EXPLORING ELECTRIC VEHICLE PURCHASE INTENTION IN JAKARTA: WHAT ATTRACTS CONSUMERS?

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Abstract

The transition to electric vehicles (EVs) is a global strategy aimed at reducing greenhouse gas emissions and mitigating the adverse effects of climate change, particularly in the transportation sector. This study seeks to analyze the factors influencing the purchase intention of EVs in Jakarta, a region with a low adoption rate despite various governmental incentives. Employing a combined framework of the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM), the research examines the influence of attitudes toward EVs, perceived usefulness, perceived risk, environmental concern, and subjective norms on purchase intention. Additionally, moderating variables such as monetary incentives, non-monetary incentives, and personal norms are evaluated to understand their role in strengthening or weakening the relationships between independent and dependent variables. Data were collected through a survey of 300 respondents in Jakarta and analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings aim to provide empirical insights to enrich the literature on environmentally friendly technology adoption and serve as a reference for policymakers and automotive industry stakeholders in formulating effective strategies to accelerate EVadoption in Indonesia.

Keywords: Electric Vehicles, Theory of Planned Behavior, Technology Acceptance Model, Purchase Intention, Perceived Usefulness, Monetary Incentives

INTRODUCTION

In the last decade, global efforts to reduce greenhouse gas emissions have intensified, driven by increasing awareness of the negative impacts of climate change on the environment and human health. One sector that significantly contributes to emissions is transportation, where fossil fuel-powered motor vehicles play a major role. According to the International Energy Agency (IEA), the transportation sector accounts for around 24% of the total global carbon emissions, with the majority originating from fossil fuel vehicles (International Energy Agency, 2023). In Indonesia, transportation contributes more than 36% of total national energy consumption (Ministry of Energy and Mineral Resources, 2023), with most vehicles in Jakarta still using fossil fuels.

To address this issue, the Indonesian government has adopted various policies to encourage the transition to more environmentally friendly vehicles, such as electric vehicles (EVs). In 2019, the government issued Presidential Regulation No. 55 concerning the Acceleration of the Battery Electric Vehicle Program, which is expected to promote EV usage in Indonesia (Ministry of Energy and Mineral Resources, 2020). In addition, at the beginning of 2023, the Ministry of Transportation also announced an ambitious target that Indonesia will produce more than 1 million electric vehicles by 2030 (Kompas, 2023). This policy aligns with the government's commitment to reducing carbon emissions by 29% in 2030, as stated in the Nationally Determined Contribution (NDC) submitted under the Paris Agreement.

Jakarta, as the capital and economic center of Indonesia, faces major challenges in terms of traffic congestion and air pollution. According to data from the Ministry of Transportation (2023), the number of motor vehicles in Jakarta continues to rise, reaching more than 20 million units in 2023. This condition significantly contributes to high carbon emissions in the area. Based on the World Air Quality Report (2022), Jakarta is listed among the cities with the worst air quality in Southeast Asia, where land transportation is one of the main contributors to pollution. To tackle this issue, the Indonesian government has started encouraging the adoption of electric vehicles (EVs). Strategic policies such as a 1% tax incentive and exemption from the odd-even traffic regulation for EVs in Jakarta are initial steps to accelerate the transition to more environmentally friendly transportation (Minister of Finance Regulation, 2022). Moreover, supporting infrastructure such as electric charging stations continues to be developed. Based on data from PLN (2023), there are more than 150 public charging stations available in Jakarta, indicating the government's commitment to supporting the electric vehicle ecosystem.

However, despite various efforts, the adoption rate of electric vehicles in Indonesia, especially in Jakarta, remains relatively low compared to other Southeast Asian countries. For comparison, the EV market share in Jakarta reached only 2% in 2023, far below Singapore's 12% in the same year (ASEAN Automotive Federation, 2023).

The Theory of Planned Behavior (TPB) is often used to analyze consumer intentions and behaviors toward electric vehicle purchases. In Jakarta's context, factors such as consumer attitudes toward EVs, subjective norms, and perceived behavioral control influence the decision to purchase EVs (Ajzen, 1991). However, there are challenges in its implementation. For example, even though tax incentives and odd-even exemptions are available, a survey conducted by the Agency for the Assessment and Application of

Technology (BPPT, 2023) shows that the lack of charging infrastructure and high EV prices are major obstacles.

In addition to TPB, the Technology Acceptance Model (TAM) is also relevant in understanding the adoption of new technologies such as electric vehicles. TAM, developed by Davis (1989), states that technology acceptance is influenced by two main factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which users believe that using a particular technology can improve efficiency or benefits, while perceived ease of use measures how easy the technology is to use. In the context of electric vehicles, perceived usefulness includes benefits such as reducing air pollution and fuel efficiency, while perceived ease of use may include ease of charging and vehicle operation. A study by Vafaei-Zadeh et al. (2022) shows that perceived usefulness significantly influences the intention to purchase electric vehicles, especially in developing countries. Thus, combining TPB and TAM can provide a more comprehensive analytical framework to understand the factors that influence EV purchase intentions in Jakarta.

