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Analysis Of Factors Influencing Consumer Purchase Intention For Electric Cars: A Case Study In Greater Jakarta

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Abstract

The demand for electric cars has significantly increased in recent years, but it represents only a small fraction of the total new vehicles sold globally. This study aims to analyze the factors influencing consumer purchase intentions towards electric cars in the Greater Jakarta area (Jabodetabek). Using a survey method, data were collected from individuals who are considered capable of purchasing electric cars, either through installment plans or cash payments, and analyzed using partial least squares structural equation modeling (PLS-SEM) to test the research hypotheses. The results indicate that government incentives, ease of access to charging infrastructure, perception of resale value, product diversification, social influence, environmental concern, and consumer attitudes significantly and positively influence purchase intentions towards electric cars. However, the perception of purchase price did not show a significant effect. The findings suggest that strategic initiatives by policymakers and manufacturers, such as continuous government incentives, expansion of charging infrastructure, and effective marketing strategies leveraging social influence and environmental benefits, are crucial for promoting electric car adoption in Jabodetabek. This study provides valuable insights for understanding consumer behavior towards electric cars in emerging markets and offers useful information for enhancing market penetration.

INTRODUCTION

Facing the challenges of global warming and rising air pollution, sustainable energy consumption is an important focus in global policy. According to the International Energy Agency (IEA), in 2022, CO_2 emissions produced from motor vehicles represent around 23% of the world's total carbon emissions. The transportation sector is the sector with the fastest growth in

Greenhouse Gas (GHG) emissions. It is estimated that its contribution will reach more than 30% of total global GHG emissions in the future (UNEP, 2023). In addition, the transportation sector is also a major producer of short-term climate pollutants and contributes greatly to air pollution.

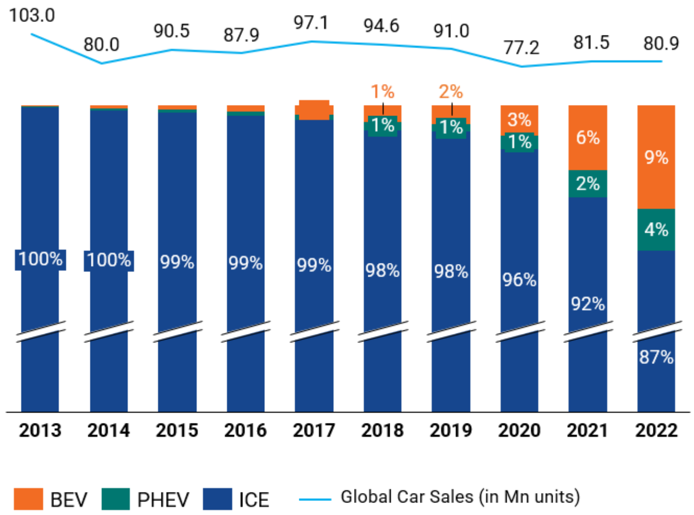
Data shows that the number of global motor vehicles is expected to double by 2050, with more than 90% of future vehicle growth occurring in low- and middle-income countries (UNEP, 2023). Indonesia, as one of the middle-income countries (World Bank, 2023), has a role in the growth of this global vehicle.

To achieve a cleaner transportation sector, a combination of policies implemented globally is needed. These policies include: better urban design, safe and comfortable pedestrian and cyclist facilities, improved public transportation, and a cleaner and more efficient fleet of vehicles on highways, including electric vehicles (UNEP, 2023). Vehicle electrification is one of the most promising steps in decarbonizing the transportation system, and is one of the various efforts to create a more sustainable and environmentally friendly transportation sector. In addition, to meet the Paris Agreement's targets on climate change and to reduce growing air pollution, it is important for low- and middle-income countries, including Indonesia, to be part of the global shift towards zero-emission electric mobility.

The land transportation sector is currently shifting towards a more sustainable system. Electric vehicles, especially Battery Electric Vehicles (BEVs) powered by low-emission electricity, have great potential to drastically reduce greenhouse gas (GHG) emissions and at the same time improve air quality (Mehlig et al., 2023).

