How government incentives shape consumer intention to adopt electric vehicles: A study in Batam City

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Abstract

This study analyzes the factors influencing the intention to purchase electric vehicles (EVs) following the implementation of financial incentives. It integrates the Theory of Planned Behavior (TPB), the Technological Acceptance Model (TAM), and extensions of TPB, including consumer knowledge, perceived risk, and financial incentives. Data were collected from 384 respondents, comprising both EV users and non-users in Batam City. The findings reveal that attitude has an insignificant effect on the intention to buy EVs, while perceived usefulness also shows an insignificant effect on attitude. In contrast, consumer knowledge and financial incentives significantly influence both attitude and purchase intention. Perceived risk negatively affects attitude and intention to buy EVs. The study highlights the need for policies providing financial incentives to consider long-term benefits for consumers to ensure sustainable adoption of EVs.

Keywords: *Attitude, Consumer knowledge, Perceived risk, Financial incentives, Purchase intention.*

JEL Classification: H23, D12, O33

INTRODUCTION

Electric vehicles (EVs) are increasingly recognized as a viable solution for improving urban transportation by reducing gasoline consumption and air pollution, thereby contributing to significant health and environmental benefits (Buekers et al., 2014). EVs also play a critical role in lowering carbon emissions, mainly when powered by renewable energy sources (Łukasz & Arkadiusz, 2020).

In Indonesia, the government has shown a strong commitment to promoting EV adoption through various regulatory initiatives. Presidential Regulation No. 55/2019 aims to accelerate the adoption of battery electric vehicles (BEVs) in road transportation (Sekretariat Negara Republik Indonesia, 2019). This effort is further supported by Minister of Finance Regulation No. 38/2023, which provides value-added tax incentives for certain battery-based motorized vehicles, effectively reducing costs for consumers (Kementerian Keuangan Republik Indonesia, 2023).

Despite these efforts, consumer enthusiasm for adopting electric vehicles remains relatively low, and the EV market share is still modest compared to conventional vehicles (Li et al., 2016; Zhang et al., 2013). However, recent data from the Ministry of Industry indicates significant growth in EV sales, rising from 7,498 units in 2021 to 33,461 units in 2022 (a growth of 344.27%) and reaching 81,115 units in 2023 (katadata.co.id, 2023). This upward trend suggests increasing consumer interest, although challenges persist in achieving widespread adoption.

The growing interest in EVs presents an opportunity to explore the factors influencing consumer behavior, particularly the impact of government financial incentives and other determinants shaping EV purchase intentions. Wang et al. (2018) summarize that consumer intentions to adopt EVs are influenced by multiple factors, including limited cruising range, inadequate charging infrastructure, lengthy charging times, uncertain performance, battery capacity issues, and safety concerns (Junquera et al., 2016; Michael et al., 2022; Wang et al., 2017, 2018). Conversely, Mahadin (2018) identifies fuel efficiency as the primary motivator for EV adoption, followed by environmental benefits, lower taxes, and advanced technological features. Barriers such as high prices, limited battery life, and insufficient information also play a significant role in slowing adoption rates.

Technological advancements and expanded charging infrastructure could address some of these barriers, yet consumer acceptance heavily depends on psychological factors, such as attitudes, values, beliefs, and perceived benefits of EVs (Larson et al., 2015; Wang et al., 2018). Examining these factors from a behavioral perspective is essential for understanding consumer intentions to purchase EVs. Specifically, analyzing how government policies influence consumer decisions and identifying additional elements that shape consumer behavior are critical areas of inquiry.

Research by Zheng et al. (2021) emphasizes the importance of subsidy policies in promoting EV sales and highlights the need for robust charging infrastructure to enhance the consumer experience. Understanding consumer perceptions of government tax incentives and EV products plays a significant role in shaping purchase intentions (Qiu et al., 2019; Sierzchula et al., 2014; Yang et al., 2019). Studies by Wang et al. (2018) and Jaiswal et al. (2021) further indicate that consumer knowledge significantly impacts perceived usefulness, attitudes, and purchase intentions. Perceived usefulness, in turn, is a key driver of interest in environmentally friendly vehicles (Wang et al., 2022).

Other studies have explored additional factors influencing EV adoption, such as attitudes toward EVs, subjective norms, and perceived behavioral control (Adnan et al., 2017; Sahoo et al., 2023; Tunçel, 2022; Wang et al., 2018). Product cognition and perceptions of financial incentives also significantly affect consumer behavior (Harichandan & Kar, 2023; Pradeep et al., 2021; Yang et al., 2019). Sahoo et al. (2023) underscore the importance of government policies—such as subsidies, tax reductions, and charging infrastructure development—in mitigating negative perceptions and boosting EV sales.