Previous research in developing countries such as Pakistan shows that price, infrastructure availability, and social norms greatly influence consumer decisions to purchase EVs (Shakeel et al., 2022). On the other hand, research in Hong Kong shows that perceptions of EV driving range and availability of charging stations have a significant impact on purchase intentions (Sun et al., 2022). However, the results of these studies cannot be fully applied to Jakarta due to differences in cultural, social, and economic contexts.

In the Jakarta context, cultural differences and consumer preferences can be important factors that have not been widely discussed in previous literature (Liobikienė et al., 2016; Uddin Chowdhury et al., 2021). In addition, although the government has provided incentives and built infrastructure (PLN, 2023; Minister of Finance Regulation, 2022), no research has comprehensively analyzed the impact of these policies on EV purchase intentions in Indonesia (BPPT, 2023).

This study analyzes the influence of attitude, subjective norms, and perceived behavioral control in the Theory of Planned Behavior (TPB) on the intention to purchase electric vehicles (EVs) in Jakarta. Additionally, it examines the impact of government policies such as tax incentives and odd-even exemptions, as well as the role of charging infrastructure on consumer perceptions and purchase intentions. This research is expected to contribute academically, provide input for the government and the automotive industry, and raise public awareness on the importance of transitioning to electric vehicles.

REVIEW OF LITERATURE

Consumer Behavior

According to Kotler and Keller (2016), consumer behavior is influenced by various factors, including cultural, social, personal, and psychological factors. In the context of electric vehicles, understanding consumer behavior is key to promoting the adoption of this technology, especially in Jakarta.

Purchase Intention

According to Ajzen (1991), purchase intention is influenced by attitude, social norms, and perceived behavioral control. In the context of electric vehicles, purchase intention indicates consumers' desire to shift from fossil-fuel vehicles to environmentally friendly vehicles.

Attitude toward Electric Vehicles

Fishbein and Ajzen (1975) state that attitude strongly influences behavioral intention. In the context of electric vehicles, a positive attitude toward EVs is often associated with the belief that electric vehicles are more environmentally friendly and energy-efficient.

Perceived Usefulness

According to Davis (1989), perceived usefulness is a major factor influencing the adoption of new technology in the Technology Acceptance Model (TAM). Consumers who perceive real benefits from electric vehicles are more likely to have the intention to purchase.

Perceived Risk

Perceived risk is the consumer's perception of potential risks associated with using electric vehicles, such as concerns about driving range, availability of charging stations, or repair costs. Bauer (1960) explains that consumers often avoid risks in their decision-making, especially when it involves new products or technologies.

Environmental Concern

Environmental concern is the extent to which consumers care about the negative impacts caused by conventional vehicles on the environment. Environmentally conscious consumers are more likely to choose eco-friendly products, including electric vehicles (Roberts & Bacon, 1997).

Subjective Norms

Subjective norms refer to the social pressure an individual feels to perform or not perform a certain behavior (Ajzen, 1991). In the context of electric vehicle purchases, social norms can influence someone to buy if they feel encouraged by friends, family, or the community.

Monetary Incentives

Monetary incentives are financial benefits such as subsidies or tax cuts provided by the government or other parties to encourage electric vehicle adoption. These incentives have been proven to increase consumer purchase intention in various countries.

Non-Monetary Incentives

Non-monetary incentives include non-financial benefits such as access to fast lanes, free parking, or other incentives not directly related to cash but provide advantages for electric vehicle owners.

Personal Norms

Schwartz (1977) states that personal norms significantly influence decisions to perform morally good actions, including the decision to buy environmentally friendly products. These personal norms often reinforce the influence of social norms in purchasing electric vehicles.

RESEARCH METHOD

This study refers to a previous study by Shakeel (2022) in Pakistan that used the Theory of Planned Behavior (TPB) to analyze the influence of attitude, subjective norms, and behavioral control on the intention to purchase electric vehicles. The study also considered monetary and non-monetary incentives as moderating factors, using the Structural Equation Modeling (SEM) method with data from 511 respondents (Shakeel, 2022). Several international studies have examined factors influencing EV purchase intentions using different approaches. In Turkey, Yeğin and Ikram added Environmental Concern and Green

Trust variables to the TPB framework and found that positive attitude, environmental concern, and trust in EVs had significant effects, while subjective norms did not. In India, Upadhyay and Kamble used the SOR model and found that pro-environmental attitudes played a major role in EV purchase intention. Meanwhile, Sun et al. in Hong Kong added variables such as range anxiety and charging infrastructure to TPB and concluded that range anxiety and lack of infrastructure were major barriers to EV adoption.

