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Integrating Behavioral Models to Understand Consumer Adoption of Battery Electric Vehicles in Indonesia

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ABSTRACT

This study integrates behavioral theories to examine battery electric vehicle (BEV) adoption in Indonesia, incorporating financial incentives to address gaps in understanding consumer motivation. A survey of 304 respondents analyzed using Partial Least Square Structural Equation Modeling (PLS-SEM) reveals that attitude towards behavior and perceived behavioral control significantly influence BEV adoption, while financial incentives, though impactful, do not directly drive intention. This means that consumers who have a positive perception of BEVs and feel confident in their ability to own and use them are more likely to adopt, regardless of financial incentives. However, key barriers such as charging infrastructure limitations, range anxiety, and limited consumer awareness prevent widespread adoption, indicating that monetary incentives alone are insufficient. To effectively promote BEV adoption, policymakers should complement financial incentives with cost-reduction strategies like battery leasing programs, targeted fleet incentives, and local production subsidies, alongside infrastructure expansion and consumer engagement through education and test-drive initiatives. This study provides actionable insights to design effective policies for accelerating BEV adoption and transitioning to sustainable transportation in Indonesia.

1. INTRODUCTION

Currently, there is a growing trend towards the adoption and expansion of electric vehicles in transportation services because of the significant rise in energy consumption. Many countries are transitioning to renewable energy sources to decrease the amount of harmful petrol emissions released into the earth's atmosphere [1].

Indonesia has significant potential to participate in the battery-powered electric vehicle (BEV) car market. Indonesia possesses the world's greatest nickel reserves, which can serve as a fundamental ingredient for battery production [2]. Indonesia Battery Holding, has been established as a merger of numerous state-owned enterprises, would transform nickel products from Indonesia into electric vehicle battery goods through a comprehensive process from upstream to downstream as a comprehensive strategy to establish itself as a significant player in the electric vehicle (EV) battery business. This approach involves utilizing its abundant nickel supplies and enacting policies to attract investment [3].

Yet, the government's preparedness must be complemented by the community's willingness to embrace this new technology. Furthermore, BEV cars are a costly commodity. Some consumers are interested in trying new products or feel an ethical obligation to safeguard the environment and minimize pollution. These consumers are likely to purchase a BEV car as a potential solution for addressing climate change by substituting internal combustion engines with electric motors [4].

BEV cars are eco-friendly and quiet, but owners may face numerous challenges. Challenges may arise due to insufficient recharging stations, the recharging procedure, the length of time needed for recharging, and the electric car's range on a single load. [5].

Potential buyers can be afraid to buy a BEV car due to insufficient information and lack of expertise with electric vehicles. Hence, the government and affiliated enterprises must gather data on consumer acceptability, satisfaction, reactions, and attitudes towards this new technology. A comprehensive study is necessary to gain insight into the elements that influence the initial acceptance of battery electric vehicle (BEV) cars among Indonesian consumers during the early phases of the industry's establishment in Indonesia.

Multiple studies have been performed to investigate the variables that influence the adoption of electric motorized vehicles. in different nations. Buranelli de Oliveira *et al.* [6], in a study done in Brazil revealed that the majority perception of electric vehicles represents a particular level of acceptance that was driven by positive attitudes, additional benefits, ease of use, adequate facilities, and social influence. Another

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study in Indonesia [7] identified comparable effects but also added variables such as distance and long-term orientation. In India, Jain, Bhaskar, and Jain [8] did a study to examine the consumer's buying intentions towards electric vehicles. The study utilized the UTAUT approach and specifically studied the influence of environmental factors, risks, and government support on these intentions. Another study in India concluded that hedonism, financial value, and personal norms are factors impacting the level of acceptance of electric vehicles in the Himalayan Region of India [9].

In China, research was conducted to examine the inclination to utilize electric trucks for the purpose of transporting commodities. It was indicated that the UTAUT approach, which includes effort expectancy, social influence, performance expectancy, and facilitating conditions along with additional risk variables, significantly influences the promotion of electric truck adoption [10]. A study was conducted in Malaysia employing the Norm Activation Model (NAM) along with the Theory of Planned Behaviour (TPB). Comprehensive findings were yielded, identifying seven factors that might affect the rate of acceptability of electric vehicles in Malaysia. These factors are positive attitudes towards electric vehicles, perceived additional benefits from using electric vehicles, personal norms, subjective norms, ease of use, awareness of obligations, and implications awareness [11].

The disparities in user intentions between conventional automobiles and electric vehicles in Vietnam, a developing country, were examined using a push-pull-mooring model. The findings demonstrated that Vietnamese individuals are motivated to switch from conventional vehicles to electric vehicles due to social considerations, pricing value, economic benefits, and advantages associated with electric vehicles [12].

Various theoretical frameworks are examined for the implementation of electric motorized vehicles. Previous studies have identified multiple models that can be employed to examine the aspects that can impact individuals' behaviour in utilising electric automobiles. A study conducted in Indonesia used the Technology Acceptance Model (TAM) along with the Theory of Planned Behavior (TPB) to forecast people's inclination towards embracing electric motorbikes [7]. Different research uses the Push-Pull-Mooring (PPM) model for the analysis of empirical data [12]. Furthermore, a few people combine the Unified Theory of Acceptance and Use of Technology (UTAUT) with cultural moderators [9]. To analyze the use of electric vehicles and consumer behavior, other researchers apply theories including the Diffusion of Innovation Theory, the Theory of Planned Behavior (TPB), and the Technology Acceptance Model (TAM) [8]. However, there is not much study on individuals' intention to utilize BEV cars in Indonesia.

This study aims to identify the key behavioral factors influencing BEV adoption among Indonesian consumers, evaluate the impact of financial incentive policies, and assess the applicability of an integrated behavioral model in predicting consumer acceptance. To achieve these objectives, this study employs an integrated theoretical framework combining the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Norm Activation Model (NAM), and Theory of Planned Behavior (TPB) to analyze BEV adoption in Indonesia. These models were selected based on their complementary strengths in explaining different aspects of consumer decision-making.

TAM and UTAUT are widely used in technology adoption studies, capturing the role of perceived ease of use, perceived usefulness, and facilitating conditions in influencing consumer acceptance [29], [36]. However, BEV adoption extends beyond technology acceptance, requiring an understanding of personal and social behavioral factors.

TPB incorporates attitude, subjective norms, and perceived behavioral control, which are critical in shaping behavioral intentions, especially in new and emerging markets where BEV adoption is still in its early stages [30][29]. Meanwhile, NAM is essential for capturing moral and social responsibility, which plays a growing role in sustainable consumer behavior and environmental decision-making [32].

The combination of these models allows for a more comprehensive and holistic understanding of BEV adoption. While TAM and UTAUT focus on technology acceptance factors, TPB accounts for individual control and social influence, and NAM introduces moral obligation and environmental awareness as critical determinants. Given the complex nature of BEV adoption, using a single framework would not sufficiently capture all influencing factors. Therefore, this study integrates these models systematically, ensuring that each contributes meaningfully to the research framework rather than being used arbitrarily.

Furthermore, our empirical analysis, using Partial Least Squares Structural Equation Modeling (PLS-SEM) on data from Indonesian consumers, presents novel findings on the key determinants influencing BEV adoption in a developing country context. Unlike previous studies that primarily focus on either behavioral intention or policy impact separately, this research uniquely bridges both perspectives, offering more profound insights into the interplay between consumer behavior and economic incentives. These findings provide a more holistic understanding of BEV adoption, particularly in emerging economies like Indonesia.

