City compared to Danang City. One possible reason for this difference is that HCM City serves as a major centre for finance, technology, and transport in Vietnam, providing residents with more opportunities to experience EMs through the numerous showrooms available in the city. The study revealed moderate effects of age, income, educational level, and location, offering insights into how EM adoption intention varies among different groups.

6.2. Practical implications

The present study offers several practical implications that can be highlighted. Primarily, the results of the present study hold significant promise for the development of interventions aimed at promoting the use of EMs in LMICs. Such interventions have the potential to bring about substantial positive impacts on health, climate action, and mobility, particularly in countries like Vietnam. Our findings highlight the critical role of psychosocial factors, particularly subjective norms and attitude, in shaping individuals' intentions to adopt EMs. To strengthen subjective norms around EM adoption in Vietnam, leveraging community influence, social networks, and public figures to create a supportive environment for EM usage should be considered. Additionally, fleet electrification policies should focus on creating positive attitude towards EMs through targeted public education campaigns that emphasize the benefits of EM adoption and address common misconceptions. While attitude towards EMs are central to this process, it is equally important to consider the broader socio-environmental context. This implies that public education initiatives, whether spearheaded by governments or industry players, should not solely target individuals. Instead, they should be crafted with an understanding of the social context in which potential EM users reside. For example, campaigns in rural areas might focus on the economic benefits of EMs, while those in urban areas might emphasise reducing air pollution and traffic congestion.

Perceived behavioural control and perceived risk also emerged as determinants of the intention to adopt EMs. This highlights the importance of both facilitating the use of EMs and ensuring their safety and reliability. In practical terms, interventions should aim to provide not only a positive and informative narrative around EMs but also mechanisms that enhance users' sense of control over their decision. Expanding the charging network, offering more financial incentives like subsidies and low-interest loans, affordable maintenance packages or free user training can enhance the confidence of the users, which in turn boosting the perceived behavioural control. Additionally, public awareness campaigns, online support communities or implementing safety certification programs can be implemented to further reduce perceived risks, making EMs a more viable and appealing option for Vietnamese consumers.

To encourage EM adoption, governments and practitioners should focus not only on addressing general risks but also on delving into specific dimensions of these risks. Not all risks are created equal, and our research identifies specific areas that deserve priority attention. The finding of this paper has demonstrated that perceived risk in the context of Vietnamese EM adoption is a multidimensional construct with various facets that collectively influence users' decisions, including explosion & fire risk, privacy risk, financial risk, time risk, and performance risk. Combined efforts which focus on mitigating these types of risks can substantially boost the adoption of EMs and contribute to the advancement of sustainable and environmentally friendly transport solutions. For instance, to reduce the perception of explosion & fire risk, the government should ensure that all EMs on the market meet stringent safety standards and promote the use of certifications that guarantee the safety and reliability of the battery and electrical systems. Besides, launching educational campaigns to inform the public about the low risks of explosion and fire with EMs, backed by statistics and expert endorsements can be implemented.

Furthermore, the findings from the multigroup analysis underscore the paramount importance of precision-targeted measures for specific groups of motorcycle riders. By directing interventions towards these demographic segments, resources can be allocated with precision, resulting in cost savings and enhanced intervention effectiveness. For instance, our study demostrates that perceived risk significantly influences the intention to adopt EMs, particularly among individuals in the middle and older age groups with lower levels of education. The development of easy-to-understand educational materials, such as brochures, videos, and infographics, that clearly explain the safety features of EMs and how to use them should be considered. Additionally, offering subsidised or free training programs on safe EM usage, focusing on practical skills like handling, battery management, and what to do in case of an emergency can be also implemented. Consequently, it becomes imperative to craft measures that specifically address and alleviate perceived risks within these demographic clusters. Such a tailored approach not only increases the likelihood of adoption among these segments but also contributes to the overall success of EM adoption initiatives in the context of diverse rider demographics.