This study aims to adapt and expand the Theory of Planned Behavior (TPB) model in the context of the EV market in Jakarta through a quantitative survey approach. The variables studied include attitudes toward EVs, perceived usefulness, perceived risk, environmental concern, and subjective norms, as well as moderating variables such as financial and non-financial incentives, and personal norms to observe their influence on electric vehicle purchase intention.

RESULTS AND DISCUSSION

Structural Equation Modeling (SEM) Model

Data Processing and Analysis Procedures

The main test stage involves constructing the PLS-SEM model with data from 570 respondents, using indicators to measure latent variables.

a. **PI1, PI2, PI3** are question indicators for measuring the variable *Purchase Intention (PI)*.
   - PI1: "I plan to buy an electric vehicle in the near future."
   - PI2: "I have a strong desire to buy an electric vehicle."
   - PI3: "I will recommend electric vehicles to others."

b. **AT1, AT2, AT3** are question indicators for measuring the variable *Attitude Toward EVs (AT)*.
   - AT1: "I think electric vehicles are the best solution to reduce carbon emissions."
   - AT2: "Electric vehicles offer significant environmental benefits."
   - AT3: "I believe electric vehicles are a responsible choice."

c. **PU1, PU2, PU3** are question indicators for measuring the variable *Perceived Usefulness (PU)*.
   - PU1: "I believe electric vehicles help reduce fuel expenses."
   - PU2: "Electric vehicles offer higher efficiency than conventional vehicles."
   - PU3: "Electric vehicles provide long-term benefits."

d. **PR1, PR2, PR3** are question indicators for measuring the variable *Perceived Risk (PR)*.
   - PR1: "I worry about the driving range of electric vehicles."
   - PR2: "I am concerned about the availability of electric vehicle charging stations."
   - PR3: "Electric vehicles require high maintenance costs."

e. **EC1, EC2, EC3** are question indicators for measuring the variable *Environmental Concern (EC)*.
   - EC1: "I feel responsible for supporting environmental sustainability."
   - EC2: "I tend to choose environmentally friendly products."
   - EC3: "I believe electric vehicles help reduce negative environmental impacts."

f. **SN1, SN2, SN3** are question indicators for measuring the variable *Subjective Norms (SN)*.
   - SN1: "People close to me support the use of electric vehicles."

- SN2: "My social environment encourages me to buy electric vehicles."
- SN3: "I feel a social responsibility to purchase an electric vehicle."

g. **MI1, MI2, MI3** are question indicators for measuring the variable *Monetary Incentives (MI)*.
- MI1: "I am interested in buying electric vehicles due to tax discounts."
- MI2: "Government subsidies encourage me to buy electric vehicles."
- MI3: "Lower EV prices make me consider purchasing one."

h. **NMI1, NMI2, NMI3** are question indicators for measuring the variable *Non-Monetary Incentives (NMI)*.
- NMI1: "Odd-even traffic rule exemption encourages me to buy electric vehicles."
- NMI2: "Electric vehicles have benefits such as special parking spots."
- NMI3: "Priority access on roads makes me consider electric vehicles."

i. **PN1, PN2, PN3** are question indicators for measuring the variable *Personal Norms (PN)*.
- PN1: "I feel obligated to choose environmentally friendly vehicles."
- PN2: "Buying electric vehicles reflects my personal values."
- PN3: "I believe buying an electric vehicle is a morally responsible act."

Indicators are used to measure latent constructs and analyze relationships among variables using PLS-SEM with a 5-point Likert scale. This analysis aims to provide an overview of the factors influencing the intention to purchase electric vehicles in Jakarta and the surrounding areas.

Measurement Model Analysis

Validity Test of the Measurement Model

Validity testing is done by checking convergent validity and discriminant validity. Convergent validity refers to the extent to which an indicator positively correlates with other indicators within the same construct.