PLS-SEM was chosen for its ability to handle complex theoretical frameworks, small to medium sample sizes, and non-normal data distributions, which are common in behavioral research [37]. This method has been widely applied in previous studies on EV adoption and sustainability behavior modeling, demonstrating its effectiveness in analyzing consumer acceptance, policy impact, and behavioral trends in sustainable transportation [30], [36], [42]. These findings provide a more comprehensive understanding of BEV adoption, particularly in emerging economies like Indonesia, where behavioral factors and financial incentives play a crucial role in shaping adoption trends.

Integration models tend to result in intuitive findings and contribute to new theoretical advancements. In various fields, including health research, integration models have been shown to generate fresh insights and innovative solutions for complex problems [13]. By combining multiple theoretical perspectives, integration models enhance the understanding of intricate phenomena, allowing researchers to approach challenges from diverse viewpoints.

In behavioral and social sciences, the integration of multiple frameworks, such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Norm Activation Model (NAM)—has been shown to provide a more comprehensive explanation of human decision-making processes [59]-[61]. Integration models in theoretical research aim to synthesize different conceptual perspectives to enhance explanatory power. This approach makes research outcomes more applicable to real-world contexts, which is particularly valuable for policy formulation and practical implementation. The ability to combine multiple theories ensures that results are not only academically robust but also actionable for practitioners and policymakers [15].

This research also utilizes the financial incentive policies designed to address the significant barrier of high prices that leads to customer reluctance in acquiring electric vehicles [16]. Financial policies refer to both direct and indirect incentives provided by the government, such as road tax discounts, rebates on value-added tax (VAT), toll exemptions, allocation of electric vehicle (EV) license plates, free parking facilities, and sufficient financing for research and development in the field of EVs [17]. Financial incentive schemes play a key part in the adoption of electric cars (EVs) for a variety of reasons, as evidenced by several studies that have been published in academic publications. As such, they can also be taken into account in this model. State and federal tax incentives greatly increase the number of EV adoptions in the US [18]. Financial incentives make electric vehicles (EVs) more appealing financially than conventional internal combustion engine (ICE) vehicles, which accelerates the market penetration of EVs. Financial incentives are positively connected with larger EV market shares in many nations [19]. This component also contributes to the advancement of EV technology. Financial incentives encourage more investment in EV infrastructure and technology by raising demand for EVs. This may result in improvements to battery technology, lower production costs, and enhanced EV performance and range. The creation and enhancement of EV technologies are financially incentivized by manufacturers, as found in a study [20]. Financial incentives can reduce the total cost of ownership (TCO) of electric vehicles (EVs), encompassing the purchase price, maintenance costs, and energy expenditures. Over the course of their lifetime, EVs are made more financially feasible by incentives including lower power prices for EV charging, toll exemptions, and lower registration fees.

Conducting this research is crucial to understanding the acceptance of BEV cars among Indonesian consumers by identifying the key factors influencing their behavior. Unlike previous studies that primarily focus on general electric vehicle adoption, this research integrates multiple theoretical frameworks—TAM, UTAUT, NAM, and TPB—along with financial incentive policies to provide a comprehensive and context-specific model for BEV adoption in Indonesia. This study offers novel insights by not only examining psychological and behavioral aspects but also incorporating economic considerations, which are often overlooked in similar research. By modeling community aspirations and preferences, this research aims to assist policymakers and stakeholders in designing more effective strategies to accelerate the adoption of BEV cars and support the successful implementation of the Accelerating Battery-Based Electric Motor Vehicle program in Indonesia.

2. MATERIAL AND METHODS

2.1 Method

This study involved purposive sampling by initially identifying several groups from a population. The research participants were potential adopters who were individuals residing in Indonesia who commute daily using oil-fuelled cars, a demographic that research has shown to be key in shaping early BEV adoption trends [19]. The sampling strategy ensures that the study captures insights from individuals most likely to transition to BEVs, as past studies indicate that daily commuters with conventional fuel-powered vehicles are more sensitive to fuel price fluctuations, environmental policies, and infrastructure developments that drive BEV adoption [54].

The research questionnaire was distributed online. The research questionnaire comprised two sections:

1. The initial section of the questionnaire included the responder's socio-demographic information.
2. Respondents rate each component using a Likert scale that ranges from 1 to 5 to produce scores for each component. Scale one signifies strong disagreement with the statement provided by the research subject. A rating of five signifies significant agreement with the statement by the research subject.

The constructs and indicator items employed in previous studies are provided in Table 1.

Table 1. Constructs and indicators from previous studies.

Construct	Definition	Item	Indicator	Reference
Perceived usefulness	Consumer perceptions about the functional efficiency of electric vehicles	Using battery electric vehicles (BEV) makes it easier for me to do my job	PU1	[30]
		Overall, BEVs are useful for me	PU2	
		Using a BEV improves my daily performance	PU3	
Perceived ease of use	Consumers' ability to learn electric vehicle operation and use electric vehicles without much effort	I think it would be easy to use BEVs	PEU1	[31]
		I think it would be easy for me to drive BEVs to anywhere I want	PEU2	
		My interaction with BEVs would be clear and understandable	PEU3	
		I don't need any help (car manual, driving training, product forcing) for a battery based electric motorized car	PEU4	
Perceived enjoyment	Shows the extent to which activities using technology with new innovations are considered enjoyable	I would find using BEVs to be enjoyable	PE1	[32], [7]
		Owning/ using BEVs would make my life more interesting	PE2	
		Using BEVs will give more enjoyment than traditional cars	PE3	
Attitude toward behaviour	Consumer attitudes towards purchasing electric vehicles	I believe that BEVs can reduce climate change	ATB1	[32]
		I think buying an BEV is a good decision	ATB2	
		In the long-term, I think owning an BEV is more cost effective than owning a conventional vehicle	ATB3	
Facilitating conditions	Individual insight into infrastructure or technical support for using a technology or system	I have access to facilities and services needed to use BEVs	FC1	[30]
		I have the knowledge, resources and ability to use BEVs	FC2	
		Resources required to use BEVs are available to me	FC3	
		I am constrained by the lack of infrastructure or resources needed to use BEVs	FC4	
Perceived behavioural control	The level of ease or challenge experienced by individuals in relation to their actions. In the researched area, PBC refers to the convenience or difficulty consumers feel in purchasing an EV.	I can largely decide whether or not to buy BEVs at home	PBC1	[34]
		I am confident that if I want to, I will definitely be able to choose a BEV for my next purchase	PBC2	
		I will have the ability to buy a BEV in the future	PBC3	
Financial incentive policies	Subsidies and preferential tax policies are provided to reduce purchase prices and encourage more people to choose electric vehicles.	I think the subsidy policy for purchasing BEVs is sufficient	FIC1	[16]
		I know well about the subsidy policy for purchasing BEVs	FIC2	
		Subsidy policy and preferential tax policies are important for me to purchase BEVs	FIC3	
Awareness of consequences	In regard to determining whether individuals are informed of the negative impacts that occur from their environmentally destructive behaviour.	My non energy saving behaviour will exacerbate climate change	AC1	[16]
		My non energy saving behaviour will exacerbate environmental pollution	AC2	
		My non energy saving behaviour will affect the quality of life for future generations	AC3	
		On the whole, my non energy saving behaviour can make some negative effects	AC4	
Ascription of responsibility	Reflects an individual's consciousness of the negative impacts of not engaging in pro-social behavior towards others or their valued things.	I should be responsible for excessive energy consumption caused by my non energy saving behaviour	AR1	[16]
		I should be responsible for the environmental pollution caused by my non energy saving behaviour	AR2	
		I should be responsible for the impact of my non energy saving behaviour on the quality of life of future generations	AR3	
		I should be responsible for the negative effects of my non energy saving behaviour	AR4	