6.3. Limitations and future research

Despite the valuable insights provided by this study on the perceived risk dimensions of EM adoption intention, it is important to acknowledge its limitations. Firstly, the generalizability of the findings may be constrained by the study's focus on Vietnam, a country with a relatively small electric motorcycle market. Future research conducted in other countries, where EMs are more prevalent, could be valuable for comparing and generalizing the results. Additionally, while this study successfully extended the Theory of Planned Behaviour model by incorporating perceived risk, it is important to recognise that other latent variables, such as perceived usefulness, perceived environment, and perceived value, may also influence adoption intention. Integrating these variables into an expanded model would likely enhance its predictive capacity, offering a more nuanced and robust framework for understanding consumer behaviour. Therefore, future research could focus on developing and testing these comprehensive theoretical models, which would ultimately contribute to a deeper and more accurate understanding of the factors influencing electric motorcycle adoption in various contexts. Moreover, the small sample size and cross-sectional design of this study limit the ability to establish causal relationships and draw definitive conclusions. Longitudinal studies or experimental designs would be beneficial for investigating the dynamic nature of perceived risk, other influential factors, and adoption intention over time. Lastly, it is essential to consider that this study focused exclusively on electric motorcycles, while other types of electric vehicles, such as electric cars or electric bicycles, may have unique adoption dynamics and considerations. Future research could explore the adoption intention of different types of electric vehicles to provide a more holistic understanding of the overall transition to sustainable transport. Despite these limitations, this study contributes valuable insights and lays the foundation for further research to expand our knowledge on the factors influencing EM adoption intention in diverse contexts.

7. Conclusion

Limited research has focused on investigating the factors influencing the adoption intention of electric motorcycles in motorcycle-dominated countries, as existing studies primarily concentrate on electric vehicles in high-income countries. This study sought to bridge this research gap by extending the Theory of Planned Behaviour with perceived risk to identify the key factors shaping EM adoption intention. Notably, a multidimensional perspective was adopted to conceptualise perceived risk, allowing for a comprehensive understanding of the various dimensions of risk. Among the identified risks, the participants highlighted explosion and fire risk as the most prominent. The structural equation modelling analysis revealed that attitude towards EMs, subjective norms, and perceived behavioural control had significant positive effects on behavioural intention, while perceived risk exhibited a negative impact. These findings hold important implications for policymakers and stakeholders in devising effective measures to promote the widespread adoption of this environmentally friendly mode of transport.

CRediT authorship contribution statement

Duy Quy Nguyen-Phuoc: Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Diep Ngoc Su:** Writing – original draft, Investigation. **Anh Truong:** Writing – original draft, Supervision. **Zhi-Chun Li:** Writing – original draft, Investigation. **Oscar Oviedo-Trespalacios:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Table A1
Measurement scales.

Measurement scales	Mean	SD	Excess Kurtosis	Skewness	Sources
Perceived Risk (PRI)					
Q1. EMs make little to no sound when driving so road users around do not sense the vehicle approaching	5.498	1.156	2.034	−1.281	Authors developed
Q2. The low levels of noise produced by EMs might cause an increase in traffic accidents involving vulnerable road users	4.646	1.596	−0.883	−0.369	Authors developed
Q3. The lack of sound can be dangerous for pedestrians who do not sense the EV approaching	4.610	1.639	−0.904	−0.426	Authors developed
Q4. There are not a sufficient number of charging points to keep EMs on the road	5.787	1.080	2.771	−1.366	Authors developed
Q5. EMs may not have sufficient power to reach the final destination	5.627	1.116	1.086	−0.942	Authors developed
Q6. EMs may run out of power and not be able to find a charging station on time to replenish the battery	5.792	1.104	2.215	−1.292	Authors developed
Q7. EMs are more likely to catch fire than conventional vehicles	4.455	1.421	−0.536	−0.094	Authors developed
Q8. The batteries of EMs may combust when damaged, overcharged or subjected to high temperatures	4.717	1.485	−0.597	−0.440	Authors developed
Q9. Explosions may occur while charging EM batteries	4.866	1.442	−0.495	−0.524	Authors developed
Q10. The cost of purchase and ownership EMs is high compared to conventional motorcycles	4.608	1.438	−0.368	−0.515	(Hwang and Choe, 2019)
Q11. The cost of EM repairs and maintenance is likely to be burdensome	4.557	1.503	−0.700	−0.373	(Hwang and Choe, 2019)
Q12. EM repairs and maintenance are likely to cost more than I thought	4.593	1.520	−0.718	−0.312	(Hwang and Choe, 2019)
Q13. I might get overcharged if I use EMs	4.494	1.484	−0.695	−0.294	(Hwang and Choe, 2019)
Q14. EM repairs and maintenance may take a longer time due to the processes involved in making the battery safe	4.906	1.282	0.297	−0.695	Authors developed
Q15. EM repairs and maintenance may take a longer time due to the shortage of sufficiently skilled technicians in the industry	4.848	1.389	−0.288	−0.591	Authors developed

(*continued on next page*)

Table A1 (*continued*)

