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Factors Affecting the Intention to Buy Electric Vehicles Through the Integration of Technology Acceptance Model and Prior Experience

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Abstract

To enhance the adoption of electric vehicles (EVs), governments have implemented regulatory policies, such as providing incentives. However, this approach is temporary and relies on the active involvement of manufacturers to better understand the driving factors behind EV adoption. While previous studies, largely based on behavioral theory, emphasize psychological and environmental factors, individual subjective factors also play a crucial role. This study introduces a novel approach by integrating variables from the Technology Acceptance Model (TAM)—perceived usefulness and perceived ease of use—with consumer experience variables, namely technology discomfort and customer experience. The goal is to improve TAM's explanatory power regarding the intention to buy EVs from the consumer perspective. The research targeted residents of Jabodetabek (Jakarta, Bogor, Depok, Tangerang, Bekasi) aged 17 and older, all of whom had prior experience with Battery Electric Vehicles (BEVs). Data was collected from 330 respondents through an online survey. Structural Equation Modeling (SEM) with AMOS was used for the analysis. The results indicated that perceived usefulness, perceived ease of use, and customer experience significantly influenced intention to buy, while perceived usefulness did not significantly affect customer experience. Customer experience mediated the relationship between perceived ease of use and intention to buy, but did not mediate the effect of perceived usefulness. Additionally, technology discomfort negatively impacted perceived usefulness and ease of use, although it did not significantly affect customer experience. These findings suggest that while government incentives remain important, a market-driven approach that focuses on improving consumer perceptions and experiences is critical for accelerating EV adoption.

Keywords: Electric Vehicle, Intention To Buy, Perceived Ease Of Use, Perceived Usefulness, Technology Discomfort, Customer Experience

1. Introduction

Poor air quality is a major concern globally, with Indonesia having the worst in ASEAN in 2022. Jakarta ranked fourth among the ten most polluted cities worldwide and is the most polluted in Indonesia [1]. Excessive fossil fuel use in transportation is a major air pollution source, thus transitioning to electricity and promoting green automotive products is essential to minimize environmental harm. One of the most widely promoted green products in recent years is electronic vehicles (EVs), which are considered a sustainable alternative to conventional gasoline-powered cars [2]. EVs utilize battery-stored energy for propulsion, making them a viable solution for reducing air pollution [3]. In Indonesia, EV adoption has surged, with electric motorcycle usage increasing 13-fold and electric car adoption 33-fold from 2020 to 2022, according to Deloitte & Foundry's 2023 study [4]. Despite this progress, Indonesia still lags behind other Asian countries in EV adoption. The Indonesia EV Consumer Survey found that Indonesia's EV adoption rate in 2021 was only 0.1%, significantly lower than Thailand (0.7%) and India (0.5%). Additionally, the Indonesia EV Outlook confirmed that although EV usage has increased, adoption rates remain far from the government's targets.

To encourage EV adoption, the Indonesian government has implemented policies and incentives, including Presidential Regulation No. 55 of 2019, which promotes the shift from fossil fuel vehicles to EVs with financial support. In 2024, PMK 8/2024 and PMK 9/2024 reduced VAT by 10% for locally made EVs and removed luxury taxes on imported

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EVs. Despite these efforts, less than 1% of the 200,000 EV subsidy units were distributed, indicating challenges in adoption. Additional initiatives focus on transitioning public sector vehicles to EVs, but obstacles such as limited charging infrastructure, high vehicle costs, and restricted driving range persist [5]. Consumer behavior plays a crucial role in EV adoption, as purchasing an EV is considered a high-involvement decision requiring significant deliberation. The TAM is widely used to study technology adoption, emphasizing two key factors: perceived usefulness (PU) and perceived ease of use (PEU) [6]. Studies show that PU significantly influences intention to buy EV (ITB), particularly due to environmental and economic benefits [7]. Additionally, PEU affects consumer adoption, as individuals are more likely to adopt new technology if they perceive it as easy to use [8]. However, external barriers such as pricing and infrastructure are often cited as the primary deterrents to EV adoption, while internal consumer factors remain underexplored [9], [10]. To bridge this gap, this study integrates prior consumer experience into the TAM framework by examining technology discomfort (TD) as an antecedent and customer experience (CE) as a mediating variable, offering deeper insights into EV adoption behaviors [11], [12].

The adoption of new technology, such as EVs, depends on how easily consumers perceive the technology can be used. Many potential consumers still find the technological innovations in EVs confusing, assuming they are difficult to operate, which discourages them from transitioning from conventional vehicles [13]. Internal consumer factors, particularly prior experience, have been less explored compared to external factors such as vehicle range and charging infrastructure. However, prior experience plays a crucial role in shaping consumer beliefs and behavior by influencing attitudes, perceived norms, and perceived behavioral control, all of which impact the intention to buy (ITB) [11]. This study integrates the TAM with prior consumer experience to provide a more comprehensive understanding of EV adoption. Two key prior experience variables examined in this study are TD and CE. TD refers to the unease or reluctance consumers feel towards EV technology, which can hinder their willingness to adopt it [14]. This discomfort can stem from concerns about EV power systems, charging infrastructure, and operational reliability [15], [16]. Studies have shown that overcoming TD is essential for boosting consumer confidence and adoption rates [17]. Meanwhile, CE encompasses consumers' overall perception and interactions with EVs, influencing their purchasing decisions [18]. Research indicates that positive CE enhance brand loyalty, word-of-mouth recommendations, and long-term engagement [19]. Since previous studies have highlighted the mediating role of customer experience (CE) in consumer behavior, this study will explore how CE mediates the relationship between key variables in the EV adoption process.

To strengthen the theoretical framework, this study integrates CE and TD with the TAM to provide a more comprehensive understanding of EV adoption. TAM, which traditionally focuses on PU and PEU, explains how individuals assess and accept new technologies. However, TAM does not fully account for the subjective factors that influence consumer behavior, such as prior experiences and discomfort with new technologies. By including CE and TD, this study acknowledges that consumer experiences and discomfort can significantly shape their attitudes toward technology, ultimately affecting their adoption decisions. CE, which reflects a consumer's overall experience with a product, can enhance PU and PEU's impact on purchase intentions, while TD, which relates to discomfort or anxiety towards technology, may dampen these effects. This integration enriches TAM by providing a more complete model that considers both psychological and experiential variables, allowing for a deeper exploration of how individual factors influence the intention to adopt EVs.

Despite the increasing number of studies on ITB, several research gaps remain. First, the transition of the EV market in Indonesia is currently policy-driven, relying on government incentives and regulations, but must eventually shift to a market-driven model where consumer preferences play a central role [20]. Second, most studies on EV purchase behavior focus on external factors such as vehicle performance, charging infrastructure, and government incentives, neglecting internal consumer factors like personal experience and TD [20]. Consumers need more direct experience with EVs to reduce uncertainty and build confidence. Many ITB studies focus on behavioral theories, highlighting environmental and social pressures but ignoring individual subjective factors. This study aims to address these gaps by integrating behavioral theories with intrinsic consumer factors to strengthen the explanatory power of TAM in predicting EV adoption. Building upon these insights, this research investigates the relationships between PU, PEU (TAM variables), and prior consumer experience (TD and CE). By integrating these variables, the study seeks to enhance the predictive capability of TAM in explaining consumer interest in purchasing EVs. Understanding these interactions will help manufacturers and policymakers develop more effective strategies to accelerate EV adoption, ultimately contributing to a more sustainable and environmentally friendly transportation sector.