Subjective norm	Information about electric vehicles derived from the Internet and subjective opinions expressed by family, acquaintances, and the media.	Most of the people who have important influence on me will save energy	SN1	[16], [30]
		My family and friends around me encourage me to save energy	SN2	
		Our country is active in saving energy	SN3	
		The government actively advocates and implements low-carbon life	SN4	
		People usually influence my purchasing intention	SN5	
		I will use electric vehicles if my friends or peer have already used it	SN6	
Personal norm	Personal consumer norms.	I think I have the consciousness of energy saving and environmental protection	PN1	[16]
		I think I have a sense of social responsibility	PN2	
		I think I can contribute to improving the environment through energy saving	PN3	
		I think I have the duty to save energy	PN4	
Behaviour intention	Attitude is an expression of intention or a prospective decision to take action.	Assuming BEVs come into use, I will be intent to use it	BI1	[31], [30]
		Assuming BEVs come into use, I would like to use it usually	BI2	
		Assuming BEVs come into use, I will be intent to recommend it to others	BI3	
		Assuming BEVs come into use, I would like to buy it	BI4	
		I expect to use electric vehicles in the future	BI5	
Personal innovativeness	Consumer acceptance of electric vehicles.	I regard electric vehicles stimulating and innovative	PI1	[30]
		I am challenged by ambiguities, new ideas and unsolved problems	PI2	
		If I heard about a new information technology, I would look for ways to experiment with it	PI3	

This study acknowledges the potential risk of single-source bias due to reliance on self-reported survey data, which may introduce systematic measurement errors. To mitigate this, a two-stage pilot test was conducted. First, five field experts reviewed the questionnaire to refine clarity, eliminate ambiguity, and ensure that potential respondents could understand and complete it within a reasonable timeframe. They were academics and industry professionals with expertise in BEV adoption, consumer behavior, and survey methodology. Their role was to ensure the clarity, accuracy, and relevance of the questionnaire before testing it with potential respondents.

Second, a preliminary quantitative pilot test was conducted with 38 respondents to assess response consistency, minimizing common method bias (CMB) and ensuring construct reliability.

Several mitigation strategies were implemented to further address potential biases. Anonymity and confidentiality were assured to respondents, reducing social desirability bias and encouraging honest responses. Additionally, question order randomization was applied to prevent priming effects that could influence response patterns.

To enhance the reliability and validity of the data, the study employed partial least squares structural equation modeling (PLS-SEM), which is particularly effective in handling measurement errors and complex interrelationships within the dataset [22]. Robustness checks were conducted using SPSS software, and validity and reliability tests were applied to ensure the integrity of the constructs. The acceptable threshold for internal consistency was a Cronbach's Alpha value of > 0.7. All questionnaire indicators, except for the facilitating condition-4 construct, had an r-count value higher than the r-table, confirming their validity. However, the Facilitating Condition-4 construct was eliminated due to its invalidity.

During the reliability test, most constructs demonstrated a Cronbach's Alpha value above 0.7, indicating a high level of reliability. However, the personal innovativeness construct showed a Cronbach's alpha value of 0.053, representing poor reliability, necessitating its removal. By implementing these measures, this study ensures data integrity, minimizes single-source bias, and strengthens the reliability of the research findings. Despite these efforts, single-source bias remains a potential limitation, as responses were collected from a single respondent per observation.

2.2 Initial Model

The research's initial model was a mixture of the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Norm Activation Model (NAM), and Theory of Planned Behaviour (TPB). The factors considered in the study were perceived usefulness, perceived ease of use, perceived enjoyment, attitude towards behaviour, facilitating conditions, perceived behavioural control, financial incentive policies, awareness of consequences, ascription of responsibility, subjective norm, personal norm, and behavioural intention. The initial model would have been verified to assess its utility in measuring individuals' intent to adopt battery-powered electric cars in Indonesia.

Based on previous studies and discussions, this investigation employed several researched hypotheses concerning the determinants that impact the inclination of Indonesian citizens to adopt electric vehicles, as indicated in Table 2.

Table 2. Hypothesis testing.

No		Hypotheses Development
1	H1	Perceived usefulness has a positive influence on attitude towards behavior
2	H2	Perceived usefulness has a positive influence on behavioral intention
3	H3	Perceived ease of use has a positive influence on perceived usefulness.
4	H4	Perceived ease of use has a positive influence on attitude towards behaviour
5	H5	Perceived enjoyment has a positive influence on perceived usefulness
6	H6	Perceived enjoyment has a positive influence on attitude towards behaviour
7	H7	Attitude towards behaviour has a positive influence on behavioral intention
8	H8	Facilitating condition has a positive influence on behavioral intention
9	H9	Perceived behavioral control has a positive influence on behavioral intention
10	H10	Financial incentive policies have positive influence on behavioral intention
11	H11	Awareness of consequences has a positive influence on personal norm
12	H12	Awareness of consequences has a positive influence on ascription of responsibility
13	H13	Ascription of responsibility has a positive influence on personal norm
14	H14	Subjective norm has a positive influence on personal norm
15	H15	Personal norm has a positive influence on behavioral intention

2.2.1 Perceived enjoyment (PE)

This factor's definition is the level of enjoyment experienced when using technology with new features. TAM [23] suggests that the level of enjoyment experienced with a technology influences the perception of how easy it is to utilize that technology. Further study has discovered the impact of perceived enjoyment on perceived usefulness is more relevant in battery-based electric vehicles compared to conventional vehicles [24].

2.2.2 Perceived ease of use (PEU)

Perceived ease of use (PEU) relates to the extent to which something can be studied or applied. People generally prefer things that are relatively basic [21]. While perceived usefulness (PU) has a considerable impact on BI, PEU may have a minimal or insignificant effect on BI [25]. PEU has significant effects on attitude towards behavior and intention to use, as indicated by previous studies [26] [27]. Furthermore, in TAM original model, PEU has an influence on PU [21].

2.2.3 Attitude towards behaviour (ATB)

Attitude towards behaviour refers to an individual's experiences that are connected to behavioural preferences. Reasoned Action Theory states that attitudes positively impact consumer intentions [28].

2.2.4 Facilitating condition (FC)

Facilitating conditions imply the individual's opinion about the existing infrastructure or technical support necessary for effectively using a technology or system. [29]. For battery-based electric cars, necessities include battery accessibility, maintenance, home and road charging infrastructure, and after-sales service. The correlation was derived, originating from the extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) theory [29].

2.2.5 Perceived behavioral control (PBC)

Perceived behavioral control describes the feeling of ease or difficulty that an individual encounters when participating in a particular behavior. PBC stands for the convenience or difficulty experienced by consumers when buying an electric automobile. Enhancing individuals' inclination to use electric automobiles can be influenced by consumers' perceived behavioral control (PBC) [30].