The present study, building on these findings, adopts Ajzen's Theory of Planned Behavior (TPB) as a theoretical framework (Ajzen, 1991). This study incorporates additional variables—consumer knowledge, perceived usefulness, perceived risk, and government financial incentives—to enhance the analysis of consumer behavior in Indonesia's EV market. This integrated framework aims to address research gaps and empirically examine how consumer attitudes influence purchase intentions and how the identified variables shape these attitudes.

In TPB, attitude is defined as an individual's favorable or unfavorable evaluation of a behavior (Fishbein & Ajzen, 1975), while subjective norms refer to perceived social pressures to engage in or avoid a specific behavior (Ajzen, 1991). Research by Deka et al. (2023) on 330 vehicle users reveals that attitudes alone do not directly influence purchase intentions but require additional drivers, such as technological understanding, charging infrastructure availability, and clarification of misconceptions about EVs. Factors like awareness, ease of use, driving experience, social needs, and pro-environmental motivations also shape consumer attitudes (Degirmenci & Breitner, 2017; Huang et al., 2021).

Additionally, perceived usefulness, derived from the Technology Acceptance Model (TAM) by Davis (1989), is integrated into this study to explore how EV adoption is influenced by utility aspects, such as reduced carbon emissions, lower transportation costs, and improved travel efficiency (Wang et al., 2018). Studies confirm that perceived usefulness positively impacts consumer behavior and purchase intentions (Wang et al., 2022; Jaiswal et al., 2021).

Perceived risk, a critical barrier to innovative product adoption, is another key variable in this research. It reflects consumer anxiety about potential financial, performance, and safety issues associated with EVs (Jaiswal et al., 2021; Featherman & Pavlou, 2003). Addressing these concerns is crucial for enhancing consumer acceptance and adoption rates.

Government incentives, including subsidies and tax reductions, play a vital role in fostering EV adoption by alleviating financial burdens and encouraging interest (Wang et al., 2018; Sierzchula et al., 2014). Research across multiple countries confirms the positive correlation between financial incentives and EV market growth (Li et al., 2016).

This study focuses on purchase intention as the dependent variable, recognizing it as a reliable proxy for actual behavior (Deka et al., 2023; Xiao & Goulias, 2022). By examining the interplay between attitudes, consumer knowledge, perceived usefulness, perceived risk, and government financial incentives, this research aims to provide actionable insights for promoting EV adoption in Indonesia.

METHODS

The study employed a cross-sectional design using an online survey strategy. An online questionnaire was developed to gather responses from educated, high-income individuals within the target population of Batam to test the hypotheses. Respondents included individuals from diverse backgrounds in terms of gender, education, and occupation, all residing in Batam City. Vehicle owners—both those who had purchased electric vehicles (EVs) and those who had not—were selected as the sample for the study.

Since the precise number of EV owners in Batam City is not known, the sample size was determined using a ratio of 15:1, where each question required 15 respondents, following the guidance of Hair et al. (2018). According to Hair et al. (2018), the sample-to-variable ratio recommends a minimum observation-to-variable ratio of 5:1, although ratios of 15:1 or 20:1 are preferred for robust analysis. With 23 items in the questionnaire, the minimum required sample size for this study was calculated to be 345 respondents. All items were measured using a 5-point Likert scale.

The constructs were measured using established indicators: attitudes were measured using four indicators based on Deka et al. (2023); customer knowledge using four indicators developed by Huang et al. (2021), Ullah et al. (2018), and S. Wang et al.

(2018); perceived risk using five indicators from Wang et al. (2018); perceived usefulness using four indicators from Madigan et al. (2017), Wang et al. (2018), and Wu et al. (2019); and financial incentives and purchase intention using three indicators from Wang et al. (2017, 2018).

Several filtering processes were applied to the sample data to ensure data quality. These included:

1. Removing respondent data that exhibited homogeneous answers with little variance.
2. Excluding data from respondents who failed to complete key questionnaire sections accurately. For example, respondents were asked questions such as "Do you already have an electric vehicle?" or "Are you planning to buy an electric vehicle in the near future?" These were followed by essential statements like "If you own an electric vehicle, do you understand the current trends in electric vehicle technology?" and "Are you aware of government incentives for purchasing electric vehicles?"

This filtering process aligns with DeVellis (2017), who emphasizes the importance of content validity. Content validity ensures that a survey comprehensively addresses all aspects of the constructs being measured and encompasses face validity, which assesses the relevance of survey items to individuals familiar with the constructs.

The data collection took place between August and November 2023, yielding a total of 400 responses. After validation, 384 valid questionnaires (94.44%) were retained for analysis, while 5.56% were excluded due to incompleteness or invalid responses.

The study employed the SEM-PLS model, with a specific conceptual framework to guide the analysis of factors influencing customer intention.