This study seeks to develop and validate an integrated model to understand ITB by combining TAM variables and prior consumer experience factors. Unlike previous studies that focused on external factors, this research emphasizes internal consumer factors affecting purchasing decisions. By integrating PU, PEU, CE, and TD, the study aims to comprehensively understand consumer behavior in EV adoption. The primary goal is to examine the direct and indirect effects of these variables on ITB, focusing on PU and PEU's impact and CE's mediating role. Additionally, it explores TD's influence on PU, PEU, and CE, as discomfort with new technology can hinder adoption. The study analyzes these relationships to assess if PEU influences PU, enhancing TAM's predictive capability in the EV context. Another key objective is to determine CE's mediating role in shaping consumer attitudes toward EVs. A positive user experience can enhance perceptions of PEU and PU, increasing ITB. Therefore, the study explores whether CE mediates the relationships between PU, PEU, and ITB, offering insights into the psychological and experiential factors driving consumer behavior. By investigating these interconnected variables, the study aims to enhance TAM's explanatory power and provide practical implications for EV manufacturers, policymakers, and marketers. The findings will help design strategies to increase EV adoption by addressing TD, improving consumer experiences, and enhancing perceived usability and benefits. This research contributes to the discussion on transitioning EV adoption from policy-driven to market-driven, ensuring consumer preferences are central to sustainable mobility solutions.

2. Literature Review

2.1. The Perception of Usefulness (PU) in EV Adoption

PU plays a critical role in the adoption of new technologies, including electric vehicles (EVs), by influencing how individuals assess the technology's benefits. PU refers to the belief that using a specific technology will improve performance, productivity, and efficiency. In the context of EVs, PU is primarily related to perceived cost savings, reduced environmental impact, and greater convenience. Consumers are more likely to adopt EVs if they recognize these benefits, such as lower operating costs, fewer emissions, and the potential for government incentives. However, without clear understanding or perception of these advantages, consumers may be hesitant to transition from conventional vehicles. As highlighted by Bhattacherjee, as cited in [13], individuals tend to favor technologies that enhance work efficiency and minimize effort, which is directly relevant to the decision-making process for adopting EVs.

In this extended TAM model, PU not only relates to operational cost reductions and environmental benefits, but also to the integration of EVs into daily routines. The perception of PU influences how users view EV performance, reliability, and their ease of integration into daily life. As noted by Venkatesh, as cited in [21], three key indicators of PU are: (1) providing tangible benefits to users, (2) improving efficiency and reducing time on tasks, and (3) enhancing overall productivity and performance. Therefore, the PU variable within the extended TAM model interacts with customer experience (CE) by shaping how users perceive the practical benefits of EVs. If consumers see EVs as beneficial to their daily lives, including cost efficiency and environmental impact, their willingness to adopt increases. However, a lack of perceived benefit, even with CE factors, may hinder the widespread adoption of EVs.

2.2. The Role of Ease of Use (PEU) in Shaping Consumer Adoption

PEU is a key component in the Technology Acceptance Model (TAM), introduced by [23], that emphasizes the importance of usability in technology adoption. PEU refers to an individual's belief that using a specific technology will be free from difficulty and require minimal effort to understand and operate [21]. The simpler the technology, the more likely it is to be accepted by consumers. In the case of EVs, PEU is particularly related to the ease of use of charging infrastructure, driving range, and other user-friendly features. Research by [24], suggests that PEU represents the degree to which individuals perceive using a technology as requiring minimal effort. If consumers find an innovation challenging to use, they may hesitate to adopt it, even if they recognize its benefits [13]. For EVs, PEU is enhanced by factors such as accessible charging stations, straightforward recharging processes, and simple vehicle interfaces.

In this extended TAM model, PEU interacts with CE by shaping how easily consumers can integrate EV technology into their daily lives. According to [22], PEU also encompasses the confidence that using technology will simplify daily activities and reduce unnecessary effort. Consumer hesitation arises when they question the practicality of a technology, which is a concern in the EV market due to issues such as charging times, the availability of charging stations, and maintenance complexities. Addressing these usability concerns is crucial for increasing consumer confidence and promoting EV adoption. Venkatesh, as cited in [21], identified four key indicators of PEU: ease of understanding, simplicity in operation, minimal effort required, and accessibility of technology. For EVs, these indicators highlight the importance of a user-friendly design, seamless charging experience, and effortless driving. The more intuitive and easier to use EV technology is perceived to be, the more likely consumers are to adopt it.

2.3. Customer Experience (CE) as a Key Driver of EV Adoption

CE plays a crucial role in shaping consumer perceptions and influencing their willingness to adopt EVs. It encompasses the entire interaction between consumers and a product or service, including pre-purchase research, product usage, and post-purchase support [25]. Gentile, as cited in [19] defines CE as the result of a series of interactions between the customer and the company, product, or service, triggering sensorial, emotional, cognitive, physical, and relational responses. In the context of EV adoption, factors such as test drives, after-sales service, brand reputation, and infrastructure availability contribute to shaping CE. Research [18] explain that CE involves a consumer's entire journey with a brand. Positive experiences, like smooth purchases and reliable vehicle performance, boost trust and satisfaction, increasing EV adoption likelihood. Negative experiences, such as poor after-sales support and high maintenance, may create resistance. Study [26] further emphasize that CE is multidimensional, involving cognitive, emotional, sensory, behavioral, and relational responses to a product or service.

In the EV industry, companies need to proactively monitor and analyze customer behavior to refine their marketing strategies and identify specific consumer segments that could benefit from competitive pricing and enhanced service quality [27]. Schmitt's CE framework outlines five fundamental dimensions: sense (sensory perception), think (cognitive engagement), feel (emotional connection), act (behavioral influence), and relate (social and cultural connections) [28]. These dimensions highlight the importance of not only technological efficiency but also consumer perception and satisfaction in driving adoption. Study by [29] identify five key indicators for measuring CE in the EV industry are: (1) sensory experience; (2) cognitive experience; (3) emotional experience; (4) behavioral experience; and (5) relational experience. Addressing these can boost consumer confidence, enhance service quality, and speed up EV adoption.

2.4. Technology Discomfort (TD) as a Barrier to Adoption

TD represents a negative perception or attitude toward new technology, often arising from an individual's lack of familiarity, control, or confidence in using it [14]. In the context of EV adoption, TD manifests as consumer uncertainty and hesitation regarding EV-related innovations. Factors such as concerns about battery reliability, charging infrastructure availability, complex maintenance requirements, and limited driving range contribute to this discomfort. Individuals who feel that they lack the necessary knowledge to operate EVs may perceive them as inconvenient, leading to a reluctance to adopt the technology [30]. TD is a subjective response to uncertainty, where consumers may feel overwhelmed by the transition to EVs due to unfamiliarity with their charging mechanisms, digital interfaces, or unique driving dynamics. Study by [31] suggest that individuals experiencing high TD require simpler, more intuitive systems to encourage adoption. Consumers who struggle to understand charging procedures or rely heavily on external assistance may be discouraged from switching to EVs. As a result, addressing this barrier is crucial for increasing consumer confidence and promoting smoother adoption.