2.2.6 Financial incentive policies (FIP)

Financial incentive measures, such as tax credits, subsidies, and reduced registration fees, are introduced to lower the overall cost of electric vehicles (EVs) and encourage their adoption. While EVs generally have a higher upfront purchasing price compared to traditional internal combustion engine vehicles, financial incentives help improve their affordability and perceived value. Rather than simply compensating for the price difference, these incentives can make EVs a more attractive option by enhancing their cost-effectiveness over time, considering factors such as fuel savings, lower maintenance costs, and environmental benefits. Wang, S. *et al.* [31] conducted studies demonstrating that such incentives positively influence consumers' willingness to purchase EVs, as they may perceive greater long-term value beyond the initial purchase price.

2.2.7 Awareness of consequences (AC)

Awareness of consequences is linked to evaluating individuals' awareness of the harmful consequences of ecologically harmful activity [32]. A sense of commitment to reducing the negative consequences can result from public awareness of the ecological damage and global warming [33].

2.2.8 Ascription of responsibility (AR)

Various research has shown that assigning responsibilities can have a favorable impact on personal norms [34] [35]. Individuals who are informed about the consequences of ecologically harmful actions tend to have a stronger sense of responsibility and moral obligation to engage in specific behaviors [34]. Consumer knowledge of the negative consequences of using traditional vehicles, along with a sense of duty, will drive the adoption of electric vehicles that offer environmental benefits and protect resources.

2.2.9 Subjective norm (SN)

Subjective norms are external social or group evaluations, either positive or negative, that individuals receive after adopting specific actions. Subjective norms are individual's judgments of the importance of other people and their actions in influencing their thoughts.

2.2.10 Personal norm (PN)

Zhang *et al.* [33] discovered that energy efficiency is positively correlated with personal norms. Personal norm has a favorable and crucial effect on the adoption of flex-fuel biofuel vehicles, leading to reduced environmental harm [36]. Personal norms in this study refer to society's ethical dedication to utilizing electric automobiles.

3. RESULT AND DISCUSSION

3.1 Profile of Respondent

Questionnaires were distributed based on specific selection criteria, and 318 individuals completed the survey. After screening, 14 respondents were excluded for not meeting the study’s criteria, leaving 304 valid responses. The demographic breakdown, as detailed in Table 3, indicates a relatively balanced gender distribution, with 51.6% male and 48.3% female respondents. In terms of age, the majority (54.9%) fell within the 24–54 years category, while 34.8% were under 24 years and 15.2% were above 54 years.

Most respondents had significant experience with conventional vehicles, with 43.7% reporting over eight years of usage, while 27.2% had used them for 1–3 years. Regarding education, 60.7% of participants held an undergraduate degree, followed by 15.6% with postgraduate education and 23.6% with a high school diploma. In terms of financial background, 65.1% of respondents earned above $210.82 per month, while their monthly expenses ranged from $90.35 to $361.41 per person.

Table 3. Profile of respondents.

Attributes	Category	Number of Respondent	Percentage
Gender	Male	104	46.43%
	Female	120	53.57%
Age	Less than 24 years old	78	34.82%
	24 to 54 years old	114	50.89%
	55 to 64 years old	30	13.39%
	More than 65 years old	2	0.89%
Duration of usage of a traditional automobile	1 to 3 years	61	27.23%
	3.1 to 5 years	44	19.64%
	5.1 to 8 years	21	9.38%
	More than 8 years	98	43.75%
Education	SMA	53	23.66%
	S1	136	60.71%
	S2	35	15.63%
Earnings per month	Less than $90.35	36	16.07%
	$90.35 to $150.59	19	8.48%
	$150.59 to $210.82	23	10.27%
	More than $210.82	146	65.18%
Monthly cost per individual	$21.32	13	5.80%
	$21.32 -$32.04	35	15.63%
	$32.04 -$72.28	59	26.34%
	$90.35 to $361.41	84	37.50%
	More than $361.41	33	14.73%

3.2 Data Adequacy Test

The Kaiser-Meyer-Olkin (KMO) and Bartlett tests were conducted using SPSS software to evaluate the data adequacy before conducting SEM analysis. The data sample of 38 that was utilized in the pilot test was insufficient for SPSS to conduct a data adequacy test. A sample study of 304 respondents was used to conduct data adequacy tests for the entire model. The data adequacy test results in SPSS indicate that the KMO test values for the three models are > 0.6, namely 0.942. With a Bartlett's test value below 0.05, the survey's size has been considered enough for accurately reflecting the population of society that is the subject of the research in each model.

3.3 Validity and Reliability Test

Validity and reliability assessments in Table 4 was conducted utilizing SMART-PLS.

A loading factor value below 0.7 in PLS-SEM indicates that the observation findings are invalid for presenting indicators [22]. Construct validity is also tested using average variance extracted (AVE). Strong convergent validity for the construct is indicated by an AVE score greater than 0.5 [37]. The minimum threshold for reliability in the test is a Cronbach's alpha value larger than 0.7 [22]. The Cronbach's alpha value can be segmented into various intervals to aid with qualitative interpretation [38]. Low Cronbach's alpha values may result from a limited number of indicators in a construct. Furthermore, reliability can be assessed by composite reliability.

Four indicators, SN2, SN4, SN5, and SN6, did not initially meet the validity standards due to factor loading levels below 0.7, as shown in Table 4. This finding was further reflected in the average variance extracted (AVE) value for subjective norm (SN), which fell below 0.5, indicating weak convergent validity. However, SN2's factor loading was close to 0.7, and rounding placed it within an acceptable range, allowing it to be retained for further analysis. To enhance the model's validity, a second test was conducted, during which SN4, SN5, and SN6 were eliminated due to their consistently low factor loading values. After excluding these indicators, all remaining items met the minimum factor loading threshold of 0.7 [37], ensuring a stronger alignment between the measurement model and the collected data.

Each structure achieved the 0.5 with average variance extracted (AVE) scores in the range of 0.611 to 0.844 were observed [37], indicating the adequacy of convergent validity for each construct. Therefore, it may be inferred that the measurement model is very compatible with the observed data.

Based on the reliability test results, the FIP construct obtained a Cronbach's alpha value of 0.686, which is slightly below the conventional threshold of 0.7. However, as rounding places it within an acceptable range for reliability, FIP was retained for hypothesis testing to ensure analytical consistency. Furthermore, the composite reliability values for all constructs ranged from 0.825 to 0.948, exceeding the recommended threshold of 0.7, which indicates strong internal consistency across the measurement model [39].

Table 4. Validity and reliability test.