Table 1.
Outer Loading and AVE Test Results

Construct	Item	Outer Loadings	AVE
Purchase Intention (PI)	PI1	0,815	0,661
	PI2	0,827	
	PI3	0,798	
Attitude toward EVs (AT)	AT1	0,819	0,657
	AT2	0,802	
	AT3	0,811	
Perceived Usefulness (PU)	PU1	0,784	0,651
	PU2	0,787	
	PU3	0,847	
Perceived Risk (PR)	PR1	0,916	0,84
	PR2	0,906	

	PR3	0,926	
Environmental Concern (EC)	EC1	0,816	
	EC2	0,76	0,648
	EC3	0,837	
Subjective Norms (SN)	SN1	0,849	
	SN2	0,849	0,713
	SN3	0,835	
Monetary Incentives (MI)	MI1	0,86	
	MI2	0,833	0,68
	MI3	0,778	
Non-Monetary Incentives (NMI)	NMI1	0,755	
	NMI2	0,84	0,659
	NMI3	0,837	
Personal Norms (PN)	PN1	0,795	
	PN2	0,836	0,674
	PN3	0,831	

Note: Outer loading > 0.708 & AVE > 0.5
Source: Processed by Researcher (2025)

Based on Table 1 above, the output values show that the outer loading is > 0.708 and the AVE is > 0.5, indicating that the indicators within the same construct are positively correlated.

Next, discriminant validity analysis is conducted to demonstrate that a construct is truly distinct from other constructs based on empirical standards. Discriminant validity is evaluated using the cross-loading approach, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT).

Table 2.
Cross-Loading Test Results

Construct	Code	PI	AT	EC	MI	NMI	PN	PR	PU	SN
Purchase Intention (PI)	PI1	0,815	0,345	0,297	0,457	0,367	0,516	0,082	0,353	0,518
	PI2	0,827	0,45	0,41	0,484	0,468	0,553	0,008	0,436	0,488
	PI3	0,798	0,443	0,4	0,437	0,416	0,528	0,106	0,454	0,495
Attitude toward EVs (AT)	AT1	0,434	0,819	0,433	0,272	0,35	0,371	0,032	0,48	0,387
	AT2	0,408	0,802	0,485	0,31	0,346	0,445	-0,016	0,484	0,352
	AT3	0,396	0,811	0,397	0,324	0,393	0,443	0,015	0,423	0,424
	EC1	0,376	0,433	0,816	0,305	0,34	0,411	0,003	0,419	0,345
	EC2	0,324	0,39	0,76	0,283	0,36	0,395	0,028	0,378	0,314

Perceived Usefulness (PU)	EC3	0,396	0,478	0,837	0,343	0,376	0,464	-0,046	0,51	0,392
Perceived Risk (PR)	MI1	0,504	0,323	0,304	0,86	0,451	0,5	-0,01	0,356	0,488
	MI2	0,447	0,332	0,315	0,833	0,429	0,507	-0,014	0,359	0,466
	MI3	0,444	0,263	0,341	0,778	0,386	0,493	0,035	0,377	0,494
Environmental Concern (EC)	NMI1	0,342	0,342	0,321	0,425	0,755	0,409	-0,083	0,343	0,388
	NMI2	0,43	0,361	0,338	0,42	0,84	0,463	0,013	0,331	0,448
	NMI3	0,467	0,385	0,415	0,411	0,837	0,508	-0,005	0,375	0,469
Subjective Norms (SN)	PN1	0,511	0,405	0,418	0,455	0,457	0,795	0,016	0,368	0,521
	PN2	0,572	0,432	0,449	0,551	0,445	0,836	0,031	0,471	0,554
	PN3	0,528	0,433	0,429	0,482	0,505	0,831	0,049	0,39	0,512
Monetary Incentives (MI)	PR1	0,069	0,021	-0,022	0,023	-0,022	0,023	0,916	-0,018	0,079
	PR2	0,059	0,01	0,015	-0,048	-0,03	0,009	0,906	-0,019	0,01
	PR3	0,085	0,007	-0,013	0,024	-0,018	0,065	0,926	0,009	0,068
Non-Monetary Incentives (NMI)	PU1	0,342	0,462	0,478	0,321	0,348	0,397	0,011	0,784	0,384
	PU2	0,382	0,439	0,442	0,347	0,323	0,37	-0,051	0,787	0,356
	PU3	0,49	0,483	0,416	0,39	0,369	0,441	0,015	0,847	0,445
Personal Norms (PN)	SN1	0,501	0,399	0,376	0,51	0,464	0,538	0,033	0,458	0,849
	SN2	0,505	0,393	0,352	0,466	0,471	0,491	0,017	0,384	0,849
	SN3	0,548	0,417	0,379	0,504	0,432	0,599	0,1	0,408	0,835

*Cross-loading values > 0.70

Source: Processed by Researcher (2025)

Based on the table above, it can be seen that the outer loading values for each construct are higher than their respective cross-loading values, indicating that each construct is distinct from the others.