Research [32] emphasize that high levels of TD can significantly hinder new technology adoption. In the EV sector, consumers often express concerns about the charging infrastructure, range limitations, and the time required for recharging compared to traditional refueling. Additionally, misconceptions about maintenance complexity, software updates, and long-term durability further contribute to consumer hesitation. Without adequate support, such as accessible technical assistance and clear user guidance, individuals may perceive EV adoption as too challenging or inconvenient. Studies identifies three key indicators of TD are uncertainty with technical issues, doubts about technical support, and difficulty understanding user manuals. To mitigate TD, focus on consumer education, improved infrastructure, and user-friendly innovations. Simplified charging solutions, charging station availability, interactive tutorials, and hands-on demonstrations can reduce anxiety and speed up EV adoption. Addressing these concerns can foster greater acceptance and encourage more consumers to switch to sustainable transportation.

2.5. Understanding Consumer Intention to Buy EV (ITB)

ITB reflects the likelihood or willingness of an individual to buy a product in the future [33]. In the context of EVs, ITB represents a consumer's interest, preference, and tendency to adopt EV technology based on perceived benefits, needs, and external influences. This intention plays a crucial role in predicting market demand and consumer behavior, allowing manufacturers and policymakers to design effective strategies to accelerate EV adoption. ITB is influenced by several psychological and external factors. Consumers tend to develop higher interest in a product when they recognize its ability to fulfill their needs or enhance their lifestyle. In the case of EVs, factors such as cost savings, environmental concerns, technological advancements, and government incentives shape consumer preferences and willingness to transition from conventional vehicles [34]. Understanding these factors is essential for identifying market trends and overcoming potential barriers to adoption.

Research [35] describes ITB as a commitment to buy or repurchase a product whenever needed, making it an important predictor of future consumer behavior and sales performance. By analyzing consumer ITB, businesses can refine marketing campaigns, promotional strategies, and product offerings to align with consumer expectations. In the EV industry, this involves enhancing charging infrastructure, improving battery efficiency, and offering attractive financial incentives to reduce adoption hesitation. Research identifies four key indicators of ITB are: (1) transactional intention, (2) referential intention, (3) preferential intention, and (4) exploratory intention. In EVs, these indicators emphasize consumer trust, information accessibility, and perceived value. Addressing these factors can help EV manufacturers, policymakers, and marketers create targeted strategies to increase consumer confidence and promote mass adoption.

3. Methodology

3.1. Research Design and Data Collection

This study adopts a quantitative research approach, which is based on the belief that all aspects of a phenomenon can be measured and analyzed statistically. Quantitative research tests hypotheses, identifies patterns, and establishes relationships using numerical data and statistical analysis. This study uses non-probability sampling with a purposive method, targeting specific criteria for consumer experience and EV adoption. Since this study involves multiple variables and a complex structural model, the sample size is determined using [36] formula, which recommends a minimum sample size of 5–10 times the number of indicators used in the study. Given that this study includes 33 research indicators, the sample size is 330 respondents. Study [36] also state that a minimum of 100 samples is required for SEM analysis, meaning that the chosen sample size of 330 respondents is appropriate and statistically valid. The study targets Jabodetabek residents with experience driving a four-wheeled BEV, through ownership, rental, corporate use, or test-driving. This region is chosen for its urbanization, technology, vehicle mobility, economic activity, and growing EV market, with Jakarta having the most EVs due to incentives and infrastructure. Data collection occur from May to July 2024. Data collection is via an online Google Forms survey shared on WhatsApp, Facebook, Instagram, Telegram, and Twitter. This method efficiently reaches a diverse group, reduces costs, and minimizes human error through automated data recording. The questionnaire has two sections: Screening Questions to ensure qualified respondents and a Main Questionnaire with Likert-scale questions measuring attitudes toward PU, PEU, TD, CE, and ITB. Data be analyzed using SEM with AMOS software to explore direct and indirect effects between variables, providing insights into factors influencing ITB.

3.2. Research Model and Hypothesis Development

This study investigates the relationships between PU, PEU, CE, TD, and ITB for EVs. The hypotheses are formulated based on the TAM and prior empirical studies exploring consumer behavior toward EV adoption. Below is a detailed explanation of each hypothesized relationship.

H1: PU Positively Influences ITB for EVs

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Several studies highlight the significant impact of PU on consumer ITB. Research by [37] found that PU strongly influences ITB, as consumers associate it with cost savings, environmental benefits, and efficiency. Similarly, [38] suggested that PU is a major driver of consumer attitudes toward EV adoption. However, [13] reported conflicting results, indicating that PU may not always have a significant impact on ITB. Given these mixed findings, this study seeks to revalidate the relationship between PU and ITB.

H2: PEU Positively Influences ITB for EVs

PEU reflects how easily consumers believe they can operate EVs, influencing their willingness to adopt the technology. Research [10] conducted a study with 692 respondents, confirming that PEU has a positive effect on EV adoption intention. Similarly, [39], [40] found that PEU significantly influences consumer willingness to transition from conventional vehicles to EVs. Other studies in different contexts, such as [13] on energy-saving devices and [24] on photovoltaic panel systems, further confirm that PEU impacts purchase decisions.

H3: CE Positively Influences ITB for EVs

Consumer experience plays a vital role in shaping perceptions and intentions toward EV adoption. Research [41] demonstrated that direct consumer experiences, such as test drives and interactions with charging infrastructure, positively impact ITB. Similarly, [42] highlighted that cognitive, sensory, and social experiences contribute to a consumer's willingness to purchase EVs. However, [43] found that CE does not always directly influence ITB, but it does affect brand perception and recommendations. Given these findings, this study aims to further examine the direct impact of CE on ITB.

H4: PU Positively Influences CE

PU has been linked to consumer satisfaction and experience in various industries. PU significantly impacts CE, as individuals tend to have better experiences with products they perceive as valuable. This has been confirmed in the hospitality sector [44] and FinTech services [45]. In the context of EVs, consumers may have more positive experiences when they believe that the vehicle offers clear benefits such as lower costs, environmental sustainability, and advanced technology.

H5: CE Mediates the Relationship Between PU and ITB

Prior research suggests that CE may act as a mediator between PU and ITB. Research [46] found that consumers are more likely to purchase a product when they find it useful and have a positive experience using it. Studies in FinTech [47] and mobile services also confirm that CE can bridge the gap between PU and consumer decisions. This study aims to explore whether the same mediating effect exists in the EV industry.

H6: PEU Positively Influences CE

PEU plays a critical role in shaping consumer experiences. Research [48] found that PEU significantly impacts CE in self-service banking technology. Similarly, [49] highlighted the importance of user-friendly online shopping platforms in enhancing CE. In the EV industry, this relationship has not been extensively studied, making it necessary to examine whether easy-to-use EVs contribute to better CE.

H7: CE Mediates the Relationship Between PEU and ITB

Research has shown that consumer experiences influence their decision to adopt new technology. Research found that individuals who find EVs easy to use develop stronger familiarity and confidence, which enhances their overall experience and willingness to adopt them. Research [50], [51] support this claim, stating that PEU enhances CE, which in turn affects adoption decisions.

H8: PEU Positively Influences PU

Several studies have confirmed that PEU enhances PU. Research [52] demonstrated that when consumers find technology easy to use, they also perceive it as more beneficial. This relationship has been validated in renewable energy adoption [53] and autonomous vehicles [54]. In the EV context, this means that if consumers find EVs intuitive and simple to operate, they will also perceive them as useful and valuable.