Construct	Indicator	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Awareness of Consequences	AC1	0.862	0.894	0.927	0.759
	AC2	0.885			
	AC3	0.869			
	AC4	0.869			
Ascription of Responsibility	AR1	0.883	0.919	0.943	0.804
	AR2	0.925			
	AR3	0.887			
	AR4	0.892			
Attitude Toward Behavior	ATB1	0.851	0.819	0.893	0.735
	ATB2	0.904			
	ATB3	0.814			
Behaviour Intention	BI1	0.889	0.919	0.939	0.756
	BI2	0.916			
	BI3	0.844			
	BI4	0.902			
	BI5	0.79			
Facilitating Condition	FC1	0.928	0.906	0.941	0.842
	FC2	0.896			
	FC3	0.928			
Financial Incentive Policies	FIP1	0.845	0.724	0.843	0.642
	FIP2	0.798			
	FIP3	0.758			
Perceived Behavioral Control	PBC1	0.771	0.753	0.858	0.668
	PBC2	0.86			
	PBC3	0.819			
Perceived Enjoyment	PE1	0.876	0.866	0.918	0.788

	PE2	0.892			
	PE3	0.895			
Perceived ease of use	PEU1	0.847	0.855	0.901	0.696
	PEU2	0.796			
	PEU3	0.85			
	PEU4	0.842			
Personal Norm	PN1	0.852	0.888	0.923	0.749
	PN2	0.859			
	PN3	0.86			
	PN4	0.891			
Perceived Usefulness	PU1	0.924	0.887	0.93	0.816
	PU2	0.875			
	PU3	0.911			
Subjective Norm	SN1	0.7	0.681	0.789	0.398
	SN2	0.698			
	SN3	0.808			
	SN4	0.649			
	SN5	0.355			
	SN6	0.463			

3.4 Discriminant Validity Test

The discriminant validity assessment utilized the Heterotrait-Monotrait (HTMT) ratio of correlations, regarded as a more rigorous method than the Fornell-Larcker criterion. Results of the discriminant validity examination are displayed in Table 5. The HTMT score between perceived ease of use (PEU) and perceived usefulness (PU) was determined to be 0.940, beyond the generally advised threshold of 0.85 [63], indicating a possible issue with discriminant validity. A bootstrap confidence interval (CI) analysis was performed in Table 6 to further validate the results. The 95% confidence interval (CI) for the HTMT value excluded 1, thereby affirming discriminant validity despite the elevated correlation.

Furthermore, confirmatory factor analysis (CFA) was conducted to verify concept validity. The findings encompass standard deviations, t-values, p-values, confidence intervals, and effect sizes for a thorough study in Table 7.

Additionally, the model's predictive capability was evaluated using PLS-Predict to determine its out-of-sample predictive significance in Table 8. The findings reveal that all Q^2 values are above zero, indicating the model's predictive usefulness [62]. This indicates that the model excels in forecasting fresh observations, hence reinforcing its robustness and practical utility.

Table 5. Discriminant validity test using HTMT.

	Ascription of responsibility	Attitude towards using	Awareness of Consequences	Behavioral Intention to Use	Facilitating Condition	Financial Incentive Policies	Perceived Behavioral Control	Perceived Enjoyment	Perceived Usefulness	Perceived ease of use	Personal Norm	Subjective Norm
Ascription of responsibility												
Attitude towards using	0.578											
Awareness of Consequences	0.691	0.602										
Behavioral Intention to Use	0.510	0.855	0.493									
Facilitating Condition	0.397	0.562	0.308	0.575								
Financial Incentive Policies	0.376	0.723	0.415	0.683	0.823							
Perceived Behavioral Control	0.599	0.701	0.562	0.777	0.765	0.737						
Perceived Enjoyment	0.395	0.767	0.388	0.700	0.476	0.585	0.633					
Perceived Usefulness	0.480	0.822	0.431	0.694	0.701	0.815	0.765	0.785				
Perceived ease of use	0.387	0.723	0.365	0.655	0.766	0.802	0.725	0.790	0.940			
Personal Norm	0.658	0.746	0.673	0.646	0.437	0.557	0.647	0.529	0.635	0.567		

Table 6. HTMT confidence interval (CI).

	Original sample (O)	Sample mean (M)	5.0%	95.0%
Attitude towards using <-> Ascription of responsibility	0.578	0.581	0.447	0.703
Awareness of Consequences <-> Ascription of responsibility	0.691	0.695	0.598	0.781
Awareness of Consequences <-> Attitude towards using	0.602	0.604	0.489	0.715
Behavioral Intention to Use <-> Ascription of responsibility	0.510	0.512	0.396	0.624
Behavioral Intention to Use <-> Attitude towards using	0.855	0.854	0.787	0.915
Behavioral Intention to Use <-> Awareness of Consequences	0.493	0.496	0.385	0.602
Facilitating Condition <-> Ascription of responsibility	0.397	0.397	0.304	0.485
Facilitating Condition <-> Attitude towards using	0.562	0.564	0.479	0.646
Facilitating Condition <-> Awareness of Consequences	0.308	0.309	0.210	0.403
Facilitating Condition <-> Behavioral Intention to Use	0.575	0.576	0.484	0.664
Financial Incentive Policies <-> Ascription of responsibility	0.376	0.380	0.253	0.503
Financial Incentive Policies <-> Attitude towards using	0.723	0.724	0.618	0.825
Financial Incentive Policies <-> Awareness of Consequences	0.415	0.417	0.296	0.531
Financial Incentive Policies <-> Behavioral Intention to Use	0.683	0.683	0.594	0.764
Financial Incentive Policies <-> Facilitating Condition	0.823	0.824	0.747	0.899
Perceived Behavioral Control <-> Ascription of responsibility	0.599	0.599	0.489	0.697
Perceived Behavioral Control <-> Attitude towards using	0.701	0.704	0.583	0.819
Perceived Behavioral Control <-> Awareness of Consequences	0.562	0.562	0.456	0.661
Perceived Behavioral Control <-> Behavioral Intention to Use	0.777	0.781	0.682	0.867
Perceived Behavioral Control <-> Facilitating Condition	0.765	0.766	0.686	0.840
Perceived Behavioral Control <-> Financial Incentive Policies	0.737	0.741	0.633	0.844
Perceived Enjoyment <-> Ascription of responsibility	0.395	0.397	0.285	0.505
Perceived Enjoyment <-> Attitude towards using	0.767	0.768	0.678	0.851
Perceived Enjoyment <-> Awareness of Consequences	0.388	0.391	0.277	0.503
Perceived Enjoyment <-> Behavioral Intention to Use	0.700	0.701	0.605	0.788
Perceived Enjoyment <-> Facilitating Condition	0.476	0.477	0.392	0.562
Perceived Enjoyment <-> Financial Incentive Policies	0.585	0.587	0.469	0.699
Perceived Enjoyment <-> Perceived Behavioral Control	0.633	0.635	0.539	0.726
Perceived Usefulness <-> Ascription of responsibility	0.480	0.482	0.382	0.575
Perceived Usefulness <-> Attitude towards using	0.822	0.822	0.766	0.874
Perceived Usefulness <-> Awareness of Consequences	0.431	0.433	0.332	0.530
Perceived Usefulness <-> Behavioral Intention to Use	0.694	0.693	0.620	0.760
Perceived Usefulness <-> Facilitating Condition	0.701	0.703	0.626	0.773
Perceived Usefulness <-> Financial Incentive Policies	0.815	0.816	0.729	0.898
Perceived Usefulness <-> Perceived Behavioral Control	0.765	0.767	0.678	0.850
Perceived Usefulness <-> Perceived Enjoyment	0.785	0.786	0.723	0.843
Perceived ease of use <-> Ascription of responsibility	0.387	0.389	0.294	0.478
Perceived ease of use <-> Attitude towards using	0.723	0.723	0.652	0.790
Perceived ease of use <-> Awareness of Consequences	0.365	0.366	0.263	0.463
Perceived ease of use <-> Behavioral Intention to Use	0.655	0.655	0.584	0.720