Measurement scales	Mean	SD	Excess Kurtosis	Skewness	Sources
Q16. If I use EMs, I am more likely to lose time because of the charging time	5.020	1.476	−0.187	−0.797	Authors developed
Q17. It will take time to learn how to drive EMs	3.650	1.623	−0.973	0.249	Authors developed
Q18. Using EMs may not protect my personal information (e.g., credit card number, phone number, address, etc.)	4.059	1.700	−1.077	−0.022	(Hwang and Choe, 2019)
Q19. Personal information (e.g., credit card number, phone number, address, etc.) when using EMs may be stolen by others	4.102	1.686	−1.064	−0.031	(Featherman and Pavlou, 2003)
Q20. Personal information (e.g., credit card number, phone number, address, etc.) could be exposed when using EMs	4.066	1.712	−1.189	0.003	(Hwang and Choe, 2019)
Q21. The probability that something is wrong with the performance of EMs is high	5.248	1.090	1.254	−0.997	(Hwang and Choe, 2019)
Q22. EMs do not seem to perform as well as conventional vehicles (low speed, less power)	5.029	1.306	0.136	−0.741	(Hwang and Choe, 2019)
Q23. EMs may not perform well and cause problems with my trips	4.573	1.439	−0.720	−0.349	(Wang et al., 2019b)
Q24. EMs may be less efficient and less powerful than I expected	5.540	1.091	1.439	−0.992	Authors developed
Q25. The usage of EMs would lead me to a psychological loss	4.666	1.495	−0.504	−0.460	(Hwang and Choe, 2019)
Q26. Using EMs makes me feel nervous	4.034	1.534	−0.836	−0.045	(Hwang and Choe, 2019)
Q27. Using EMs makes me feel anxiety	3.909	1.545	−0.870	0.061	(Hwang and Choe, 2019)
Q28. The requirement of mining for manufacturing batteries and other related components in EMs is not environmentally friendly	4.941	1.348	0.107	−0.686	(Krishna, 2021)
Q29. There is a negative environmental impact due to the toxicity of the materials used in making the battery	5.126	1.324	0.275	−0.729	(Krishna, 2021)
Subjective Norms (SUN)					
Most people who are important to me support that I should use EMs	4.498	1.422	−0.422	−0.279	(Lee et al., 2012)
Most people who are important to me agree that I should use EMs	4.513	1.472	−0.600	−0.265	(Lee et al., 2012)
Most people who are important to me recommend that I should use EMs	4.329	1.485	−0.688	−0.149	(Lee et al., 2012)
Perceived Behavioural Control (PBC)					
I am capable of using EMs	5.369	1.175	1.432	−1.101	(Lee et al., 2012)
If I want, I can easily use EMs	5.337	1.239	1.205	−1.089	(Lee et al., 2012)
I have enough money to buy EMs	5.081	1.514	0.102	−0.925	(Lee et al., 2012)
Attitude (ATT)					
I think that using EMs is valuable	5.400	1.156	0.697	−0.768	(Lee et al., 2012)
I think that using EMs is right	5.316	1.057	0.312	−0.522	(Lee et al., 2012)
I think that using EMs is necessary	5.095	1.140	0.403	−0.499	(Lee et al., 2012)
Adoption of EMs (AEM)					
I will use EMs in the future	4.264	1.572	−0.780	−0.317	(Lee et al., 2012)
I have an intention to use EMs in the future	4.203	1.589	−0.882	−0.323	(Lee et al., 2012)
I am likely to use EMs in the future	4.277	1.628	−0.788	−0.423	(Lee et al., 2012)

Table A2a

Results of invariance measurement testing using permutation (Step 1 and Step 2).

Group	Constructs	**Step 1**	**Step 2**		Partial Measurement Invariance Established
		Configural Invariance (Same algorithm for both groups)	Compositional Invariance		
			Original Correlation	Confidence Interval	
Female vs Male	SUN	Yes	1.000	[1.000;1.000]	Yes
	ATT	Yes	0.999	[0.999;0.999]	Yes
	PBC	Yes	0.999	[0.997;0.999]	Yes
	PRI	Yes	9.968	[0.956;0.978]	Yes
	AEM	Yes	1.000	[1.000;1.000]	Yes
Young vs Middle & Older	SUN	Yes	1.000	[1.000;1.000]	Yes
	ATT	Yes	0.999	[0.999;0.999]	Yes
	PBC	Yes	0.999	[0.997;0.999]	Yes
	PRI	Yes	0.971	[0.957;0.978]	Yes
	AEM	Yes	1.000	[1.000;1.000]	Yes
Low Income vs Middle & High income	SUN	Yes	1.000	[1.000;1.000]	Yes
	ATT	Yes	0.999	[0.999;0.999]	Yes
	PBC	Yes	0.999	[0.996;0.999]	Yes
	PRI	Yes	0.787	[0.942;0.970]	No