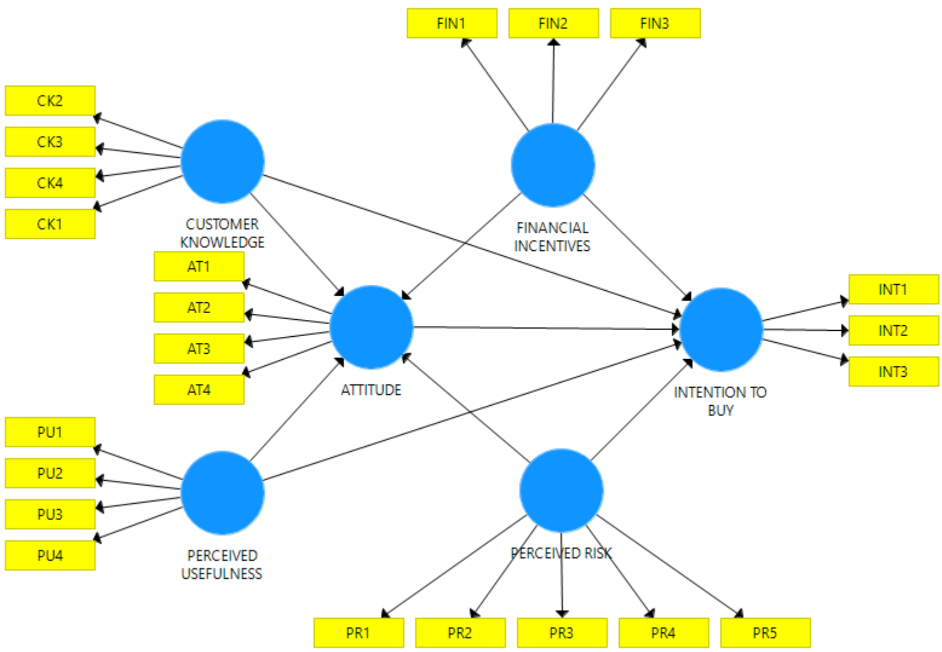

Figure 1. Research model

The evaluation of the outer model focuses on assessing the validity and reliability of the constructs by examining their relationships with their respective indicators. This process involves multiple aspects. Convergent validity, for instance, is determined by the factor loading of each indicator on its latent variable, with an expected value greater than 0.7, as suggested by Hair et al. (2018). A high factor loading indicates that the indicator effectively measures its intended construct.

Discriminant validity, on the other hand, is evaluated by examining cross-loading values. Specifically, the loading of an indicator on its intended construct must be higher than its loading on any other construct. This ensures that the constructs are distinct from each other. Composite reliability (CR) is another critical measure, reflecting the internal consistency of the construct. A CR value greater than 0.7 is deemed acceptable. Similarly, the Average Variance Extracted (AVE) should exceed 0.5, as proposed by Sarstedt et al. (2020), to confirm that the construct explains a substantial portion of the variance in its indicators.

The inner model focuses on the structural relationships between the latent constructs. The R-square (R^2) value indicates the proportion of variance explained by the exogenous constructs in the model. A higher R^2 value signifies a stronger explanatory power of the model. The path coefficients are also crucial, representing the strength and direction of the relationships between constructs. These coefficients are calculated through the bootstrapping procedure, which enhances the reliability of the results.

Prediction relevance (Q^2), derived from Stone-Geisser's criterion, assesses the model's predictive capability. This measure uses the blindfolding procedure and is applicable to endogenous constructs with reflective indicators. A Q^2 value of 0.02 indicates small predictive relevance, 0.15 indicates medium relevance, and 0.35 reflects large predictive relevance, as recommended by Hair et al. (2018).

In this study, several hypotheses are tested to explore the relationships among constructs.

H1: Customer attitude has a direct and positive relationship with the intention to buy an electric vehicle;
H2: Customer knowledge has a direct and positive relationship with attitude
H3: Customer knowledge has a direct and positive relationship with the intention to buy electric vehicles.
H4: Perceived usefulness has a direct and positive relationship with attitude toward EV
H5: Perceived usefulness has a direct and positive relationship with the intention to buy electric vehicles.
H6: Perceived Risk has a direct and negative relationship with attitude towards EV
H7: Perceived Risk has a direct and negative relationship with the intention to buy electric vehicles
H8: Financial incentives have a direct and positive relationship with attitude toward EV
H9: Financial incentives have a direct and positive relationship with intention to buy electric vehicles

By evaluating these hypotheses using the SEM-PLS model, the study aims to provide a comprehensive understanding of the factors influencing consumer intention in the context of electric vehicle adoption. This approach ensures a robust examination of both measurement and structural aspects of the model.