Perceived ease of use <-> Facilitating Condition	0.766	0.767	0.701	0.827
Perceived ease of use <-> Financial Incentive Policies	0.802	0.804	0.716	0.888
Perceived ease of use <-> Perceived Behavioral Control	0.725	0.726	0.641	0.806
Perceived ease of use <-> Perceived Enjoyment	0.790	0.790	0.729	0.846
Perceived ease of use <-> Perceived Usefulness	0.940	0.941	0.906	0.974
Personal Norm <-> Ascription of responsibility	0.658	0.658	0.534	0.775
Personal Norm <-> Attitude towards using	0.746	0.747	0.641	0.838
Personal Norm <-> Awareness of Consequences	0.673	0.674	0.564	0.775
Personal Norm <-> Behavioral Intention to Use	0.646	0.646	0.549	0.736
Personal Norm <-> Facilitating Condition	0.437	0.437	0.347	0.519
Personal Norm <-> Financial Incentive Policies	0.557	0.559	0.443	0.667
Personal Norm <-> Perceived Behavioral Control	0.647	0.647	0.557	0.731
Personal Norm <-> Perceived Enjoyment	0.529	0.533	0.427	0.636
Personal Norm <-> Perceived Usefulness	0.635	0.636	0.554	0.714
Personal Norm <-> Perceived ease of use	0.567	0.567	0.487	0.642
Subjective Norm <-> Ascription of responsibility	0.570	0.574	0.466	0.676
Subjective Norm <-> Attitude towards using	0.477	0.482	0.362	0.600
Subjective Norm <-> Awareness of Consequences	0.463	0.465	0.358	0.569
Subjective Norm <-> Behavioral Intention to Use	0.407	0.409	0.292	0.522
Subjective Norm <-> Facilitating Condition	0.423	0.424	0.316	0.525
Subjective Norm <-> Financial Incentive Policies	0.475	0.480	0.351	0.606
Subjective Norm <-> Perceived Behavioral Control	0.450	0.452	0.344	0.558
Subjective Norm <-> Perceived Enjoyment	0.347	0.350	0.227	0.470
Subjective Norm <-> Perceived Usefulness	0.488	0.491	0.382	0.594
Subjective Norm <-> Perceived ease of use	0.474	0.476	0.362	0.584
Subjective Norm <-> Personal Norm	0.586	0.592	0.483	0.700

Table 7. Confirmatory factor analysis.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Confidence Interval 5.0%	Confidence Interval 95.0%
Ascription of responsibility -> Personal Norm	0.273	0.272	0.092	2.971	0.001	0.130	0.431
Attitude towards using -> Behavioral Intention to Use	0.498	0.487	0.079	6.327	0.000	0.355	0.609
Awareness of Consequences -> Ascription of responsibility	0.635	0.639	0.050	12.627	0.000	0.552	0.716
Awareness of Consequences -> Personal Norm	0.346	0.343	0.073	4.736	0.000	0.221	0.461
Facilitating Condition -> Behavioral Intention to Use	0.025	0.025	0.072	0.340	0.367	-0.091	0.150
Financial Incentive Policies -> Behavioral Intention to Use	0.079	0.079	0.053	1.502	0.067	-0.005	0.168
Perceived Behavioral Control -> Behavioral Intention to Use	0.285	0.295	0.071	4.002	0.000	0.179	0.413
Perceived Enjoyment -> Attitude towards using	0.320	0.325	0.077	4.164	0.000	0.198	0.454
Perceived Usefulness -> Attitude towards using	0.495	0.490	0.085	5.807	0.000	0.347	0.629
Perceived Usefulness -> Behavioral Intention to Use	-0.018	-0.025	0.069	0.253	0.400	-0.139	0.089
Perceived ease of use -> Attitude towards using	-0.005	-0.004	0.071	0.073	0.471	-0.119	0.114
Perceived ease of use -> Perceived Usefulness	0.823	0.824	0.020	41.845	0.000	0.791	0.855
Personal Norm -> Behavioral Intention to Use	0.072	0.079	0.067	1.073	0.142	-0.027	0.193
Subjective Norm -> Personal Norm	0.219	0.225	0.065	3.395	0.000	0.120	0.333

Table 8. PLS-predict result.

	Q^2predict
AR1	0.276
AR2	0.344
AR3	0.334
AR4	0.342
ATB1	0.283
ATB2	0.404
ATB3	0.359
BI1	0.405
BI2	0.403
BI3	0.453
PU1	0.619
PU2	0.493
PU3	0.531
PN1	0.292
PN2	0.289
PN3	0.333
PN4	0.329

3.5 Model Development

Structural model evaluation can be performed by utilizing multiple squared correlation coefficients (R2) that indicate the level that the model describes the variability in constructs. Hair *et al.* [37] suggests that values greater than 0.25 are appropriate. In the overall model, the corrected R2 values for AR, ATB, BI, PU, and PN range from 0.402 to 0.704. This suggests that a major amount of the model's variance is compensated for represented by those factors.

The hypothesis was assessed by examining the path coefficients, t-values, and p-values using the bootstrapping technique with 5000 resamples. If the value of the p-value is below or equal to 0.05, it indicates a statistically significant connection between the constructs [22]. The route coefficient in Table 4 reveals the direction of the association between the two constructs, whereas a t-value greater than 1.96 in Table 4 is considered appropriate.

According to Table 9, PU (β = 0.495; p = 0) has a big favorable effect on ATB, supported by a t value of 5.865, leading to the acceptance of H1. PU did not have a significant effect on BI, resulting in the refusal of hypothesis H2 (β = -0.007; p = 0.918). PEU has a positive and significant effect on PU, supported by a t value of 14.856, leading to the acceptance of H3. However, PEU does not significantly affect ATB, resulting in the rejection of H4. The t-value of 4.429 confirms the significant and positive impact of PE on PU, which leads to the acceptance of H5. PE has a favorable and substantial effect on ATB, as indicated by the t-value of 4.006, leading to the acceptance of hypothesis H6. The effect of ATB on BI is positive and relevant, supported by a t-value of 6.984, leading to the acceptance of hypothesis H7 (β = 0.511; p = 0). FC has a non-relevant effect on BI, leading to the rejection of hypothesis H8. Additionally, the positive and significant influence of PBC (β = 0.302; p = 0) on BI is confirmed by the t-value of 3.992, leading to the acceptance of H9. Nevertheless, FIP had no significant impact on BI, leading to the rejection of hypothesis H10 (β = 0.093; p = 0.078). Additionally, the variable AC has a positive and substantial effect on PN, supported by a t value of 4.586, leading to the acceptance of hypothesis H11. AC has a strong positive effect on AR, supported by a t value of 12.235, leading to the acceptance of hypothesis H12. The relationships between AR (β = 0.274; p = 0.003) on PN, SN (β = 0.218; p = 0.001) on PN, and PN (β = 0.035; p = 0.579) on BI do not have a significant influence, leading to the rejection of H13, H14, and H15.

The data obtained from Table 6 will be utilized to construct a model depicted in Figure 1, which will subsequently present the results of the hypothesis test.

Table 9. Hypothesis test.