H9: TD Negatively Influences PU

TD refers to the fear or hesitation consumers feel toward new technology. Study [55] found that TD negatively impacts PU, as consumers who struggle to use a product often fail to recognize its benefits. However, [56] suggested that TD does not always influence PU. Given these mixed findings, this study aims to further explore this relationship in the EV industry.

H10: TD Negatively Influences PEU

Consumers with high TD often perceive a product as difficult to use. Research [57] found a negative relationship between TD and PEU in digital tools and software. If applied to EVs, this means that consumers who feel anxious or hesitant about new technology may struggle to see EVs as easy to use, thereby affecting adoption.

H11: TD Negatively Influences CE

TD may lead to poor user experiences due to frustration and difficulty in interacting with new technology. Study [58] found that negative experiences with technology significantly reduced customer satisfaction. Research [59] highlighted that consumers with low technological readiness struggle to adapt, affecting their overall experience. This study examines whether similar challenges exist in EV adoption. The conceptual framework for this study is illustrated in figure 1, depicting the hypothesized relationships among the research variables:

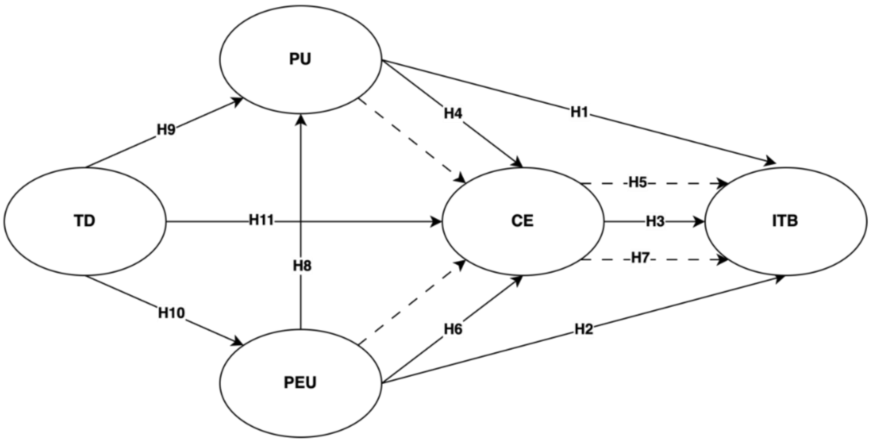

Figure 1. Research Framework

Here is the research model diagram illustrating the hypothesized relationships among the study variables. Each directed arrow represents a proposed relationship between the constructs. Let me know if you need any modifications or further explanations.

3.3. Measurement Instruments

The measurement instruments for the variables in this study were developed by adapting items from existing literature and modifying them to fit the context of electric vehicle adoption. The scales were carefully selected and refined to ensure their relevance and reliability for the target population as shown in table 1.

Table 1. Questionnaire Items

Item*)	Questionnaire		Source
PU	PU1	Driving an electric car is beneficial to reducing air pollution.	[38], [60]
	PU2	I think electric cars are beneficial for environmental protection.	
	PU3	Using an electric car everyday can save money.	
	PU4	Using an electric car everyday can increase productivity.	
	PU5	Energy-saving appliances are very useful.	
	PU6	Electric cars are more efficient than conventional vehicles.	
	PU7	Electric cars can save my energy.	

Item*)	Questionnaire		Source
PEU	PEU1	I easily understand how to use an electric car.	[60], [61]
	PEU2	Compared to conventional cars, electric cars are relatively easy to use.	
	PEU3	I think that the functions of electric cars are not complicated.	
	PEU4	The use of electric cars is more flexible.	
	PEU5	I can easily use an electric car.	
	PEU6	It doesn't take much effort to become skilled at using an electric car.	
	PEU7	Electric cars are easy to obtain nowadays.	
TD	TD1	The manual for using an electric car is difficult to understand.	[62]
	TD2	I feel uncomfortable using an electric car because I am worried about my safety.	
	TD3	I feel hesitant if I experience problems when using an electric car.	
	TD4	Public Electric Vehicle Charging Stations (SPKLU) are difficult to find, making me anxious.	
	TD5	Technical support for using the technology is not yet available	
CE	CE1	I think the overall design of electric cars is attractive.	[47], [63], [64]
	CE2	The experience of driving an electric car is very pleasant.	
	CE3	The experience of driving an electric car allows me to exchange experiences with others.	
	CE4	From my driving experience, I know the details of using (e.g. charging, maintenance) an electric car.	
	CE5	I want to share what I experience when using an electric car.	
	CE6	I feel enthusiastic when using an electric car.	
	CE7	When using an electric vehicle, I feel suitable.	
ITB	ITB1	I will buy an electric car.	[38], [60], [61]
	ITB2	I would recommend an electric car to others.	
	ITB3	I prefer to buy an electric car compared to a conventional car.	
	ITB4	I always look for the latest information about electric cars.	
	ITB5	I intend to buy an electric car.	
	ITB6	I will consider buying an electric car.	
	ITB7	I hope to buy an electric car in the near future.	

*) PU: Perceived Usefulness, PEU: Perceived Ease of Use, TD: Technology Discomfort, CE: Customer Experience, ITB: Intention to Buy

The constructs used in this study aim to measure various factors influencing the ITB of EVs by assessing the perceptions and experiences of potential consumers. The construct PU includes items that evaluate how consumers view the benefits of driving electric cars. For example, items such as PU1 and PU2 focus on environmental impact, with statements like "Driving an electric car is beneficial to reducing air pollution" and "I think electric cars are beneficial for environmental protection." Additionally, PU3 to PU7 address practical benefits such as cost savings, productivity, efficiency, and energy conservation, helping to capture the overall usefulness of electric cars in daily life. The PEU construct examines how easy consumers find electric cars to operate. Items like PEU1 ("I easily understand how to use an electric car") and PEU2 ("Compared to conventional cars, electric cars are relatively easy to use") reflect the simplicity and ease with which consumers interact with the technology. Other items assess flexibility, accessibility, and the effort required to become proficient in using an electric car. TD evaluates the negative feelings or discomfort associated with using electric cars. For instance, TD1 addresses difficulty in understanding the manual, while TD2 and TD4 focus on concerns such as safety and anxiety regarding charging station accessibility. The CE construct measures overall satisfaction with electric cars. Items such as CE1 ("I think the overall design of electric cars is attractive") and CE2 ("The experience of driving an electric car is very pleasant") evaluate the design and enjoyment of using EVs. Additional items explore the social aspects of driving electric cars, the ease of use, and emotional engagement. Finally, the ITB construct reflects consumers' purchase intentions, using items like ITB1 ("I will buy an electric car") and ITB2 ("I would recommend an electric car to others"). This construct helps assess how likely consumers are to purchase an electric vehicle based on their experiences and perceptions.

3.4. Data Analysis

This study employs AMOS software to analyze the collected data. The data analysis process is structured into several key steps to ensure that the results are accurate and reliable. Initially, descriptive statistics will be used to provide a clear summary of the respondents' demographic information. This includes understanding the general characteristics of the sample, such as age, gender, and other relevant factors, which will be conducted using SPSS. After gathering the data, the next step involves validating the measurement model, followed by testing the structural model. These steps ensure that the constructs are being measured accurately and that the hypothesized relationships between the variables are tested thoroughly. The measurement model evaluation is done through reliability and validity tests, such as Cronbach’s alpha, composite reliability, and convergent and discriminant validity. Once the measurement model is validated, the structural model is evaluated by analyzing the path coefficients, performing hypothesis testing, and checking the overall model fit through goodness of fit indices.