In recent years, the development of electric cars has shown a significant increase. According to statistical data from the International Energy Agency (IEA) in 2023, BEV (Battery Electric Vehicle) car sales increased from 4.6 million in 2021, to more than 7.3 million units in 2022, which shows an increase of 59% from 2021 which can be seen in Figure 1.

Figure 1 Car Sales In The Global Market (IEA, 2023)



Likewise with PHEV (Plug-In Hybrid Electric Vehicle) cars or commonly called hybrid cars. Where hybrid cars experienced an increase in sales also from 2021 by 1.9 million units, to 2.9 million units in 2022, which shows an increase of 53%.

This research will focus on the intention to purchase BEV (Battery Electic Vehicle) electric cars considering that the goal of electrification from all countries globally is to achieve Zero

Emission Vehicle (ZEV). Where countries in Europe have targeted to ban the sale of ICE (Internal Combustion Engine) cars or only sell ZEV cars starting from 2025 to Norway, followed by Ireland, the Netherlands, and Slovenia in 2030. As well as other countries with a maximum time of 2045 (Tu, 2019). Meanwhile, Indonesia itself will reach 100% of ZEV sales by 2060 (Ministry of Finance, 2022).

The development of electric vehicles in Indonesia is predicted to be more massive in the future along with the flow of investment from electric vehicle manufacturers. The Government of Indonesia has issued Presidential Regulation 79 of 2023 as an update of Presidential Regulation 55 of 2019 to accelerate the development of the electric vehicle ecosystem in Indonesia. Until the beginning of the fourth quarter of 2023, domestic sales of electric cars were recorded at 11,916 units with 911 Public Electric Vehicle Charging Stations (SPKLU) (Coordinating Ministry, 2023). Where the Government has a target to reach 2 million units of electric cars on the road in Indonesia by 2030. Along with the target of providing SPKLU around 30 thousand units (Ministry of Energy and Mineral Resources, 2021).

Various countries have adopted policies to increase the use of energy-efficient vehicles, such as electric vehicles, in response to growing awareness of the benefits of such vehicles in energy conservation and environmental protection. However, despite claims from consumers about their concern about environmental issues and their positive attitudes, this has not been fully reflected in the purchase behavior of energy-efficient vehicles (Wang, 2022).

Despite many empirical studies on the adoption of electric vehicles and their advantages, the adoption rate of electric cars is still below expectations. Despite the fact that customer preferences for electric vehicles vary depending on a combination of symbolic, environmental, economic, and pro-social benefits, there is a lack of research that addresses the various variables that influence the adoption of electric vehicles (Kumar and Alok, 2020). Research on interest in electric vehicles in Indonesia is still relatively minimal. Previous research has mostly focused on developed countries, which have different geographical conditions, culture, infrastructure, and living standards from Indonesia. Therefore, special research is needed in Indonesia to find out the factors that affect the interest of the Indonesian people in electric vehicles. This is important to support the government's program in increasing the adoption of electric vehicles in Indonesia.

These identified factors include various aspects that affect consumer purchase intention. Such as macro-level factors including financial incentives from the government, odd-even regulatory policies in Jakarta, and their availability (Khurana, 2020). Then the product-level factors, namely battery life, purchase cost, mileage, and charging time are considered product-level factors (Habich-Sobiegalla, 2018), which in this study is simplified into product diversification. Another factor is price, which is also confirmed as a key element in consumer preferences in buying electric vehicles according to De Rubens (2018). In this study, the price is divided into two additional variables, namely the purchase price and the resale price, to determine a more specific influence on purchase intent.

The study identified the factors influencing interest in buying electric cars in Greater Jakarta, Indonesia's economic hub, with a focus on the influence of environmental and sustainability concerns as well as other factors such as government incentives, infrastructure, and prices. Consumer attitudes towards electric cars are considered an important factor influencing purchase intentions. The research aims to provide in-depth insights to governments, the automotive industry, and academics on consumer behavior related to the adoption of electric cars, with the hope of supporting environmental sustainability efforts and responsible economic growth. The limitations of the study include focusing on the Greater Jakarta area, the exclusion of non-electric cars, and the selection of certain variables that are relevant to the research objectives. It is hoped that the results of this study will provide a better understanding and more appropriate recommendations to increase the adoption of electric cars in Greater Jakarta.