Hypothesis	Path	Hypothesis Test			Result
		Path Coefficient	p value	t-statistic	
1	PU -> ATB	0.495	0	5.865	Accepted
2	PU -> BI	-0.007	0.918	0.103	Rejected
3	PEU -> PU	0.663	0	14.856	Accepted
4	PEU -> ATB	-0.003	0.962	0.047	Rejected
5	PE -> PU	0.232	0	4.429	Accepted
6	PE -> ATB	0.317	0	4.006	Accepted
7	ATB -> BI	0.511	0	6.984	Accepted
8	FC -> BI	0.013	0.851	0.187	Rejected
9	PBC -> BI	0.302	0	3.992	Accepted
10	FIP -> BI	0.093	0.078	1.765	Rejected
11	AC -> PN	0.346	0	4.586	Accepted
12	AC -> AR	0.635	0	12.235	Accepted
13	AR -> PN	0.274	0.003	2.943	Rejected
14	SN -> PN	0.218	0.001	3.501	Rejected
15	PN -> BI	0.035	0.579	0.555	Rejected

3.6 Validation of the Model of Community Intentions in using Battery-Based Electric Cars in Indonesia

This study integrates behavioral theories to explore the factors influencing the adoption of battery-based electric vehicles (BEVs) in Indonesia. While some findings align with global research, others highlight unique adoption patterns shaped by the local context. The discussion below presents the key results, their real-world implications, and actionable insights for policymakers and industry stakeholders.

As presented in Figure 2, the study confirms that perceived usefulness significantly shapes consumer attitudes toward BEVs (H1 Accepted), reinforcing the Technology Acceptance Model (TAM) [21]. This means that Indonesian consumers recognize BEVs as beneficial due to their long-term cost savings, energy efficiency, and environmental impact, mirroring findings from China [40] and Brazil [6]. However, in reality, recognizing benefits does not always translate into widespread adoption. Many consumers hesitate due to affordability concerns and infrastructural limitations. To bridge this gap, campaigns should emphasize practical benefits beyond environmental concerns, such as reduced fuel dependency and long-term savings. Research by Rezvani *et al.* [51] indicates that pragmatic messaging focused on financial savings and reliability increases consumer willingness to adopt BEVs. Additionally, studies in Germany suggest that highlighting the total cost of ownership (TCO) can appeal to rational decision-makers and shift attitudes toward more favorable adoption [52].

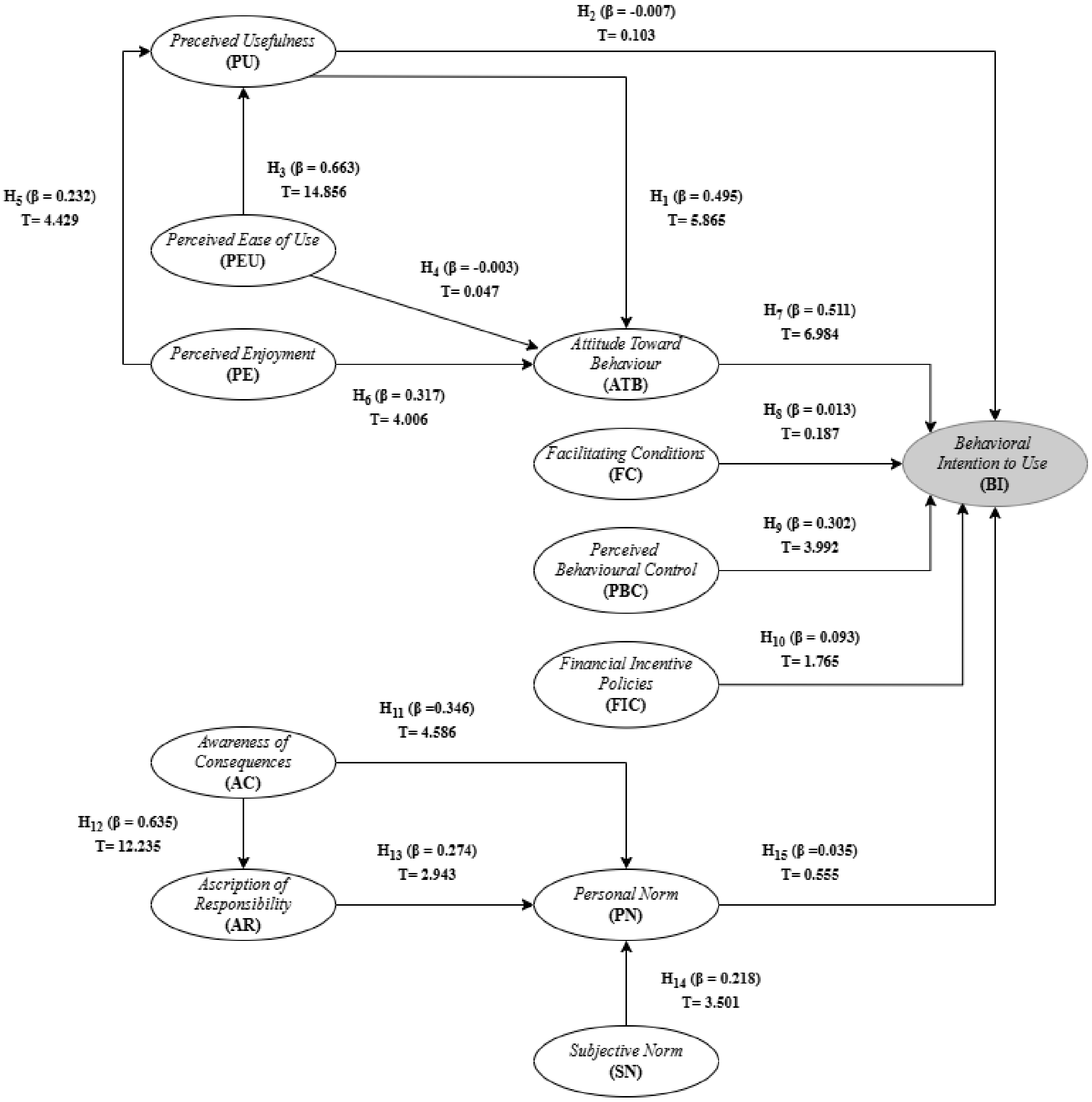

Fig. 1. Hypothesis test result.

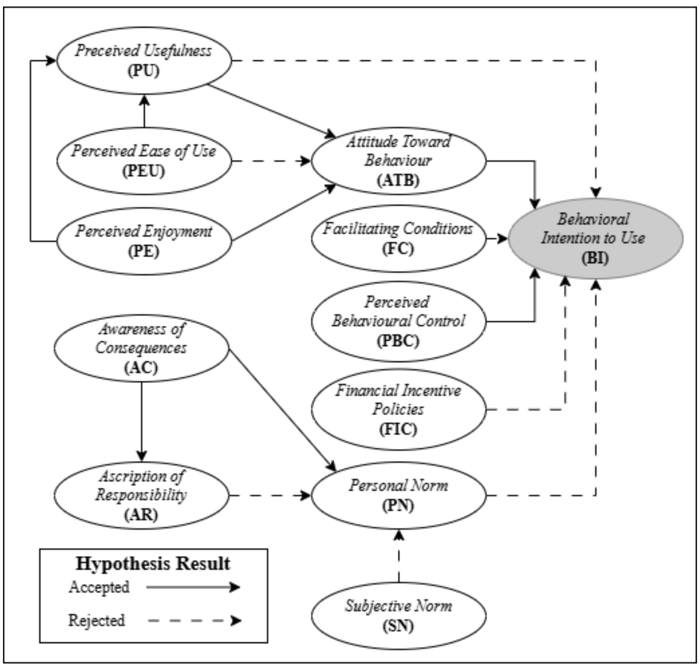

Fig. 2. Summary of hypothesis test result.