The first part of data analysis focuses on evaluating the measurement model to ensure that the constructs are valid and reliable. Reliability is assessed using Cronbach’s alpha and composite reliability. Cronbach’s alpha should be greater than 0.6 to indicate an acceptable level of internal consistency. Composite reliability should ideally be greater than 0.7, which indicates that the construct reliably measures the variable. In addition to reliability, validity is crucial for ensuring the accuracy of the measurement model. Convergent validity will be assessed by calculating the Average Variance Extracted (AVE). A value of 0.50 or higher for AVE indicates that the construct explains more than 50% of the variance in its indicators, which is considered a good level of convergent validity. Discriminant validity will also be examined by ensuring that the square root of the AVE for each construct is greater than the correlations between the construct and others, ensuring that the constructs are distinct from each other. These evaluations are carried out using AMOS, which will compute the necessary statistics and provide insights into the measurement model’s validity and reliability. The model will be accepted if these criteria are met.

Once the measurement model is validated, the focus shifts to evaluating the structural model. The path coefficients are analyzed to determine the strength and direction of the relationships between the constructs. A P-value less than 0.05 indicates that the relationship is statistically significant, supporting the rejection of the null hypothesis (H0) and the acceptance of the alternative hypothesis (H1). If the P-value is greater than 0.05, H0 will be accepted, indicating that there is no significant relationship between the variables. In addition to path coefficients, hypothesis testing will be performed to determine the validity of the proposed relationships between the variables. A P-value less than 0.05 confirms that the hypothesis is supported, while a P-value greater than 0.05 suggests that the hypothesis is not supported. The goodness of fit for the model will be assessed using various fit indices, including Chi-Square, Probability Level, RMSEA (Root Mean Square Error of Approximation), GFI (Goodness of Fit Index), AGFI (Adjusted Goodness of Fit Index), CMIN/DF (Chi-square/df), and TLI (Tucker-Lewis Index). These indices help to ensure that the model fits the data well and that the results can be interpreted with confidence. A Chi-Square value close to zero and a P-value greater than 0.05 suggest that the model fits the data well. Similarly, RMSEA values less than 0.08 and TLI values greater than 0.95 indicate a good model fit.

Once both the measurement model and structural model are evaluated, AMOS will generate a report that includes the path coefficients, P-values, and various fit indices, allowing the researcher to assess the model's validity. If the path coefficients are significant and the model fits the data well, the hypotheses will be accepted, providing insights into the factors that influence electric vehicle adoption. These results will help in understanding the relationships between the PU, PEU, CE, and other variables that play a role in determining consumer ITBs for electric vehicles.

4. Results and Discussion

4.1. Descriptive Statistics

The descriptive statistics provide an overview of the demographic characteristics of the sample, which was gathered through an online survey (shown in table 2). The sample consists of 365 respondents, with the data collected across several key demographic categories such as age, location, gender, occupation, income, and education level. This breakdown offers insight into the composition of the respondents, which is useful for understanding the broader context in which the study's findings apply.

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Table 2. Demographic Data

Characteristic	Category	Frequency	Percentage
Age	17-20	76	20.8%
	21-25	40	11.0%
	26-30	19	5.2%
	31-36	20	5.5%
	>36	210	57.5%
Location	Jakarta	195	53.4%
	Bogor	16	4.4%
	Depok	18	4.9%
	Tangerang	76	20.8%
	Bekasi	60	16.4%
Gender	Male	257	70.4%
	Female	108	29.6%
Occupation	Students	116	31.8%
	Public Employee	16	4.4%
	Private Employee	131	35.9%
	Entrepreneur	76	20.8%
	Other	26	7.1%
Income	< USD 300	114	31.5%
	USD 300-900	56	15.3%
	USD 900-1500	45	12.3%
	USD 1500-2100	28	7.7%
	> USD 2100	122	33.4%
Education	High School	38	10.4%
	Diploma	11	3.0%
	Undergraduate	224	61.4%
	Master	80	21.9%
	Doctor	12	3.3%

The respondents' age distribution shows a heavy skew towards older age groups. The majority, 57.5%, are aged over 36 years, reflecting a large proportion of the sample consisting of more mature individuals. The second largest group, 20.8%, falls within the 17-20 age range, while the remaining age groups, 21-25 years (11%), 26-30 years (5.2%), and 31-36 years (5.5%), represent smaller segments of the sample. Geographically, the respondents are primarily from Jakarta, which accounts for 53.4% of the sample. Tangerang follows with 20.8%, and Bekasi contributes 16.4%. The remaining respondents are from Bogor (4.4%) and Depok (4.9%), indicating that most participants come from urban areas with significant levels of mobility and access to electric vehicle technology.

The sample shows a male-dominated composition, with 70.4% of respondents identifying as male, while 29.6% are female. This gender distribution is typical in certain regions or industries where male respondents may have a higher engagement with technology, such as electric vehicles. The largest occupational group in the sample is private employees, accounting for 35.9%, followed by students (31.8%). Entrepreneurs make up 20.8%, while public employees represent a smaller group at 4.4%. The category other comprises 7.1%, which may include retired individuals or those not fitting into the traditional categories.

Regarding income, the sample shows a diverse spread. 33.4% of respondents earn more than USD 2,100, indicating a significant portion of individuals with higher disposable incomes. On the other hand, 31.5% of respondents have an income of less than USD 300, while the remaining sample is spread across income ranges of USD 300-900 (15.3%), USD 900-1500 (12.3%), and USD 1500-2100 (7.7%). This income range distribution suggests that the sample includes both budget-conscious individuals and higher-income earners, likely influencing their ITBs for electric vehicles. The educational background of the respondents is diverse. The majority of respondents, 61.4%, hold an undergraduate degree, while 21.9% have completed a Master's degree. Smaller portions of the sample hold high school (10.4%), diploma (3%), or Doctoral (3.3%) qualifications. This indicates that the study primarily attracts individuals with higher educational levels, who may be more inclined to adopt new technologies like electric vehicles.

Descriptive analysis is a statistical method employed to summarize or describe the characteristics of a dataset, providing a general overview without testing hypotheses. This technique is particularly useful in this research for better understanding and presenting data in a more digestible format, focusing on respondents' answers to various survey questions. The analysis of PU reveals that a majority of respondents strongly agree with statements highlighting the benefits of EVs in reducing air pollution and environmental protection, as well as in saving costs for daily activities. Similarly, the PEU variable shows a generally favorable view, with respondents finding EVs relatively easy to use compared to conventional vehicles. This ease of use could positively influence their willingness to adopt EVs.

However, the descriptive analysis also identifies areas of concern, particularly regarding TD. While a significant percentage of respondents disagree with the difficulty of understanding EV guides, some discomfort is reported, especially with issues like finding charging stations and insufficient technical support. These concerns could act as barriers to broader EV adoption. In terms of CE, the feedback is generally positive, with respondents finding the design attractive and the driving experience enjoyable. The social aspect of EV ownership is also emphasized, as many respondents enjoy exchanging experiences with others. Finally, the ITB variable suggests a favorable inclination towards purchasing EVs, with a notable percentage of respondents expressing a desire to buy one soon and recommending them to others. Despite these positive findings, the need to address TD remains a crucial factor in encouraging wider EV adoption.