RESULTS AND DISCUSSION

Demographic characteristics and EV knowledge

The identification results show that the majority of respondents in this study, who are motorized vehicle owners, do not currently own an electric vehicle. Respondents are predominantly male (73.44%) and primarily fall within the age range of 35–40 years (60.68%). The educational profile reveals that most respondents hold a bachelor's degree (71.35%), followed by post-graduate degrees (12.24%) and high school education (16.41%). This high level of education indicates that respondents are likely capable of comprehending and critically evaluating information about electric vehicles (EVs) and associated technologies. Furthermore, individuals with higher education levels are generally more receptive to adopting new technologies, as they tend to have greater awareness of environmental and economic benefits. However, 16.41% of respondents with only a high school education may require simplified and targeted educational campaigns to enhance their understanding and mitigate any perceived complexities related to EV technologies. Tailoring outreach efforts to address varying levels of technological literacy can help bridge the knowledge gap and increase the overall adoption rates (Table 1).

Table 1. Respondent demographics and EV knowledge

Demographic	Frequency	%
Gender		
Male	282	73.44
Female	102	26.56
Age		
<35	47	12.24
35-40	233	60.68
>40	104	27.08
Education		
High School	63	16,41
Graduate	274	71,35
Post-Graduate	47	12,24
Occasion		
Employee	101	26.30
Entrepreneurs	227	59.11
Civil Servant	13	3.39
Others	43	11.20
Income		
< Rp30,000,000	87	22.66
Rp30,000,000 - Rp45,000,000	211	54.95
Rp45,000,000 - Rp80,000,000	55	14.32
>Rp80,000,000	31	8.07
Do you have an EV?		
Yes	73	23.48
No	311	76.52
If you say 'No,' please continue to the next question!		
Do you plan to purchase an EV?		
Yes	162	52.09
No	149	47.91
Do you know about the EV technologies?		
Yes	281	73.18
No	103	26.82
Do you know about government financial incentives for EV?		
Yes	278	72.40
No	106	27.60

The income distribution shows that 77.51% of respondents earn below Rp45 million, placing them within the middle-income category. A smaller proportion (14.32%) earn between Rp45 million and Rp80 million, while only 8.07% earn above Rp80 million. This distribution highlights a significant segment of respondents with the financial capacity to consider purchasing an electric vehicle (EV), particularly those in the higher-income brackets. However, the large share of middle-income earners suggests that affordability remains a critical factor, underscoring the importance of financial incentives or subsidies to make EV ownership more accessible to this group.

Occupation data further reveals a diverse representation of potential EV buyers, with the majority being entrepreneurs (59.11%), followed by private sector employees (26.30%), civil servants (3.39%), and individuals in other occupations (11.20%). Entrepreneurs, who often have greater financial flexibility, may prioritize EVs as a cost-effective long-term investment. On the other hand, employees and civil servants might require clearer justifications for the economic or environmental benefits of EV ownership due to fixed income structures. This occupational diversity emphasizes the need for tailored marketing strategies and incentive programs that cater to varying financial and lifestyle priorities across different occupational groups.

Electric vehicle ownership is currently low, with only 19.01% of respondents owning an EV, while 80.99% do not. However, among non-owners, 52.09% expressed an intention to purchase an EV in the future, indicating a strong latent interest. The remaining 47.91% are hesitant or unwilling to adopt EVs, suggesting barriers such as cost, infrastructure, or lack of perceived benefits may still influence decisions.

Awareness of electric vehicle (EV) technology is relatively high, with 73.18% of respondents indicating familiarity, while 26.82% are not aware. This level of awareness suggests that informational campaigns have been effective in reaching a majority of the population. However, the remaining 26.82% highlights a notable gap, indicating the need for more inclusive outreach efforts to ensure that awareness penetrates all demographic groups, particularly those who may face barriers to accessing information, such as individuals with lower education levels or limited exposure to technology.

Similarly, 72.40% of respondents are aware of government incentives for EV purchases, while 27.60% remain unaware. This gap in awareness of financial incentives is significant, as these policies are often key motivators for EV adoption, especially among middle-income groups who are sensitive to initial costs. Targeted campaigns leveraging digital platforms, community events, and partnerships with local organizations could help bridge this gap, ensuring that more potential buyers are informed about the benefits and opportunities associated with EV ownership. Additionally, simplifying the communication of government incentives can further enhance understanding and encourage adoption.

Outer model testing

Model quality indicators are assessed based on Cronbach's Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) values. The Cronbach's Alpha (CA) values presented in Table 2 demonstrate that the model's reliability meets the required criteria, as all values exceed 0.7. Similarly, the Composite Reliability (CR) values indicate high model reliability, with all values exceeding 0.8. Furthermore, the Average Variance Extracted (AVE) values, as shown in the table, confirm the validity of the model, as each value is greater than 0.5.