Table 3.
Fornell-Larcker Criterion Test Results

Construct	AT	EC	MI	NMI	PI	PN	PR	PU	SN
AT	0,81								
EC	0,541	0,805							
MI	0,372	0,387	0,825						
NMI	0,448	0,445	0,513	0,812					
PI	0,51	0,456	0,565	0,515	0,813				
PN	0,516	0,527	0,606	0,57	0,655	0,821			
PR	0,013	-0,009	0,004	-0,025	0,079	0,039	0,916		
PU	0,571	0,545	0,44	0,43	0,511	0,501	-0,008	0,807	
SN	0,478	0,438	0,585	0,539	0,615	0,645	0,061	0,493	0,844

Note: The square root of the construct's AVE > the correlation between that construct and other constructs

Source: Processed by Researcher (2025)

The results of the Fornell-Larcker Criterion test show that the square root values of the AVE for each construct are higher than the correlations between that construct and other constructs, indicating that each construct is discriminant from the others.

Table 4.
HTMT Test Results

Construct	AT	EC	MI	NMI	PI	PN	PR	PU	SN
AT									
EC	0,734								
MI	0,496	0,519							
NMI	0,604	0,6	0,683						
PI	0,684	0,613	0,748	0,682					
PN	0,692	0,707	0,795	0,756	0,87				
PR	0,036	0,052	0,047	0,051	0,097	0,051			
PU	0,772	0,747	0,583	0,581	0,675	0,664	0,047		
SN	0,622	0,57	0,749	0,696	0,797	0,826	0,071	0,638	

Note: HTMT < 0.9

Source: Processed by Researcher (2025)

Table 3 shows that the HTMT values for almost all constructs are below 0.9, indicating that each construct is distinct from the others.

Measurement Model Reliability Test

Reliability assessment is conducted by evaluating the composite reliability and Cronbach's Alpha values. The output shows that the composite reliability and Cronbach's Alpha values for each construct are above 0.70, indicating that all constructs are reliable.

Table 5.
Composite Reliability and Cronbach's Alpha Test Results

	Cronbach's alpha	**Composite reliability (rho_c)**
AT	0,739	0,852
EC	0,729	0,847
MI	0,764	0,864
NMI	0,742	0,852
PI	0,744	0,854
PN	0,758	0,861
PR	0,906	0,94
PU	0,735	0,848
SN	0,799	0,881

Note: Composite Reliability > 0.70 & Cronbach's Alpha > 0.70

Source: Processed by Researcher (2025)

Based on Table 4, all constructs in this study have Composite Reliability and Cronbach's Alpha values exceeding 0.70. This indicates that the indicators within each construct demonstrate good internal consistency and can be reliably used in structural model testing. Thus, all constructs in the model meet the reliability requirements.

Structural Model Analysis

Multicollinearity Test

The collinearity test is conducted by evaluating the VIF (Variance Inflation Factor) values. If the VIF values between constructs exceed 5, this indicates a collinearity issue. The test results in the following table show that the VIF values for each relationship between constructs are below 5, indicating that each construct is distinct from the others.

Table 6.

Multicollinearity Test Results

	AT	EC	PI	PU	SN
AT			1,93		
EC			1,971		
MI			1,951		
NMI			2,033		
PI					
PN			2,935		
PR			1,026		
PU			1,99		
SN			2,179		

Source: Processed by Researcher (2025)

Structural Model Fit Test

The structural model fit test (model fit measure) allows for assessing how well the structural model fits the empirical data, thereby helping to identify model specification errors (Hair et al., 2017). In this study, the researcher uses the standardized root mean square residual (SRMR) to assess model fit. A value of 0 (zero) indicates a perfect fit. In CB-SEM, an SRMR value < 0.08 is considered a good fit, but this threshold may be too low for PLS-SEM due to differences in the roles of observed correlations and implied model correlations in CB-SEM and PLS-SEM (Hair et al., 2017).

Table 7.

Model Fit Test Result

	Saturated Model	**Estimated Model**
SRMR	**0,068**	0,069

Source: Processed Primary Data (2025)

Hypothesis Testing

Hypothesis testing is conducted by analyzing the criteria of path coefficients, t-statistics, and p-values. The results of the hypothesis testing can be seen in Table 7 below.

Table 8.

Hypothesis Testing Results

Hypotesis	**Statement**	**Original Sample (O)**	**T Statistics**	**P Values**	**Conclusions**
H1	AT -> PI	0,124	2,705	0,007	Accepted
H2	PU -> PI	0,099	2,364	0,018	Accepted
H3	PR -> PI	0,054	2,009	0,045	Accepted
H4	EC -> PI	-0,002	0,038	0,970	Rejected
H5	SN -> PI	0,186	2,914	0,004	Accepted

H6a	MI x AT -> PI	0,002	0,041	0,968	Rejected
H6b	MI x PU -> PI	-0,038	0,897	0,370	Rejected
H7a	NMI x EC -> PI	-0,016	0,315	0,753	Rejected
H7b	NMI x SN -> PI	0,11	2,802	0,006	Accepted
H8a	PN x EC -> PI	-0,031	0,694	0,488	Rejected
H8b	PN x SN -> PI	-0,076	2,100	0,036	Accepted