(*continued on next page*)

Table A2a (*continued*)

Group	Constructs	Step 1	Step 2		Partial Measurement Invariance Established
		Configural Invariance (Same algorithm for both groups)	Compositional Invariance		
			Original Correlation	Confidence Interval	
	AEM	Yes	1.000	[1.000;1.000]	Yes
No university degree vs Have a university degree	SUN	Yes	1.000	[1.000;1.000]	Yes
	ATT	Yes	0.999	[0.999;0.999]	Yes
	PBC	Yes	0.999	[0.997;0.999]	Yes
	PRI	Yes	0.951	[0.950;0.978]	Yes
	AEM	Yes	1.000	[1.000;1.000]	Yes
DN vs HCM	SUN	Yes	1.000	[1.000;1.000]	Yes
	ATT	Yes	0.999	[0.999;0.999]	Yes
	PBC	Yes	0.997	[0.997;0.999]	Yes
	PRI	Yes	0.959	[0.956;0.978]	Yes
	AEM	Yes	1.000	[1.000;1.000]	Yes

Table A2b
Results of invariance measurement testing using permutation (Step 3).

Group	Constructs	Step 3, Part 1			Step 3, Part 2			Full Measurement Invariance Established
		Equal Mean Assessment			Equal Variance Assessment			
		Mean Original Difference	Confidence Interval	Equal	Variance Original Difference	Confidence Interval	Equal	
Female vs Male	SUN	−0.078	[-0.096;0.095]	Yes	0.052	[-0.123;0.122]	Yes	Yes
	ATT	0.114	[-0.100;0.097]	No	0.046	[-0.155;0.154]	Yes	No
	PBC	0.144	[-0.095;0.099]	No	−0.036	[-0.168;0.163]	Yes	No
	PRI	−0.221	[-0.098;0.093]	No	0.149	[-0.116;0.110]	No	No
	AEM	0.062	[-0.096;0.096]	Yes	−0.062	[-0.107;0.104]	Yes	Yes
Young vs Old	SUN	0.068	[-0.095;0.096]	Yes	−0.129	[-0.123;0.118]	No	No
	ATT	0.051	[-0.095;0.096]	Yes	−0.221	[-0.156;0.151]	No	No
	PBC	0.208	[-0.097;0.096]	No	−0.354	[-0.162;0.158]	No	No
	PRI	−0.177	[-0.098;0.094]	No	−0.101	[-0.114;0.112]	Yes	No
	AEM	0.029	[-0.094;0.096]	Yes	0.020	[-0.105;0.104]	Yes	Yes
Low Income vs High Income	SUN	−0.148	[-0.104;0.106]	No	0.016	[-0.127;0.137]	Yes	No
	ATT	0.042	[-0.107;0.104]	Yes	−0.017	[-0.159;0.180]	Yes	Yes
	PBC	0.395	[-0.106;0.100]	No	−0.376	[-0.170;0.183]	No	No
	PRI	−0.303	[-0.100;0.106]	No	0.122	[-0.117;0.123]	Yes	No
	AEM	0.237	[-0.105;0.104]	No	−0.071	[-0.111;0.119]	Yes	No
No university degree vs Have a university degree	SUN	0.255	[-0.096;0.098]	No	−0.092	[-0.123;0.125]	Yes	No
	ATT	0.107	[-0.096;0.093]	No	−0.149	[-0.152;0.155]	Yes	No
	PBC	−0.076	[-0.100;0.097]	Yes	0.022	[-0.170;0.169]	No	No
	PRI	0.017	[-0.100;0.096]	Yes	0.009	[-0.110;0.114]	Yes	Yes
	AEM	−0.023	[-0.093;0.098]	Yes	0.158	[-0.106;0.102]	No	No
DN vs HCM	SUN	0.039	[-0.094;0.097]	Yes	0.207	[-0.120;0.120]	No	No
	ATT	−0.004	[-0.096;0.098]	Yes	0.411	[-0.158;0.159]	No	No
	PBC	0.054	[-0.097;0.096]	Yes	0.359	[-0.165;0.168]	No	No
	PRI	0.216	[-0.096;0.094]	No	−0.193	[-0.114;0.113]	No	No
	AEM	−0.166	[-0.096;0.097]	No	0.013	[-0.105;0.101]	Yes	No

Data availability

Data will be made available on request.

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