Table 2. Cronbach Alpha, Composite Reliability, Average Variance Extracted

Variable	Item	CA	CR	AVE
Attitude	AT1, AT2, AT3, AT4	0.795	0.864	0.615
Consumer Knowledge	CK1, CK2, CK3	0.834	0.889	0.668
Financial Incentives	FI1, FI2, FI3	0.800	0.882	0.714
Intention to Buy	INT1, INT2, INT3	0.817	0.891	0.731
Perceived Risk	PR1, PR2, PR3, PR4, PR5	0.867	0.904	0.653
Perceived Usefulness	PU1, PU2, PU3, PU4	0.828	0.885	0.659

Based on Table 3, all the indicators have outer loading values greater than 0.7. This demonstrates that the indicators are reliable and meet the specified criteria, as outlined by Hair et al. (2018). The high outer loading values indicate a strong correlation between each indicator and its respective construct, ensuring the measurement model's robustness.

Table 3. Outer loading

	ATT	CK	FIN	PR	PU	INT
AT1	0.708					
AT2	0.820					
AT3	0.779					
AT4	0.824					
CK1		0.847				
CK2		0.812				
CK3		0.854				
CK4		0.752				
FIN1			0.823			
FIN2			0.848			
FIN3			0.863			
PR1				0.808		
PR2				0.854		
PR3				0.797		
PR4				0.817		
PR5				0.763		
PU1					0.797	
PU2					0.830	
PU3					0.816	
PU4					0.803	
INT1						0.852
INT2						0.853
INT3						0.860

For the Attitude (ATT) construct, the outer loading values range from 0.708 to 0.824, confirming that all four indicators (AT1 to AT4) significantly contribute to the construct. Similarly, the Customer Knowledge (CK) construct demonstrates reliability with outer loading values between 0.752 and 0.854, indicating that all indicators (CK1 to CK4) are suitable for further analysis.

In the case of Financial Incentives (FIN), the outer loading values (0.823 to 0.863) show strong reliability for all three indicators (FIN1 to FIN3). The Perceived Risk (PR) construct also shows consistency, with values ranging from 0.763 to 0.854 across its five indicators (PR1 to PR5), confirming the adequacy of the measurement model for this construct.

For Perceived Usefulness (PU), the outer loading values (0.797 to 0.830) demonstrate the validity of the four indicators (PU1 to PU4), reinforcing their contribution to the construct. Lastly, the Intention to Buy (INT) construct shows the highest outer loading values among all constructs, ranging from 0.852 to 0.860, underscoring the reliability of its three indicators (INT1 to INT3).

These results confirm that all constructs in the model exhibit sufficient indicator reliability. The consistently high outer loading values indicate that the measurement items effectively capture their respective latent variables. Therefore, all indicators can be retained for further analysis, providing a solid foundation for examining the relationships among the constructs in the structural model.

Discriminant validity

Discriminant validity is assessed using the Fornell-Larcker criterion and cross-loading tests. According to the Fornell-Larcker criterion, discriminant validity is considered satisfactory when the square root of the AVE for each construct is higher than its correlation with any other latent variable. Meanwhile, for the cross-loading test, an indicator is deemed valid if its loading value for its respective construct is higher than its loadings on other constructs (Sekaran & Bougie, 2013).

Based on Table 4, the square root of the AVE for each construct is higher than the correlation of that construct with other latent variables. This confirms that the discriminant validity of the constructs is satisfactory according to the Fornell-Larcker criterion. For example, the square root of the AVE for Attitude (ATT) is 0.784, which is higher than its correlations with other constructs, such as Customer Knowledge (CK) at 0.782 or Intention (INT) at 0.763. Similarly, Customer Knowledge (CK) has a square root of AVE at 0.817, exceeding its correlations with constructs such as Financial Incentives (FIN) at 0.647 and Perceived Risk (PR) at 0.684.

These results indicate that each construct explains more variance in its associated indicators than it shares with other constructs, satisfying the Fornell-Larcker criterion. This demonstrates that the latent variables are distinct from one another, reinforcing the measurement model's validity.

Table 4. Fornell-Larcker Criterion

	ATT	CK	FIN	INT	PR	PU
ATT	**0.784**					
CK	0.782	**0.817**				
FIN	0.583	0.647	**0.845**			
INT	0.763	0.980	0.596	**0.855**		
PR	0.750	0.684	0.725	0.639	**0.808**	
PU	0.628	0.687	0.966	0.628	0.751	**0.812**

Furthermore, Table 5 confirms that the cross-loading values for each indicator are higher for their respective constructs than for other constructs, further validating the discriminant validity of the model. For instance, the loading of AT1 on Attitude (ATT) is 0.708, which is higher than its loadings on other constructs, such as Customer Knowledge (CK) at 0.516 or Financial Incentives (FIN) at 0.432. Similarly, CK1 loads highly on Customer Knowledge (CK) at 0.847, compared to its lower loadings on constructs like Perceived Risk (PR) at 0.609 or Attitude (ATT) at 0.824.