LITERATURE REVIEW

Consumer behavior is the study of the processes involved when individuals or groups select, purchase, use, or dispose of products, services, ideas, or experiences to satisfy needs and wants (Solomon, 2020). In green products, consumer purchasing behavior is influenced by two variables: socio-environmental concern and the use of reported information on socio-environmental commitments (Rossi and Rivetti,2022).

Sustainable consumption refers to patterns of reducing consumption of natural resources, changing lifestyles and consuming environmentally friendly products to meet the needs of present and future generations (Biswas and Roy, 2014). Electric vehicles are a vehicle with relatively new technology. Consumer behavior towards the acceptance of new technology has been widely studied in previous studies.

The Technology Acceptance Model (TAM) is a model framework that is commonly used to predict the adoption of new technologies using a perceptual and motivational perspective (Braun, 2013). From a social and control perspective, the Theory of Planned Behavior has been used to investigate the impact on behavioral intentions of three factors, namely attitude, perceived norms, and perceived behavioral control (Ajzen, 2002).

Environmentally friendly behavior is defined as actual behavior carried out by a person by carrying out activities that can protect the environment and buying environmentally friendly products (Fraj & Martinez, 2006). One aspect that makes consumers interested in buying electric cars is the green lifestyle. Environmentally friendly vehicles are alternative fuel vehicles and the impacts resulting from the use of these vehicles are not harmful to the environment. Switching fuel to environmentally friendly fuel is one effort to reduce greenhouse gases and reduce pollution, so that it can help minimize global warming which is largely triggered by vehicle pollution. The pressure on the health system will also be reduced because air quality will be better. This pollution is reduced compared to the use of fuel. The use of conventional oil-fueled cars has an impact on increasing CO2 emissions. The sound produced by electric cars is not noisy and quieter.

METHODS

This study uses the Technology Acceptance Model (TAM) as a framework to analyze factors that affect consumer attitudes and intentions towards the adoption of electric cars in Jakarta. By expanding the focus of previous research, this study specifically explores consumers' intentions to buy a four-wheeled electric car.

The quantitative survey method was used with a questionnaire developed based on the TAM theory. The collected data will be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to identify the main factors that affect the intention to purchase an electric car. In data collection, the non-probability sampling method was chosen with a minimum number of respondents of 200 people.

Online surveys are conducted through Google Forms to reach a wide audience. The results of the analysis are expected to provide an in-depth understanding of the factors that affect the intention to purchase electric cars in Jakarta, as well as provide a basis for the development of effective marketing strategies and public policies.

Results AND DISCUSSION

In this section, the results of the analysis of data that have been obtained by researchers in the field will be discussed. The analysis started from a descriptive analysis to find out the perception of each respondent towards the research variables, then continued with a validity test and reliability test and the last is an inferential analysis using Smart PLS. The variables in this study are the benefits of government incentives, ease of access to charging infrastructure, perception of purchase prices, perception of resale prices, perception of product diversification, social influence, concern for the environment, consumer attitudes towards purchasing electric cars and consumer intentions to buy electric cars which were distributed to 154 respondents.

Overview Of Research Variables

The description of the data from the respondents' responses can be used to enrich the discussion, through the description of the respondents' response data, it can be known how the condition of each variable indicator being studied is.
In order to make it easier to interpret the variables being studied, categorization of respondents' responses was carried out based on respondents' response scores. The categorization of respondents' response scores was carried out based on the maximum score range and the minimum score divided by the number of desired categories using the following formula. The respondents' responses to each statement item were categorized into 4 categories of very good, good, not good and very bad with the following calculations:

- Maximum Index Value = Highest scale = 4
- Minimum Index Value = Lowest scale = 1
- Interval Distance = [maximum value - minimum value] : 4

= (4 –1) : 4 = 0.75
So that the following criteria are obtained:

Table 1 Respondent Characteristics: Guidelines For Categorization Of Respondent Response Scores