4.2. Measurement Model Evaluation

The reliability and validity of the measurement model used in the study are evaluated to ensure the accuracy and consistency of the constructs measured, as shown in table 3. Reliability refers to the consistency of the measurement instruments, while validity refers to whether the instruments measure what they are intended to measure.

Table 3. Reliability Analysis and Convergent Validity

Construct	Variable	Factor Loading	Cronbach's Alpha
PU	PU1	0.724	0.877
	PU2	0.787	
	PU3	0.813	
	PU4	0.722	
	PU5	0.671	
	PU6	0.821	
	PU7	0.782	
PEU	PEU1	0.823	0.887
	PEU2	0.746	
	PEU3	0.840	
	PEU4	0.649	
	PEU5	0.876	
	PEU6	0.773	
	PEU7	0.706	
TD	TD2	0.789	0.835
	TD3	0.830	
	TD4	0.797	
	TD5	0.827	
CE	CE1	0.515	0.884
	CE2	0.789	
	CE3	0.813	

Construct	Variable	Factor Loading	Cronbach's Alpha
	CE4	0.755	
	CE5	0.759	
	CE6	0.751	
	CE7	0.754	
	CE8	0.805	
	ITB1	0.918	
	ITB2	0.881	
	ITB3	0.852	
ITB	ITB4	0.737	0.926
	ITB5	0.894	
	ITB6	0.696	
	ITB7	0.850	

The factor loadings in this study indicate the strength of the relationship between each item and its respective construct. For the PU construct, the loadings range from 0.671 to 0.821, with the highest loading on PU3 (0.813), which shows a strong contribution of this item to the construct. Similarly, for PEU, the loadings range from 0.649 to 0.876, with PEU5 showing the highest loading (0.876), highlighting its significant role in measuring PEU. The TD construct has strong loadings, with TD3 (0.83) and TD5 (0.827) being the most influential. The item CE1, which measures the "overall design of electric cars" in terms of attractiveness, has a factor loading of 0.515, indicating a relatively lower strength in its relationship with the CE construct. However, it was retained in the model due to its theoretical importance in capturing the aesthetic appeal and visual design, which are known to influence consumer perceptions of a product. In the context of EV, design can play a significant role in shaping customer experience, especially as the automotive industry increasingly emphasizes style and innovation in EV models. Although the factor loading for CE1 is modest, it provides valuable insight into the holistic experience of the consumer, beyond just functionality and usability. Given the growing emphasis on product aesthetics in consumer decision-making, CE1 remains an important aspect of the overall customer experience with electric vehicles. Therefore, its inclusion is justified, as it adds depth to the construct by capturing an essential component of the EV adoption process.

Reliability was assessed using Cronbach's alpha and composite reliability. Cronbach's alpha is a widely used measure to assess the internal consistency of a construct, and a value above 0.7 is considered acceptable. The Cronbach's alpha values for the constructs in this study were all above the threshold of 0.7, indicating strong internal consistency. The values for each construct are as follows: PU had a Cronbach's alpha of 0.877, PEU had 0.887, TD had 0.835, CE had 0.884, and ITB had 0.926. These high values confirm that the instruments used to measure these constructs are reliable and consistently provide meaningful results. Additionally, the composite reliability for all constructs exceeded the threshold of 0.7, further supporting the reliability of the measurement model.

For validity, both convergent validity and discriminant validity were assessed. Convergent validity ensures that the items measuring a construct are strongly correlated with each other. This was evaluated by examining the factor loadings, which indicate the strength of the relationship between each item and its respective construct. A factor loading above 0.7 is generally considered strong, and most of the items in this study showed factor loadings above this threshold. For instance, the items for PU such as PU1 (0.724), PU2 (0.787), and PU3 (0.813) had good loadings, as did most items for PEU (PEU) and other constructs. However, there were a few items with lower factor loadings, such as CE1 (0.515) and PEU4 (0.649), which slightly weakened the convergent validity. Despite these exceptions, the majority of items displayed adequate factor loadings, meaning that the constructs largely exhibited good convergent validity.

Discriminant validity ensures that a construct is distinct from other constructs, which was assessed by comparing the square root of the Average Variance Extracted (AVE) with the correlations between constructs. The results of this analysis suggest that the constructs are sufficiently distinct from one another, confirming that they measure different underlying concepts. In summary, the measurement model demonstrates strong reliability, with high Cronbach's alpha values indicating consistency in the measurements. The validity tests show that the constructs have good convergent validity, with most factor loadings above 0.7, and the discriminant validity was also established, confirming that the constructs are distinct from one another. Although a few items had lower factor loadings, the overall evaluation suggests that the measurement model is sound and appropriate for further analysis.

4.3. Structural Model Evaluation and Hypothesis Testing Results

The structural model evaluation presents the results from testing the hypothesized relationships between the variables using SEM with the AMOS software. This evaluation involves assessing the path coefficients, t-values, and significance levels for each hypothesis, as well as evaluating the model fit indices to determine how well the model explains the relationships between the constructs. The goodness-of-fit indices for the full model SEM analysis indicated that the model did not initially meet the necessary fit criteria (Table 4). The Chi-square value was 0.816, which is relatively high and indicates a lack of fit, as lower values are preferred. The probability level was 0.000, which also suggests poor model fit since values greater than 0.05 are desired. Other indices such as RMSEA (0.092), GFI (0.816), AGFI (0.698), CMIN/DF (4.072), and TLI (0.800) also did not meet the desired thresholds. As a result, several indicators were eliminated to improve the model fit.

Table 4. Goodness of Fit Indices Initial Model Results

Goodness of Fit Indices	Cut Off Value	Results	Model Evaluation
Chi-square	Expectedly small	0.816	Lack of fit
Probability level	≥ 0.05	0.000	Lack of fit
RMSEA	≤ 0.08	0.092	Lack of fit
GFI	≥ 0.90	0.816	Lack of fit
AGFI	≥ 0.90	0.698	Lack of fit
CMIN/DF	≤ 2.00	4.072	Lack of fit
TLI	≥ 0.95	0.800	Lack of fit

In the fitted model SEM, the modifications led to improved goodness-of-fit indices, as shown in the updated model evaluation (Table 5). The Chi-square value decreased to 0.995, and the probability level improved to 0.121, which is now within the acceptable range. The RMSEA was reduced to 0.025, indicating a good fit, and the GFI and AGFI values increased to 0.972 and 0.954, respectively. The CMIN/DF value dropped to 1.224, and the TLI value improved to 0.994, both indicating a better fit. These changes indicate that the adjusted model satisfies the fit criteria and is deemed suitable for further analysis.