This pattern is consistent across all constructs, confirming that each indicator uniquely measures its intended construct. The high cross-loading values on their respective constructs, combined with values exceeding the 0.7 threshold, indicate that all indicators are valid and reliable.

Table 5. Cross loading

	ATT	CK	FIN	INT	PR	PU
AT1	**0.708**	0.516	0.432	0.490	0.553	0.474
AT2	**0.820**	0.517	0.491	0.487	0.644	0.526
AT3	**0.779**	0.449	0.406	0.428	0.543	0.446
AT4	**0.824**	0.847	0.487	0.852	0.609	0.516
CK1	0.824	**0.847**	0.487	0.852	0.609	0.516
CK2	0.534	**0.812**	0.477	0.853	0.495	0.501
CK3	0.595	**0.854**	0.563	0.860	0.533	0.593
CK4	0.573	**0.752**	0.620	0.606	0.611	0.672
FIN1	0.487	0.584	**0.823**	0.525	0.540	0.830
FIN2	0.458	0.466	**0.848**	0.413	0.611	0.816
FIN3	0.526	0.578	**0.863**	0.555	0.682	0.803
INT1	0.824	0.847	0.487	**0.852**	0.609	0.516
INT2	0.534	0.812	0.477	**0.853**	0.495	0.501
INT3	0.595	0.854	0.563	**0.860**	0.533	0.593
PR1	0.607	0.585	0.638	0.554	**0.808**	0.629
PR2	0.688	0.642	0.601	0.606	**0.854**	0.631
PR3	0.548	0.505	0.541	0.463	**0.797**	0.559
PR4	0.621	0.535	0.610	0.480	**0.817**	0.642
PR5	0.551	0.478	0.535	0.458	**0.763**	0.567
PU1	0.554	0.586	0.613	0.526	0.597	**0.797**
PU2	0.487	0.584	0.823	0.525	0.540	**0.830**
PU3	0.458	0.466	0.848	0.413	0.611	**0.816**
PU4	0.526	0.578	0.863	0.555	0.682	**0.803**

Inner model testing

The structural model is evaluated using the R-Square (R^2) indicator. Table 6 shows the results of the data processing, where the R^2 value for the Attitude variable is 0.704 (70.4%) and for the Intention to Buy variable is 0.965 (96.5%). These findings indicate that all independent variables collectively explain 70.4% of the variance in the Attitude variable and 96.5% of the variance in the Intention to Buy variable.

This implies that 29.6% of the variance in Attitude is attributable to other factors not included in this research. Similarly, 3.5% of the variance in the Intention to Buy variable is influenced by factors outside the scope of this study. These results confirm that the independent variables investigated in this study have a strong and substantial contribution, both individually and collectively, in influencing attitudes and intentions to purchase electric vehicles.

Table 6. R-Square

	R Square	R Square Adjusted
Attitude	0.704	0.700
Intention To Buy	0.965	0.965

The Q-Square Predictive Relevance is calculated using the following formula:

Q = 1 – (1- R2 Attitude) x (1 – R2 Intention to Buy)
= 1 – (0.296) x (0.035)
= 0,99

A Q-Square value greater than 0 indicates that the structural model has strong predictive relevance for explaining attitudes and intentions to buy.

Additionally, the model fit is evaluated using the Standardized Root Mean Square Residual (SRMR) and other model fit indicators. The results presented in Table 7 show that the SRMR value is 0.063, which is less than the threshold of 0.10. According to Ghozali & Latan (2012), achieving satisfactory results in two or more Goodness of Fit indicators supports the conclusion that the model is robust and well-fitted.

Table 7. Model fit

Model Fit	Saturated Model	Standard Value	Result
SRMR	0.063	<0.10	Good
d_ULS	1.014	> 2.00	Less
d_G	0.774	> 0.90	Less
Chi-Square	1320.555	Minimal in Size	Good
NFI	0.770	> 0.90	Less
Rms Theta	0.172	> 0.102	Good

The results of the SRMR and Chi-Square tests indicate that the model is a good fit, while d_ULS, d_G, and NFI show marginal results. Nevertheless, as SRMR is a key indicator, the model is deemed valid and well-fitted. The findings provide strong evidence that the structural model is predictive and capable of explaining the relationships between variables effectively.