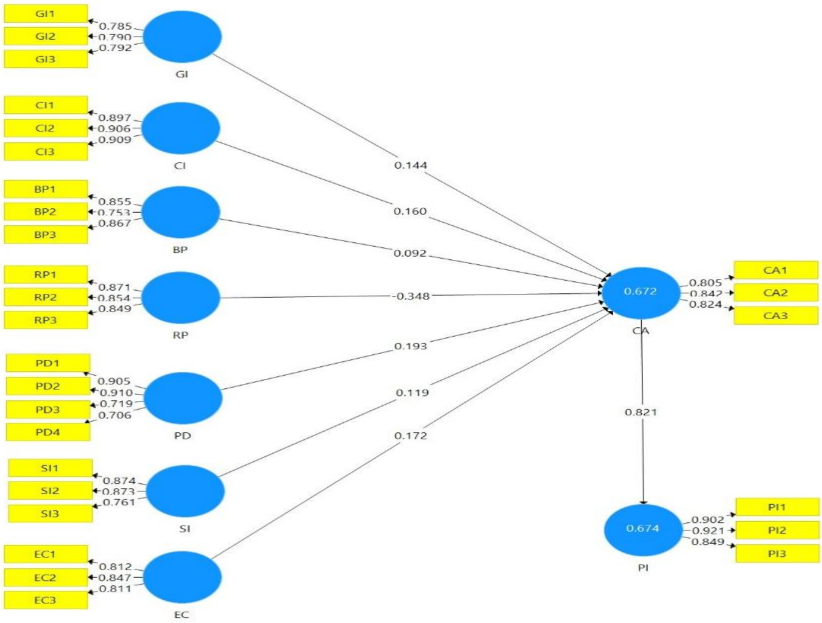
Average Index			Category
3,26	-	4,0	Excellent
2,51	-	3,25	Good
1,76	-	2,50	Bad
1	-	1,75	Very bad

Results of Testing the Partial Least Square Structural Model

In this study, there are two test models carried out by SmartPLS, namely the measurement model or commonly referred to as the outer model and the structural model or commonly referred to as the inner model. First, it starts with the measurement of the model (outer model), which is used to determine the validity and reliability of reflective indicators that connect reflective indicators with latent variables that are tested using three measurement methods. After conducting a confirmatory factor analysis and all indicators were declared valid and reliable. So the next is to test the structural model (inner model) as a whole. This structural model (inner model) is carried out by evaluating the percentage of variance (R2) for the modeled endogenous latent variable influenced by the exogenous latent variable and also testing is carried out with the t-value obtained from bootstrapping to see if the effect is significant or not (Indrawati et al., 2017).

Based on the Partial Least Square estimation method, a Full Structural Model path diagram is obtained as seen in the following figure:

Figure 2 Full Structural Model (PLS Algorithm)



From figure 2. above, it can be seen that the yellow box shows each indicator and the blue circle shows the latent variable. And there are numbers on each arrow that show the validity value of each indicator and test the reliability of the variable construct studied. In the PLS-SEM analysis, the indicator is considered valid if it has a loading factor value greater than 0.70. This shows that the indicator has a significant and strong contribution in measuring latent variables. According to Hair et al. (2017), when the value of an indicator's loading factor is more than 0.70, the indicator is valid because it has a strong enough correlation with the measured construct.

Testing The Measurement Model (Outer Model)

The measurement model (outer model) describes the relationship between the latent variable and the manifest variable (indicator). The evaluation of the measurement model was carried out through *Confirmatory Factor Analysis* (CFA) to test the validity and reliability of latent constructs. Testing measurement models involves convergent validity, discriminatory validity, and reliability.

Convergent validity is related to the principle that the indicators of a construct must have a high correlation with each other. As a general guideline, the *loading factor* value should be more than 0.70 for confirmatory research, while the *loading* value between 0.60-0.70 is still acceptable for exploratory research (Hair et al., 2017). In addition, the *Average Variance Extracted* (AVE) value must be more than 0.50 to indicate good convergence validity (Henseler et al., 2015). In the early stages of the development of the measurement scale, the loading factor value of 0.50-0.60 is still considered quite adequate (Hair et al., 2017).

Reliability tests are carried out to measure the accuracy, consistency, and accuracy of the instrument in measuring the construct. Composite Reliability (CR) is used to assess the reliability of constructs, with a CR value expected to be more than 0.70 for confirmatory research, and a value between 0.60-0.70 is still acceptable for exploratory research (Hair et al., 2017).