Interestingly, while perceived usefulness strongly influences attitude, it does not directly impact behavioral intention to adopt BEVs in Indonesia (H2 rejected). This finding contradicts research in China [40] but aligns with studies that indicate affordability, infrastructure, and government policies moderate the link between perceived usefulness and actual adoption [41]. In real-world terms, the evidence suggests that Indonesian consumers are aware of the benefits but remain hesitant due to high upfront costs and the limited variety of models available. Research from Zhang *et al.* [53] found that installment plans and leasing models significantly increased BEV adoption among price-sensitive consumers, while Norway's success with local BEV production incentives [49] demonstrates the effectiveness of policy-driven cost reduction strategies.

Another key finding is that ease of use positively influences perceived usefulness (H3 accepted), supporting the notion that when consumers find BEVs easy to operate, they are more likely to perceive them as beneficial, as posited by TAM [23]. Similar findings in Europe, China, and North America suggest that simplified interfaces and intuitive designs enhance BEV adoption [42]. However, despite its impact on perceived usefulness, ease of use does not significantly shape consumer attitudes toward BEVs (H4 rejected). This result suggests that Indonesian consumers prioritize financial and infrastructural concerns over usability, a pattern also observed in Malaysia and Vietnam [12]. In practical terms, this means that focusing solely on improving the user interface or making BEVs easier to operate is insufficient. Instead, policymakers and industry stakeholders should prioritize affordability and charging infrastructure development, as seen in Thailand, where government efforts to subsidize charging stations proved more effective than improving vehicle interfaces [58].

Beyond usability and cost, emotional factors also influence adoption. The study finds that perceived enjoyment significantly enhances attitudes toward BEVs (H5 and H6 accepted), supporting previous research that positive emotional experiences drive technology acceptance [44]. This means that consumers who enjoy driving BEVs—whether due to smooth acceleration, silent operation, or high-tech features—are more likely to develop favorable attitudes toward them. A study in Sweden showed that the thrill of driving a BEV increased the likelihood of adoption [36], which has real-world implications for marketing strategies. Hardman *et al.* [54] found that test drive experiences significantly increase BEV purchase intent, while gamified incentives, such as eco-driving rewards, have successfully engaged consumers in the Netherlands [50]. This suggests that campaigns should go beyond traditional advertisements and create interactive experiences that allow consumers to feel the excitement of driving a BEV firsthand.

One of the study's most surprising findings is that financial incentives do not significantly impact BEV adoption in Indonesia (H10 rejected). While research in the U.S. and China suggests that subsidies are a strong driver of adoption [18][16], similar to Malaysia, financial incentives alone are not enough when range anxiety and infrastructure limitations persist [47]. This means that simply offering tax breaks or subsidies will not be sufficient to encourage widespread BEV adoption in Indonesia. Instead, structural incentives, such as battery leasing programs, can improve affordability while also addressing range anxiety concerns. Research by Sierzchula *et al.* [19] found that flexible financing models significantly increased adoption rates in various markets. Additionally, studies in Singapore highlight the importance of fleet-targeted incentives, where BEV adoption among commercial fleets, taxis, and ride-hailing services has outpaced private ownership due to tailored government policies [57].

Environmental awareness plays a crucial role in shaping pro-environmental behavior (H11 and H12 Accepted), consistent with the Norm Activation Model (NAM) [32]. However, subjective norms and moral commitment do not significantly influence BEV adoption in Indonesia (H13-H15 Rejected), likely due to external constraints such as cost and infrastructure [11]. This means that while Indonesians recognize the environmental benefits of BEVs, many still hesitate to switch due to practical limitations. Research in China suggests that shifting from moral appeals to financial benefits—such as emphasizing fuel independence and long-term savings—can be a more effective strategy [55]. Additionally, public recognition programs, such as priority lanes and green license plates, have successfully encouraged adoption in Norway by creating a sense of exclusivity and status for BEV owners [49].

The findings highlight that Indonesia must go beyond financial incentives to drive BEV adoption. Real-world examples indicate that a combination of cost reduction strategies, infrastructure development, and behavioral incentives is necessary for a successful transition. Norway's approach, which combined subsidies with widespread charging station development and production incentives, significantly accelerated adoption [49]. Similarly, expanding home and workplace charging infrastructure has mitigated range anxiety in other markets [53], which could be a key strategy for Indonesia. Another promising direction is the electrification of commercial fleets. Countries like Singapore have successfully increased BEV adoption among taxis and ride-hailing services by providing targeted incentives for fleet operators [57], a model that could be replicated in Indonesia.

To strengthen social norms, behavioral incentives such as priority parking, lower tolls, and dedicated BEV lanes could be effective. Research in the Netherlands has shown that these policies create a positive perception of BEVs and encourage wider adoption [50]. Additionally, comprehensive public awareness campaigns should shift their messaging focus from environmental concerns to financial and performance benefits, as studies suggest that consumers are more likely to adopt BEVs when they see clear economic advantages [55]. Test drive experiences and interactive marketing strategies can further familiarize consumers with BEVs, reducing hesitation and uncertainty [54].

Overall, by integrating economic, infrastructural, and behavioral factors, Indonesia can accelerate BEV adoption and transition toward a more sustainable transportation future. The findings suggest that while environmental awareness and usability contribute to positive attitudes, affordability and infrastructure remain the most critical factors in translating intention into action. Addressing these concerns through well-designed policies and consumer engagement strategies will be essential for ensuring Indonesia's successful transition to electric mobility.

4. CONCLUSION AND FUTURE RESEARCH

This study identifies attitudes toward behavior and perceived behavioral control as the primary drivers of BEV adoption in Indonesia, whereas financial incentives do not show a significant direct effect on behavioral intention. The results from hypothesis testing support the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), Norm Activation Model (NAM), and Theory of Planned Behavior (TPB) as an integrated framework to explain consumer behavior. Specifically, perceived usefulness and perceived enjoyment positively influence attitudes toward behavior, which in turn significantly impacts behavioral intention. Similarly, perceived ease of use influences perceived usefulness but does not directly affect attitudes toward behavior. Meanwhile, perceived behavioral control plays a significant role in shaping BEV adoption intentions, reinforcing the importance of consumer confidence and control in decision-making. However, facilitating conditions and financial incentive policies do not significantly impact behavioral intention, suggesting that external factors such as infrastructure readiness and regulatory support may play a more substantial role in consumer decision-making.

Despite these contributions, some limitations should be noted. The study relies on self-reported survey data, which may introduce single-source bias, despite mitigation measures such as pilot testing, common method bias checks, and PLS-SEM validation. Future research should incorporate multi-source data, experimental approaches, or real-world behavioral tracking to enhance robustness. Additionally, the study focuses on Indonesian consumers, limiting generalizability. Cross-country comparative studies could help assess the applicability of this framework in other contexts. Furthermore, longitudinal studies could track evolving consumer perceptions and adoption trends over time, providing deeper insights into behavioral shifts.

Addressing these limitations will strengthen the understanding of BEV adoption and improve policy and business strategies for accelerating sustainable transportation. The findings highlight the need for non-monetary interventions, such as infrastructure improvements, consumer education, and policy incentives beyond direct financial support, to enhance BEV adoption in Indonesia. Policymakers should prioritize building charging infrastructure, increasing public awareness, and ensuring regulatory support to foster a more conducive environment for BEV adoption. Additionally, targeted incentives for manufacturers and dealers to improve vehicle accessibility and affordability may be more effective than direct consumer subsidies alone. These strategic interventions can drive greater consumer confidence and accelerate the transition to sustainable mobility in Indonesia and other emerging economies.

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