Source: Processed Primary Data (2025)

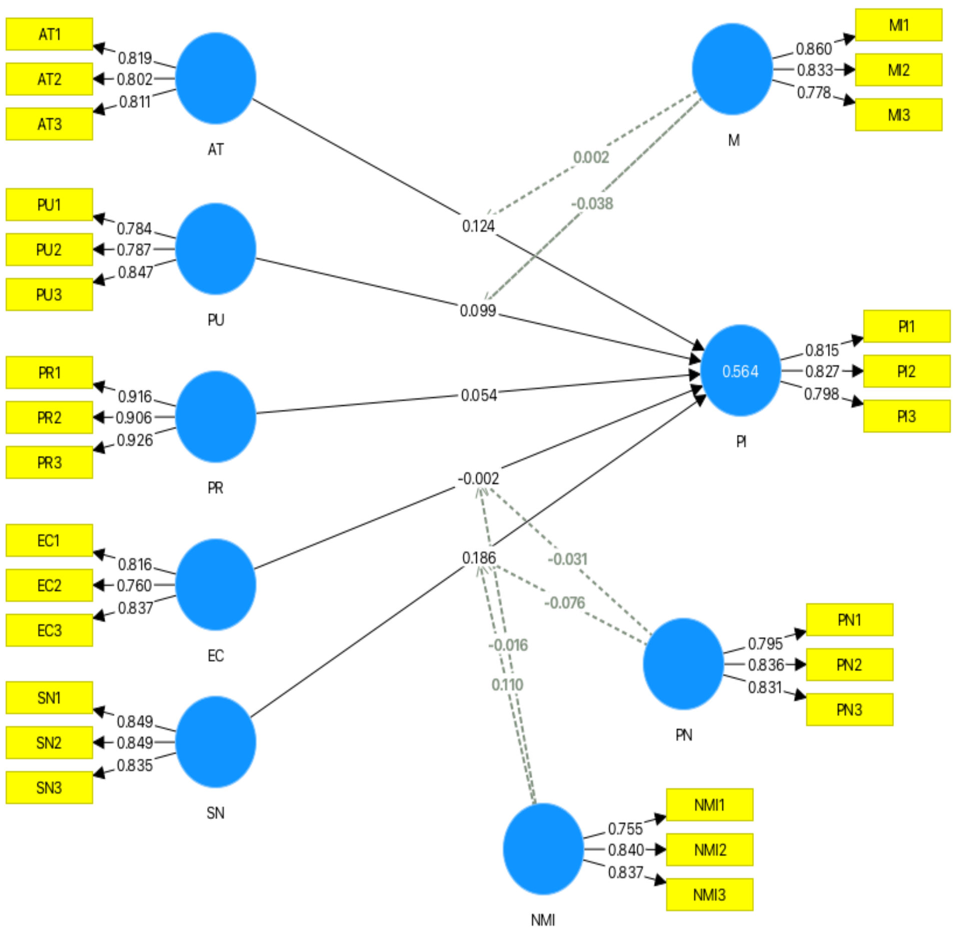

Figure 1.

Source: Processed Primary Data (2025)

Coefficient of Determination (R^2)

The next step is to evaluate the coefficient of determination (R^2), which is a measure of predictive strength within the sample data. In the following table, the R^2 value for the variable Purchase Intention falls into the Moderate category.

Table 9.
Coefficient of Determination (R^2) Results

Variabel	R Square	R Square Adjusted
Purchase Intention	0,556	0,551

Source: Processed Primary Data (2025)

Effect Size (f^2)

Effect size (f^2) is used as an indicator to evaluate whether an exogenous construct has a substantive effect on an endogenous construct. Hair et al. (2017) state that a variable with a small f^2 value is still relevant if it contributes to the R^2 and is supported by theory. The following table shows the Effect Size (f^2) values.

Table 10.
Effect Size (f^2) Results

Variabel	PI
AT	0,018
EC	0
M	0,021
NMI	0,019
PN	0,036
PR	0,006
PU	0,011
SN	0,036

Source: Processed Primary Data (2025)

Predictive Relevance (Q^2)

Next, a blindfolding procedure is conducted to obtain the Q^2 value, which is used to measure the predictive power of a research model or its predictive relevance. In the following table, the Q^2 output values for each endogenous construct are above 0 (zero), indicating that the model has predictive relevance, and thus the model's predictive accuracy is acceptable.