Covergent Validity

Convergent validity is carried out to test the level of an accurate item to measure the object of research. In this study, *a loading factor test was used*. The following are the results of the *loading factor score.*

Table 2 Convergent Validity Test

Variable	Indicator	Loading Factor	Information
Benefits of government incentives	GI1	0.785	Valid
	GI2	0.790	Valid
	GI3	0.792	Valid
Easy access to charging infrastructure	CI1	0.897	Valid
	CI2	0.906	Valid
	CI3	0.909	Valid
Perception of purchase price	BP1	0.855	Valid
	BP2	0.753	Valid
	BP3	0.867	Valid
Perception of resale price	RP1	0.871	Valid
	RP2	0.854	Valid
	RP3	0.849	Valid
Perception of product diversification	PD1	0.905	Valid
	PD2	0.910	Valid
	PD3	0.719	Valid
	PD4	0.706	Valid
Social Influence	SI1	0.874	Valid
	SI2	0.873	Valid
	SI3	0.761	Valid
Concern for the environment	EC1	0.812	Valid
	EC2	0.847	Valid
	EC3	0.811	Valid
Consumer attitudes towards buying electric cars	CA1	0.805	Valid
	CA2	0.842	Valid
	CA3	0.824	Valid
Consumer intent to buy an electric car	PI1	0.902	Valid
	PI2	0.921	Valid
	PI3	0.849	Valid

Source : Researcher Data

The table above provides information about the loading factor value for each manifest variable, nilai *loading factor* of all indicators for the latent variable shows >0.7, so that all of these indicators are declared valid.

Tabel 3 Average Variance Extracted (AVE)

Variable	Average Variance Extracted (AVE)
Benefits of government incentives (GI)	0.622
Easy access to charging infrastructure (CI)	0.818
Perception of purchase price (BP)	0.683
Perception of resale price (RP)	0.736
Perception of product diversification (PD)	0.666
Social Influence (SI)	0.702
Environmental Concern (EC)	0.678
Consumer attitudes towards the purchase of electric cars (CA)	0.679
Consumer intention to buy an electric car (PI)	0.795

In the table above, it can be seen that all variables have an AVE value greater than the specified value, which is 0.5. So that all variables are declared valid in explaining the latent variables which shows that the use of the manifest variable has met the requirements of AVE.

Therefore, all manifest variables are declared to have met the requirements of *convergent validity*. *Convergent validity* itself is a validity that is proven if the score obtained by an instrument that measures a concept or measures a concept with different methods has a high correlation.

Discriminant Validity

Discriminant Validity can be seen from the cross-loading *factor* calculation with the construct and the comparison of AVE with the correlation of latent variables. If the correlation between the cost of measurement and the subject of measurement (each indicator) is greater than the size of other buildings, then it is said that the variable has high discriminatory validity. The cross *loading values* are presented as follows:

Table 4 Cross Loading Factor Test Results

	BP	CA	THERE	EC	GIVE	PD	PI	RP	YES
BP1	0.855	0.427	0.338	0.457	0.344	0.470	0.372	-0.177	0.483
BP2	0.753	0.268	0.130	0.223	0.268	0.282	0.265	-0.089	0.215
BP3	0.867	0.436	0.213	0.337	0.231	0.431	0.358	-0.174	0.331
CA1	0.410	0.805	0.468	0.373	0.453	0.503	0.578	-0.484	0.477
CA2	0.432	0.842	0.388	0.440	0.346	0.462	0.607	-0.461	0.428
CA3	0.331	0.824	0.342	0.431	0.496	0.498	0.817	-0.545	0.413
CI1	0.268	0.453	0.897	0.294	0.451	0.325	0.418	-0.260	0.320
CI2	0.259	0.421	0.906	0.227	0.281	0.270	0.410	-0.266	0.285
CI3	0.252	0.430	0.909	0.145	0.278	0.280	0.399	-0.233	0.264
EC1	0.263	0.375	0.136	0.812	0.230	0.209	0.320	-0.251	0.355
EC2	0.275	0.429	0.265	0.847	0.296	0.206	0.417	-0.252	0.331
EC3	0.500	0.437	0.201	0.811	0.227	0.341	0.377	-0.221	0.323
GI1	0.154	0.490	0.386	0.292	0.785	0.333	0.539	-0.301	0.362
GI2	0.350	0.366	0.245	0.194	0.790	0.341	0.406	-0.178	0.433
GI3	0.333	0.371	0.226	0.220	0.792	0.316	0.398	-0.206	0.344
PD1	0.441	0.549	0.254	0.298	0.371	0.905	0.536	-0.392	0.394
PD2	0.400	0.521	0.304	0.255	0.415	0.910	0.525	-0.350	0.450
PD3	0.370	0.361	0.235	0.127	0.319	0.719	0.279	-0.131	0.357
PD4	0.390	0.474	0.261	0.297	0.254	0.706	0.413	-0.317	0.380
PI1	0.366	0.778	0.362	0.431	0.500	0.489	0.902	-0.529	0.396
PI2	0.352	0.711	0.409	0.363	0.523	0.475	0.921	-0.430	0.477
PI3	0.375	0.703	0.444	0.417	0.529	0.514	0.849	-0.376	0.500
RP1	-0.188	-0.510	-0.238	-0.236	-0.320	-0.320	-0.466	0.871	-0.237
RP2	-0.171	-0.538	-0.248	-0.207	-0.207	-0.340	-0.456	0.854	-0.157
RP3	-0.117	-0.513	-0.234	-0.312	-0.244	-0.318	-0.370	0.849	-0.269
SI1	0.242	0.354	0.234	0.325	0.380	0.380	0.323	-0.197	0.874
SI2	0.355	0.510	0.277	0.315	0.342	0.404	0.434	-0.220	0.873
SI3	0.464	0.441	0.286	0.383	0.483	0.429	0.503	-0.221	0.761

Based on the table of results from the PLS software shown above, the cross-loading factor value for each indicator with its latent construct is higher than the cross-loading value with other latent constructs. These findings show that each indicator has a stronger correlation with the latent construct it measures compared to other latent constructs. Thus, it can be concluded that the indicators used to measure latent variables have met the requirements for the validity of discrimination. Discriminatory validity is an important aspect of the measurement model, as it ensures that the indicator actually measures the construct in question and does not measure other constructs. According to Hair et al. (2017), the validity of good discrimination is characterized by a higher loading value on the measured construct compared to the cross-loading value on other constructs. In the table presented, all the loading values of the indicators on the construct correspond to higher than the cross-loading values with other constructs, indicating that this measurement model has sufficient discriminatory validity.

Tabel 5 Fornell-Lacker Criterion

	BP	CA	THERE	EC	GIVE	PD	PI	RP	YES
BP	0.827								
CA	0.470	0.824							
THERE	0.288	0.481	0.904						
EC	0.426	0.505	0.247	0.823					
GIVE	0.338	0.529	0.375	0.306	0.789				
PD	0.491	0.593	0.323	0.309	0.419	0.816			
PI	0.409	0.821	0.453	0.454	0.580	0.552	0.892		
RP	-0.185	-0.607	-0.280	-0.292	-0.299	-0.380	-0.502	0.858	
YES	0.432	0.532	0.321	0.408	0.479	0.485	0.511	-0.256	0.838

Based on the results of the PLS software in table 5, it can be seen that the correlation value between the latent construct and the corresponding indicator (diagonal value) is higher than the correlation value with other latent constructs.

This indicates that the indicators used to measure latent variables have met the requirements for the validity of discrimination. Validity of discrimination is one of the important aspects of the measurement model, which can be evaluated using the Fornell-Larcker Criterion.

According to this criterion, the validity of discrimination is considered adequate if the square root of the Average Variance Extracted (AVE) of any latent construct is greater than the correlation of that latent construct with other constructs (Fornell & Larcker, 1981).

In the table presented, the diagonal value (square root of AVE) for each latent construct is higher than the correlation with other constructs, suggesting that this measurement model has good discriminatory validity (Hair et al., 2017).