Hypothesis test result

The hypothesis testing results from the structural equation model (SEM) provide insights into the relationships between independent and dependent variables. As shown in Table 8, nine hypotheses were tested, of which seven were accepted and two were rejected. The results highlight the significance and direction of the relationships as well as their implications.

Table 8. Path coefficient analysis

	Hypothesis	Original Sample	T Statistics	P Values	Result
H1	Attitude (AT)-> Intention To Buy (INT)	0.031	1.818	0.070	Rejected
H2	Customer Knowledge (CK)-> Attitude (AT)	0.518	11.743	0.000	Accepted
H3	Customer Knowledge (CK)-> Intention To Buy (INT)	1.033	78.156	0.000	Accepted
H4	Perceived Usefulness (PU)-> Attitude (AT)	0.155	1.299	0.195	Rejected
H5	Perceived Usefulness (PU)-> Intention To Buy (INT)	-0.172	3.796	0.000	Accepted
H6	Perceived Risk (PR) -> Attitude (AT)	-0.440	8.950	0.000	Accepted
H7	Perceived Risk (PR) -> Intention To Buy (INT)	-0.035	2.250	0.025	Accepted
H8	Financial Incentives (FIN)-> Attitude (AT)	-0.221	1.990	0.047	Accepted
H9	Financial Incentives (FIN)-> Intention To Buy (INT)	0.100	2.288	0.023	Accepted

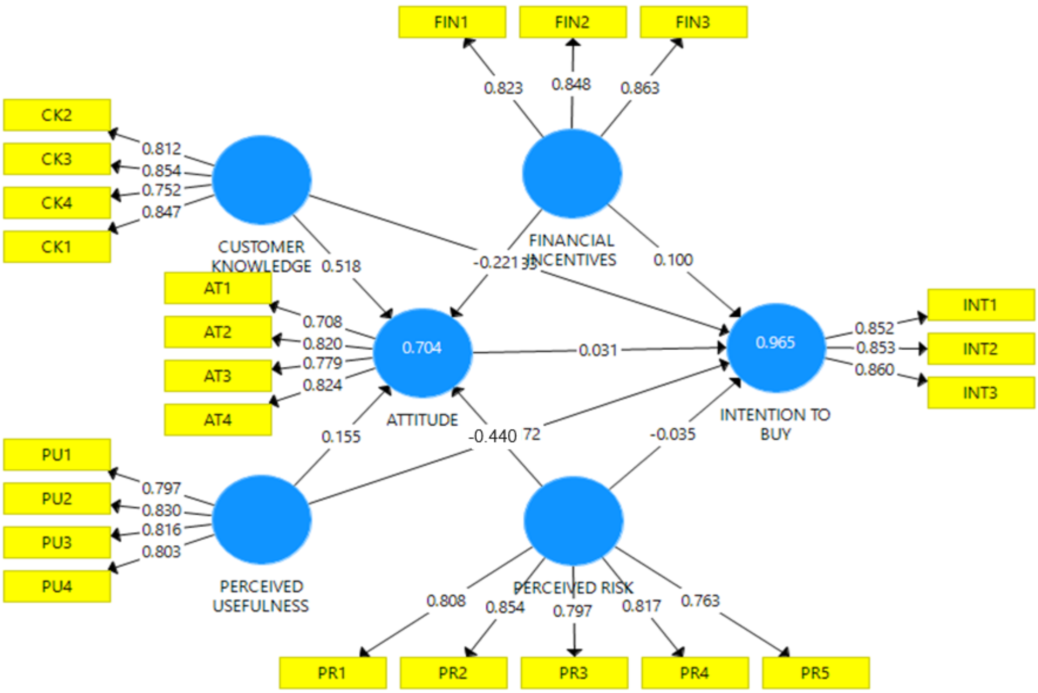

Figure 2. SEM-PLS result

The results of the first hypothesis indicate that attitude has an insignificant effect on the intention to buy an electric vehicle. These findings align with the studies conducted by Ray and Harito (2023) and Deka et al. (2023), which also observed an insignificant relationship between attitude and intention to adopt electric vehicles. However, this result is inconsistent with prior research by Sreen et al. (2018), Tunçel (2022), and Wang et al. (2022). This study demonstrates that a more positive consumer attitude toward electric vehicles does not necessarily increase the likelihood of purchase intention. Empirically, the findings fail to validate the role of attitude as a critical predictor of consumer behavior in Batam City. Several obstacles, such as high prices, perceived benefits, limited availability of spare parts, and insufficient recharging facilities in public areas, may explain this outcome.

A study by Tunçel conducted in Turkey revealed that consumers with high hedonically motivated innovativeness tend to have a favorable attitude toward purchasing electric vehicles. In contrast, those with high cognitively motivated innovativeness are more likely to proceed with purchasing decisions. Similarly, Sreen's research in India showed that attitude is significantly related to collectivism. In collectivist societies, individuals often prioritize group goals over personal goals and make decisions that align with societal approval.