Table 11.
Predictive Relevance (Q^2) Results

Variabel	Q2
AT	0,314
EC	0,301
M	0,357
NMI	0,321
PI	0,322
PN	0,344
PR	0,625
PU	0,303
SN	0,411

Source: Processed Primary Data (2025)

Analysis of Hypothesis Testing Results

Influence of Independent Hypotheses

H1: Effect of Attitude Toward EV (AT) on Purchase Intention (PI)

Hypothesis 1 tested the influence of a positive attitude toward electric vehicles (AT) on purchase intention (PI), yielding a path coefficient of 0.124. This result is supported by a T-statistic of 2.595 and a P-value of 0.010, thus the hypothesis is accepted. This indicates that the more positive a consumer's attitude toward electric vehicles, the higher their intention to purchase one.

This finding aligns with Shakeel (2022), who found that a positive attitude toward EVs, especially when supported by financial and non-financial incentives, significantly increases consumer purchase intention. Upadhyay and Kamble (2023) also emphasized that pro-environmental attitudes play a key role in promoting EV purchase intention in India. In Jakarta's context, this suggests that marketing campaigns highlighting EV advantages, such as energy efficiency and eco-friendliness, can be effective in shaping positive perceptions and increasing purchase interest.

H2: Effect of Perceived Usefulness (PU) on Purchase Intention (PI)

Hypothesis 2 tested the influence of perceived usefulness (PU) on purchase intention, with a path coefficient of 0.099, T-statistic of 2.366, and P-value of 0.020. Therefore, the hypothesis is accepted, indicating that perceived usefulness (e.g., fuel cost savings and good performance) has a positive effect on PI.

This is consistent with the Technology Acceptance Model (TAM) by Davis (1989), which posits perceived usefulness as a key factor in technology adoption. Sun et al. (2022) also support this result, showing that consumers who perceive real benefits from EVs (e.g., reduced operating costs) tend to have stronger purchase intentions. The implication is that companies need to educate consumers on the functional advantages of EVs to increase purchase intention.

H3: Effect of Perceived Risk (PR) on Purchase Intention (PI)

Hypothesis 3 examined the impact of perceived risk (PR) on PI, with a path coefficient of 0.054, T-statistic of 1.901, and P-value of 0.044. The result is significant, and the relationship direction is negative. This shows that the higher the perceived risk, the lower the consumer's purchase intention.

For instance, consumers concerned about limited battery range or insufficient charging stations may delay or avoid switching to EVs. This finding is supported by prior studies: Sun et al. (2022) identified technological and infrastructure uncertainty as key contributors to increased perceived risk among EV buyers. Similarly, Jaiswal et al. (2021) noted that consumers often hesitate to adopt new technologies if perceived risks outweigh expected benefits. In the EV context, perceived risks include both technical issues and psychological factors like fear of technology failure or user inconvenience.

H4: Effect of Environmental Concern (EC) on Purchase Intention (PI)

Hypothesis 4 tested the impact of environmental concern (EC) on PI, with a path coefficient of -0.002, T-statistic of 0.039, and P-value of 0.971. Therefore, H4 is rejected, indicating that environmental concern does not significantly influence EV purchase intention in Jakarta.

This contradicts studies by Yeğin & Ikram (2022) and Upadhyay & Kamble (2023), which found that pro-environmental values drive EV adoption. However, in Jakarta, practical factors such as price, incentives, and infrastructure may outweigh environmental motivations. This implies that EV marketing strategies in Jakarta should emphasize economic and practical benefits rather than just environmental aspects. Though environmental issues are gaining global traction, Jakarta's public may not yet prioritize these concerns in purchasing decisions. This could be attributed to Indonesia's cultural traits, where consumers respond more to practical benefits than environmental motivations. As noted by Wang et al.

(2018), in developing countries like Indonesia, environmental awareness is often not strong enough to drive green behavior.

H5: Effect of Subjective Norms (SN) on Purchase Intention (PI)

Hypothesis 5 examined the impact of subjective norms (SN) on PI, with a path coefficient of 0.186, T-statistic of 2.856, and P-value of 0.004. Thus, H5 is accepted, indicating that social pressure from surroundings (family, friends, or community) significantly affects EV purchase intention.

This aligns with Ajzen's (1991) Theory of Planned Behavior (TPB), which asserts that subjective norms play a vital role in shaping behavioral intentions. Shakeel (2022) also found that recommendations from close peers can enhance EV purchase interest. The implication is that marketing campaigns involving influencers or EV user testimonials may effectively influence consumer decisions.