Table 5. Goodness of Fit Indices Fitted Model Results

Goodness of Fit Indices	Cut Off Value	Results	Model Evaluation
Chi-square	Expectedly small	0.995	Fitted
Probability level	≥ 0.05	0.121	Fitted
RMSEA	≤ 0.08	0.025	Fitted
GFI	≥ 0.90	0.972	Fitted
AGFI	≥ 0.90	0.954	Fitted
CMIN/DF	≤ 2.00	1.224	Fitted
TLI	≥ 0.95	0.994	Fitted

The next step involved testing the hypotheses proposed in the research model to understand the relationships between the constructs. Hypothesis testing in SEM is performed by evaluating path coefficients, t-values, and p-values. A path coefficient represents the strength and direction of the relationship between two variables, and the t-value and p-value help determine the statistical significance of these relationships, as shown in table 6 and depicted in figure 2. For direct effects, several hypotheses were supported by the results. Hypotheses H1 (PU → ITB), H2 (PEU → ITB), and H3 (CE → ITB) all showed significant positive relationships, with β of 0.464, 0.386, and 0.315, respectively. These relationships were confirmed by their low p-values (all below 0.05), indicating that they are statistically significant. In contrast, Hypothesis H4 (PU → CE) was not supported, as the β was negative (-0.079) and not statistically significant (p = 0.428). Other significant relationships included H6 (PEU → CE), with a strong positive relationship (β = 0.634, p

< 0.05), and H8 (PEU → PU), with a β = 0.632, which was also statistically significant. However, H9 (TD → PU) and H10 (TD → PEU) showed significant negative relationships, with β = -0.119 and β = -0.514, respectively. The results indicated that TD had a negative impact on both PU and PEU, with both relationships being statistically significant (p < 0.05). For indirect effects, Hypothesis H5 (PU → CE → ITB) was found to be non-significant (p = 0.419), indicating that CE did not mediate the relationship between PU and ITB. On the other hand, H7 (PEU → CE → ITB) showed a significant mediating effect (β = 0.417, p = 0.013), suggesting that CE plays an important role in linking PEU with ITB.

Table 6. Inner Model Results (Summary)

Hypothesis	Path	Coefficient	S.E.	Critical Ratio	P-Value	Conclusion
H1	PU → ITB	0.464	0.097	4.766	0	Positively Significant
H2	PEU → ITB	0.386	0.113	3.410	0	Positive Significant
H3	CE → ITB	0.315	0.090	3.484	0	Positively Significant
H4	PU → CE	-0.079	0.100	-0.793	0.428	Not Significant
H5	PU → CE → ITB	-0.020	-	-	0.419	Not Significant
H6	PEU → CE	0.634	0.099	6.406	0	Positively Significant
H7	PEU → CE → ITB	0.417	-	-	0.013	Significant
H8	PEU → PU	0.632	0.066	9.627	0	Positively Significant
H9	TD → PU	-0.119	0.055	-2.154	0.031	Negative Significant
H10	TD → PEU	-0.514	0.060	-8.608	0	Negative Significant
H11	TD → CE	-0.034	0.057	-0.594	0.552	Not Significant

The results of the structural model evaluation and hypothesis testing provide several key insights (figure 2). The fitted model demonstrates a good fit, with all relevant indices meeting the required thresholds. Among the direct relationships, several hypotheses, such as the influence of PU, PEU, and CE on ITB, showed significant positive relationships. However, the influence of TD on CE was found to be non-significant, indicating that the discomfort associated with technology did not significantly impact consumer experiences in this study. The indirect effect of PEU on ITB via CE was found to be significant, indicating the importance of CE in shaping ITBs. Overall, the structural model supports the majority of the hypotheses, with several critical insights into the relationships between the constructs in the context of electric vehicle adoption.

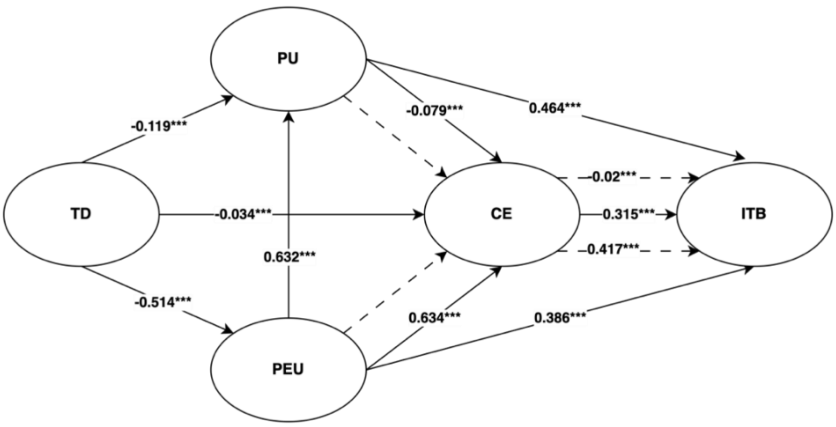

Figure 2. Structural Model Results Framework

4.4. Discussion

The findings from this study provide valuable insights into the factors influencing the ITB EVs and contribute to the growing body of literature on consumer behavior in the context of emerging technologies. The study highlights the importance of PU, PEU, CE, and TD in shaping consumer ITBs. Each of these variables played a critical role in influencing the ITB EVs, but their effects were not always aligned with previous research, offering new perspectives and potential avenues for future research. The relationship between PU and ITB electric vehicles was found to be significant and positive, with a strong path coefficient. This result supports the findings of [37], who found that the PU of a technology positively influences consumers' ITBs. Consumers in this study recognized the practical benefits of electric vehicles, such as cost efficiency and environmental impact, which in turn boosted their willingness to adopt this technology. However, the results contrast with the study by [13], who found no significant effect of PU on ITBs. This discrepancy may arise due to contextual differences, such as regional factors or differing levels of consumer familiarity with electric vehicles. Nevertheless, the findings of this study reinforce the idea that consumers' belief in the practical benefits of a technology is crucial in shaping their purchasing decisions.

Similarly, the relationship between PEU and ITB was also positive and significant. This result aligns with the research by [10], [40], both of whom demonstrated that the PEU significantly influences consumer intentions to adopt technology. In the context of electric vehicles, consumers who found the technology easy to operate and understand were more likely to express a desire to purchase. This suggests that simplifying the user experience, including charging and vehicle maintenance, could enhance the adoption of electric vehicles. The importance of ease of use in adoption is consistent with the TAM, which emphasizes the role of PEU in shaping technology acceptance. CE also played a significant role in influencing the ITB. The path coefficient between CE and ITB was positive and significant, highlighting that a positive interaction with electric vehicles, whether through test drives or the overall experience with the vehicle, can significantly increase the likelihood of purchase. This finding is consistent with previous studies, such as [41], [65], who found that CE positively affects ITBs. It emphasizes the importance of providing a satisfying and seamless experience to potential buyers, including factors like product quality, after-sales service, and user-friendly interfaces.

An unexpected result in this study was the non-significant relationship between PU and CE. Contrary to the findings of [44], who found a positive relationship between PU and CE, this study suggests that the perception of usefulness does not directly influence the overall CE. This could indicate that while consumers recognize the utility of electric vehicles, this perception may not necessarily translate into an improved experience unless it is accompanied by other factors, such as ease of use or personal involvement with the product. Therefore, companies should focus not only on communicating the benefits of electric vehicles but also on improving other aspects of the user experience that contribute to overall satisfaction. The indirect effect of PU on ITB through CE was found to be insignificant, which contrasts with previous research [47] suggesting that CE mediates the relationship between PU and ITB. This unexpected result could be explained by the fact that while consumers may acknowledge the practical benefits of electric vehicles (such as cost efficiency and environmental sustainability), these perceived advantages may not directly influence their overall experience with the product. One possible explanation is that PU may primarily shape cognitive attitudes towards the product, whereas CE might be more influenced by direct, hands-on interactions with the vehicle, such as test drives or user interface familiarity. Furthermore, the mediation effect of CE might be stronger for variables like PEU, which directly impacts the ease with which a consumer engages with the technology. Thus, while PU can influence the initial attraction towards electric vehicles, its impact may not be sufficiently reinforced through CE, which might require more experiential factors, such as user satisfaction or brand loyalty, to strengthen the relationship.