The results of the second hypothesis demonstrate that consumer knowledge significantly affects attitude. Consumers with more knowledge about green products, such as familiarity with the performance attributes of electric vehicles (e.g., charging time, acceleration, driving comfort, mileage, cost of use), as well as their benefits and advantages, are more likely to develop positive attitudes and increase their intention to purchase. Similarly, the third hypothesis confirms that consumer knowledge significantly affects purchase intention. These findings support previous studies by Degirmenci & Breitner (2017), Huang et al. (2021), and Wang et al. (2017), which observed a positive relationship between consumer knowledge and intention to use electric vehicles. Electric vehicles are considered environmentally friendly social products. However, consumer knowledge primarily focuses on environmental benefits and often overlooks the role of technological knowledge (Wu et al., 2019; Xu et al., 2019).

The fourth hypothesis shows that perceived usefulness has an insignificant impact on attitudes toward electric vehicles. In contrast, the fifth hypothesis reveals a significant influence of perceived usefulness on purchase intention. These results suggest that the more customers perceive the usefulness of electric vehicles, the less it impacts their attitudes. This finding is inconsistent with prior studies by Wang et al. (2018) and Wang et al. (2022), which found a positive relationship between perceived usefulness and attitude. Nevertheless, the significant influence of perceived usefulness on purchase intention is consistent with studies by Prabaharan and Selvalakshmi (2020). Recognizing the usefulness of electric vehicles (e.g., improved travel efficiency, better living quality, reduced household expenditure, physical and mental fatigue relief, and environmental protection) plays a crucial role in shaping purchase decisions (Wang et al., 2022).

The sixth and seventh hypotheses reveal that perceived risk has a negative and significant effect on both attitude and intention to buy an electric vehicle. A lack of knowledge about electric vehicles and the high perceived risks associated with their use may lead consumers to make adverse decisions and avoid adopting them (Wang et al., 2018). Efforts to promote electric vehicle adoption in Indonesia should focus on improving consumer knowledge and mitigating perceived risks.

The results of the eighth hypothesis show that financial incentives have a significant but negative effect on attitudes toward purchasing electric vehicles. Greater financial incentives provided by the government fail to influence consumer attitudes positively. This result is inconsistent with expectations and prior findings by Wang et al. (2021), which noted that perceptions of financial incentive policies can directly shape purchase intentions through attitudes. However, Wang’s study also found no significant effect of government incentives on attitudes toward electric vehicles.

In contrast, the ninth hypothesis confirms that financial incentives have a positive and significant impact on purchase intention. This finding is consistent with the increase in electric vehicle sales in the domestic market between 2020 and 2023 and prior research by Ma et al. (2017), Li et al. (2015), and Yang et al. (2019), which identified incentive policies and product cognition as critical determinants of adoption intentions.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This research examined the effects of financial incentives, customer knowledge, perceived risk, and perceived usefulness on attitudes and consumer intentions to purchase electric vehicles (EVs). The findings reveal that financial incentives and customer knowledge significantly influence both attitudes and purchase intentions, while perceived risk negatively impacts both. Perceived usefulness has an insignificant effect on attitudes, and attitude itself does not significantly affect purchase intentions.

Financial incentives introduced by the Indonesian government, including tax reductions, have been effective in boosting EV purchase intentions. However, EV adoption remains limited among lower-middle-income groups, with higher-income groups being the primary adopters. Knowledge about EV technology and the performance of these vehicles plays a critical role in shaping positive attitudes and increasing purchase intentions. Conversely, perceived risks regarding EV safety and performance remain significant barriers to adoption.

Recommendations

To increase EV adoption, policymakers and the EV industry should focus on addressing barriers to adoption, such as perceived risks and limited accessibility for lower-income groups. Efforts should prioritize fostering positive attitudes by educating consumers about EV performance, benefits, and environmental advantages. Collaborative outreach programs between government institutions and EV manufacturers can enhance public awareness and understanding of EVs' advantages.

Future research could incorporate additional variables, such as cultural orientation (Luo et al., 2014; Song et al., 2022; Sreen et al., 2018), to explore societal norms and their influence on EV adoption. Expanding the Technological Acceptance Model (TAM) to include perceived ease of use (Jaiswal et al., 2021; Zhang et al., 2022) and perceived value (Hu et al., 2022) would further refine an understanding of consumer behavior.

The geographical scope should be expanded beyond Batam City to encompass regional variations in attitudes, intentions, and the effectiveness of financial incentives. Broader coverage would provide valuable insights into diverse consumer behaviors and preferences across Indonesia, enabling the development of more inclusive policies tailored to different demographic and socioeconomic segments.

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