Effect of Moderating Variables

H6a: The Role of Monetary Incentives (MI) in Moderating the AT → PI Relationship

Hypothesis 6a tested whether monetary incentives (MI) strengthen the AT → PI relationship. The interaction result MI x AT → PI shows a coefficient of 0.002, T-statistic of 0.042, and P-value of 0.968, which is not significant. Thus, H6a is rejected. This contradicts Li & Zhang (2023), who found that government subsidies enhance the link between positive attitudes and EV purchase interest. However, this result suggests that financial incentives (like price discounts) have a more direct effect on PI rather than as a moderator. Consumers in Jakarta seem to respond to financial incentives independently of their initial attitude toward EVs. This aligns with Li & Zhang (2023), who noted that government subsidies often drive purchasing decisions regardless of consumer attitudes. Furthermore, Jakarta's limited EV infrastructure (e.g., charging stations) may cause skepticism toward long-term EV benefits despite financial incentives.

H6b: The Role of Monetary Incentives (MI) in Moderating the PU → PI Relationship

Hypothesis 6b tested whether financial incentives (MI) strengthen the PU → PI relationship. The interaction MI x PU → PI yielded a coefficient of -0.038, T-statistic of 0.875, and P-value of 0.368, which is not significant. Thus, H6b is rejected.

This contradicts Bohnsack et al. (2012), who found that financial incentives can enhance perceived benefits of EVs. In Jakarta's context, however, monetary incentives may influence purchase decisions more directly than by altering how consumers perceive EV usefulness. This may be explained by the dominance of external factors in Jakarta consumers' decisions. As noted by Bohnsack et al. (2012), financial incentives are more effective as direct motivators than moderators.

H7a: The Role of Non-Monetary Incentives (NMI) in Moderating the EC → PI Relationship

Hypothesis 7a tested whether non-financial incentives (NMI) strengthen the EC → PI relationship. The interaction NMI x EC → PI showed a coefficient of -0.016, T-statistic of 0.315, and P-value of 0.751, which is not significant. Therefore, H7a is rejected. This contradicts Bohnsack et al. (2012), who found that non-financial incentives (like special lane access) can strengthen the link between environmental motivations and EV interest. However, the result is consistent with previous findings that EC itself is not significant in Jakarta, so its interaction with NMI is also ineffective. In developing countries like Indonesia, environmental concerns rarely drive purchasing decisions. Jakarta consumers are more focused on practical benefits like free parking or toll access, unrelated to environmental concern.

H7b: The Role of Non-Monetary Incentives (NMI) in Moderating the SN → PI Relationship

Hypothesis 7b tested whether non-financial incentives (NMI) strengthen the SN → PI relationship. The interaction NMI x SN → PI showed a coefficient of 0.11, T-statistic of 2.733, and P-value of 0.006, which is significant. Therefore, H7b is accepted. This supports Müller & Schmidt (2023), who found that non-financial incentives (like free parking) can strengthen the effect of social recommendations on EV purchase interest. In Jakarta, benefits like toll-free access, exemption from odd-even rules, or priority parking can make peer recommendations more persuasive.

H8a: Personal Norms Strengthen the EC → PI Relationship

The analysis showed that the interaction between personal norms (PN) and environmental concern (EC) on PI has a negative path coefficient (-0.031), a T-statistic of 0.708 (below the significance threshold of 1.96), and a P-value of 0.475 (above 0.05). Thus, H8a is rejected.

This indicates that personal norms are not strong enough to enhance the relationship between environmental concern and purchase intention. This contradicts Schwartz's (1977) theory, which asserts the importance of personal norms in pro-environmental behavior in developed countries. In Jakarta, however, social pressure (subjective norms) appears to dominate over personal moral obligations. As Ajzen (1991) noted, subjective norms are often more influential in collective cultures like Indonesia.

H8b: Personal Norms Strengthen the SN → PI Relationship

The interaction between personal norms (PN) and subjective norms (SN) on PI shows a negative path coefficient (-0.076), with a T-statistic of 2.063 (above 1.96) and a P-value of 0.039 (below 0.05). This means the interaction is statistically significant, though the direction is negative.

Therefore, H8b is accepted, but the negative direction suggests that the stronger the interaction between personal and subjective norms, the lower the intention to purchase EVs. This is consistent with Schwartz (1977) and Priessner et al. (2018), who noted that personal norms can moderate the relationship between social norms and behavior, but in some cases, they may result in negative effects—especially when personal values conflict with social expectations

CONCLUSION

This study examines the influence of various factors on the intention to purchase electric vehicles in Jakarta, including attitude, perceived usefulness, subjective norms, environmental concern, and perceived risk, as well as the role of moderating variables such as incentives and personal norms. The results indicate that positive attitude, perceived usefulness, and subjective norms have a significant impact, while environmental concern does not. Perceived risk has a negative effect. Non-financial incentives strengthen the influence of subjective norms, whereas personal norms appear to conflict with social norms. These findings are important for marketing strategies and public policies aimed at promoting EV adoption.

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