Reliability Test

The reliability test in Partial Least Square (PLS) can use two methods, namely Composite Reliability (CR) and Cronbach's Alpha, which are presented as follows:

Tabel 6 ***Uji Composite Reliability (CR) And Cronbach's Alpha***

Variable	Cronbach's Alpha	Composite Reliability
Benefits of government incentives (GI)	0.702	0.832
Easy access to charging infrastructure (CI)	0.889	0.931
Perception of purchase price (BP)	0.773	0.866
Perception of resale price (RP)	0.821	0.893
Perception of product diversification (PD)	0.827	0.887
Social Influence (SI)	0.787	0.876
Environmental Concern (EC)	0.763	0.863
Consumer attitudes towards the purchase of electric cars (CA)	0.765	0.864
Consumer intention to buy an electric car (PI)	0.870	0.921

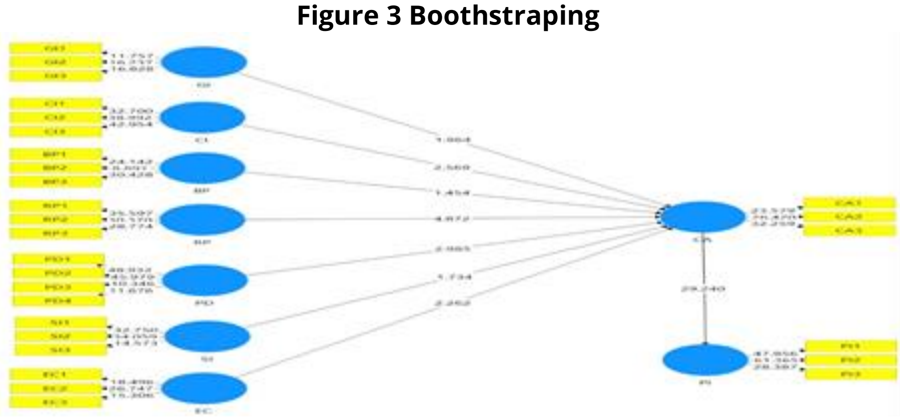
Based on table 6, it can be seen that all variables have high *Composite Reliability* (CR) and *Cronbach's Alpha* values, indicating that the indicators used to measure latent variables have good reliability. *Composite Reliability* (CR) and *Cronbach's Alpha* are two important methods of measuring construct reliability in measurement models. *Cronbach's Alpha* measures the internal reliability of a set of indicators, and a value above 0.70 is considered acceptable, while a value above 0.80 indicates excellent reliability (Hair et al., 2017).

Composite Reliability (CR) provides a more accurate estimate of the reliability of a construct by taking into account the different contributions of each indicator. A CR value greater than 0.70 indicates adequate construct reliability (Hair et al., 2017).

Testing The Structural Model (Inner Model)

The application of this structural model is to test the influence of one latent variable with another latent variable. Based on the figure, we can see the value of path coefficients that connect various latent variables. Using the bootstrapping method, the values of the path coefficients are tested for statistical significance. Values such as t-statistic or p-value can be obtained from the bootstrapping results to determine if the path coefficient is statistically significant. In the figure, it appears that the values of the coefficient of the presented pathways have gone through significance testing, suggesting that the relationships are significant in the context of the structural model being tested. The following is a picture of the results of boothstrapping carried out in this study:

Figure 3 Boothstraping



R square Test

The influence of the dependent variable can be displayed by the value of the R-square. The following is the R-square value.

Table 7 R Squares Results

Variable	R Square
Consumer attitudes towards the purchase of electric cars (CA)	0.672
Consumer intention to buy an electric car (PI)	0.674

Source : Researcher Data

The value of the R-square is used to assess how much variation in the dependent variable can be explained by the independent variables in the structural model. Based on table 4.25, the R-square value for the variable "Consumer attitude towards the purchase of electric cars (CA)" is 0.672, and for the variable "Consumer intention to buy electric cars (PI)" is 0.674. These values show that the tested structural model is able to explain 67.2% and 67.4% of the variation in consumer attitudes and intentions towards the purchase of electric cars, respectively. According to Hair et al. (2017), an R-square value of 0.50 or more indicates that the model has moderate to high ability to explain data variations, so it can be concluded that this model is effective in explaining factors that affect consumer attitudes and intentions in the context of this study.