The study confirmed a significant positive relationship between PEU and CE. This result is in line with prior research, such as [49], which found that ease of use contributes to a more positive CE. In the context of electric vehicles, this suggests that consumers who find the technology easy to use and understand are more likely to have a positive experience. This highlights the importance of making the electric vehicle experience as user-friendly as possible, including easy-to-understand features and accessible charging infrastructure. The mediation effect of CE between PEU and ITB was found to be significant. This result aligns with the findings of [50], who demonstrated that a positive user experience strengthens the relationship between PEU and the ITB. For electric vehicles, this suggests that making the technology easier to use can indirectly influence the likelihood of purchase by enhancing the overall experience. The role of CE in mediating the relationship between ease of use and ITB underscores the importance of providing consumers with not only an easy-to-use product but also a satisfying and engaging experience.

TD was found to negatively influence PU, a result consistent with [55]. This suggests that when consumers feel uncomfortable with the technology, they are less likely to perceive it as useful, which could impede adoption. In the case of electric vehicles, discomfort related to factors like charging infrastructure, vehicle performance, or lack of knowledge can diminish the perceived benefits of the technology. Similarly, TD negatively affected PEU. This finding is consistent with the studies by [62], which found that discomfort with technology reduces consumers' perception of its ease of use. In the context of electric vehicles, this implies that consumers who experience discomfort with the technology—whether due to unfamiliarity or concerns about functionality—may find it more difficult to use, thereby reducing their overall willingness to adopt the technology. The relationship between TD and CE was found to be negative but not significant, leading to the rejection of Hypothesis H11 (TD → CE). This finding contrasts with prior studies, such as [59], which highlighted the significant effect of technology readiness on CE. One possible explanation for this result could be that discomfort with technology does not necessarily translate into a negative user experience with electric vehicles. While TD may influence certain aspects of consumer perception, its impact on overall customer experience may be less pronounced if other factors, such as positive interactions with the vehicle or strong product features, counterbalance these discomforts. Furthermore, the nature of technology discomfort could be more related to initial barriers such as unfamiliarity with the technology, rather than ongoing experiences. It is also possible that consumers' willingness to adopt electric vehicles may not be significantly impacted by discomfort in the short term, as long as their other experiences—such as ease of use or environmental benefits—outweigh initial hesitations. Thus, while previous literature suggests a stronger influence of TD on CE, the findings from this study imply that addressing discomfort factors, while important, may not be sufficient on its own to significantly alter the consumer experience with EVs.

To address the gendered implications of the study, it is important to note that the sample shows a male dominance, with 70.4% of respondents identifying as male. This demographic disparity could influence the findings, particularly in relation to ITB. Research has shown that gender can affect consumer perceptions and purchasing behaviors, with men generally exhibiting higher levels of interest and intention to adopt new technologies, including EV. Therefore, future studies could explore whether male consumers are more likely to prioritize factors like technological efficiency and cost savings, while female consumers may place more importance on environmental benefits or social responsibility. Understanding these gendered differences could provide valuable insights into how to better tailor marketing strategies for EVs, ensuring that they resonate with both male and female consumers. This consideration would also help in creating more inclusive and effective policies and interventions to encourage wider adoption of EVs across different demographic groups.

5. Conclusion

This study set out to explore the factors influencing the ITB of EVs in the Jabodetabek region, integrating the TAM with variables that relate to prior consumer experience, namely TD and CE. The findings revealed that both PU and PEU significantly influenced the ITB of EVs. Specifically, consumers who perceive electric vehicles as useful and easy to operate are more likely to have a strong ITB. Moreover, CE was found to play an important role as a mediator between TAM factors and ITB. Positive CEs, including ease of operation, comfort, and emotional satisfaction, strengthened consumers' intent to adopt electric vehicles. However, TD emerged as a more complex factor, where consumers who felt discomfort or anxiety regarding new technologies like charging stations or vehicle features had lower perceptions of usefulness and ease of use. Despite this, effective management of CEs can minimize the negative effects of discomfort. Overall, the study concluded that the adoption of electric vehicles is not only determined by external factors like government policies or financial incentives but also by how manufacturers and stakeholders can improve consumer perceptions and manage user experiences effectively. The combination of psychological factors (PU and ease of use) and direct consumer experiences plays a key role in shaping ITBs.

This research contributes significantly to the development of the TAM by incorporating CE as a mediating factor in explaining the ITB electric vehicles. This approach extends the understanding of how internal factors such as PU and ease of use interact with consumer experiences to influence technology adoption, particularly in the context of evolving technologies like electric vehicles. The integration of CE into the TAM framework provides new insights into the complexities of adoption behavior, highlighting the importance of emotional and practical factors in shaping consumer perceptions and decisions. This study strengthens the existing literature on technology adoption by adding a consumer experience dimension, which has not been widely explored in similar contexts.

The findings of this study have important practical implications for various stakeholders in the EV industry. Manufacturers should focus on reducing TD by implementing consumer education initiatives, such as test drives and interactive product demonstrations. These experiences can help familiarize consumers with EVs, thereby addressing discomfort and enhancing their PEU. By allowing consumers to experience the vehicles firsthand, manufacturers can directly address concerns related to unfamiliarity with the technology, making it easier for consumers to see the practical benefits of EVs. Additionally, investing in the expansion and accessibility of charging infrastructure is essential, as it directly improves PEU by making the technology more convenient and user-friendly. A more accessible charging network can alleviate concerns over charging time and availability, which are key factors influencing consumer adoption. While government incentives remain important, a more long-term strategy could involve subsidies for battery technology, which would enhance the PU of EVs by reducing operational costs. Public awareness campaigns, especially those involving current EV users, could further promote PEU by reinforcing the practical advantages of using electric vehicles. Future research should aim to expand beyond Jabodetabek to include other regions of Indonesia, considering different demographic and cultural contexts. Incorporating variables like environmental awareness or social influence could also provide a more comprehensive understanding of the factors that drive EV adoption.

This study acknowledges several limitations that could be addressed in future research. Since the research was confined to the Jabodetabek area, the findings may not be fully representative of the broader Indonesian population. Expanding the research to include other regions could provide more comprehensive insights into the factors influencing electric vehicle adoption across different parts of Indonesia. The study relied on online surveys, which could introduce biases as individuals who are already familiar with technology are more likely to participate. Future research might consider employing alternative data collection methods, such as face-to-face interviews, or using mixed methods to gather data from a more diverse sample. While the study focused on key variables such as PU, PEU, CE, and TD, other factors such as the availability of charging infrastructure, the comparison with conventional vehicles, and environmental consciousness could also play important roles. Future studies could incorporate these variables to further understand the dynamics of EV adoption.

6. Declarations

6.1. Author Contributions

Conceptualization: H.N.S., H.M., C., and A.M.S.; Methodology: A.M.S.; Software: H.N.S.; Validation: H.N.S., A.M.S., and C.; Formal Analysis: H.N.S., A.M.S., and C.; Investigation: H.N.S.; Resources: A.M.S.; Data Curation: A.M.S.; Writing Original Draft Preparation: H.N.S., A.M.S., and C.; Writing Review and Editing: A.M.S., H.N.S., and C.; Visualization: H.N.S.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. 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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