F^2 ***Effect Size Test***

The F2 Effect Size test is used to evaluate the relative influence of each independent variable on the dependent variable in the structural model. The value ***of F2*** provides information about how much each independent variable affects the dependent variable, which cannot be explained by the R-square value alone. According to Hair et al. (2017), the F2 value is interpreted as follows: ***F2*** ≥ 0.02 indicates a small effect, ***F2*** ≥ 0.15 indicates a moderate effect, and ***F2*** ≥ 0.35 indicates a large effect, with the following details:

Table 8 *F2* Effect Size Test

Influence	Effect Size	Information
Benefits of government incentives (GI)-->Consumer attitudes towards the purchase of electric cars (CA)	0.042	Small Effect
Ease of access to charging infrastructure (CI)-->Consumer attitudes towards the purchase of electric cars (CA)	0.062	Small Effect
Perception of purchase price (BP)-->Consumer attitude towards electric car purchase (CA)	0.027	Small Effect
Perception of resale price (RP)-->Consumer attitude towards electric car purchase (CA)	0.291	Medium Influence
Perception of product diversification (PD)-->Consumer attitudes towards the purchase of electric cars (CA)	0.067	Small Effect
Social Influence (SI)-->Consumer attitudes towards the purchase of electric cars (CA)	0.026	Small Effect
Concern for the environment (EC)-->Consumer attitudes towards the purchase of electric cars (CA)	0.065	Small Effect
Consumer attitudes towards the purchase of electric cars (CA) --> Consumer intentions to buy electric cars (PI)	2.072	Influential

Source : Researcher Data

Based on the table above, it can be seen that the variable "Consumer attitude towards the purchase of electric cars (CA)" has a great influence on "Consumer intention to buy electric cars (PI)" with an ***F2*** value of 2.072, indicating that consumer attitudes are a very strong predictor of purchase intention. This emphasizes the importance of a positive attitude in increasing consumer intentions to buy electric cars. And the variable "Perception of resale price (RP)" has a moderate influence on "Consumer attitude towards electric car purchase (CA)" with an ***F2*** value of 0.291.

Predictive Relevance (Q2)

Q-square measures how well the observance value generated by the model and also the estimation of its parameters. A Q-square value greater than 0 (zero) indicates that the model has a predictive relevance, while a Q-square value less than 0 (zero) indicates that the model does not have a predictive relevance. To calculate Q2 can be used the formula, as follows:

$Q2 = 1-(1-R1^2)(1-R2^2)$

$Q2 = 1 – (1-0,672)(1-0,674)$

$Q2 = 1 – (0,328)(0,326)$

$Q2 = 1 – 0,107$

$Q2 = 0,893$

The Predictive Relevance (Q^2) test measures how well the observation value produced by the model and its parameter estimation in PLS-SEM analysis. A Q^2 value greater than 0 indicates that the model has predictive relevance, which means that the model is able to predict dependent variables with good accuracy (Hair et al., 2017). From the figure shown, the calculation of the Q^2 value using the R^2 value of "Consumer attitude towards the purchase of electric cars (CA)" of 0.672 and "Consumer intention to buy electric cars (PI)" of 0.674 results in a Q^2 value of 0.893. This value indicates that the model has very high predictive relevance, indicating that the independent variables in the model make a significant contribution in explaining the variation of dependent variables. Thus, the tested model can be considered accurate in predicting consumer attitudes and intentions regarding the purchase of electric cars.

Evaluasi Goodness Of Fit

The Goodness of Fit (GoF) index is used to validate the model as a whole, by combining the performance of the measurement model (outer model) and the structural model (inner model). GoF is calculated based on the average AVE (Average Variance Extracted) and the average R^2, which are multiplied and taken from the root. Here is the Gof index formula:

$$\boldsymbol{Gof = \sqrt{rata - rata\ AVE\ x\ rata - rata\ R2}}$$

$$\boldsymbol{Gof = \sqrt{0,709\ x\ 0,673}}$$

$$\boldsymbol{Gof = \sqrt{0,477} = 0.691}$$

From the calculations shown in the figure, a GoF value of 0.691 indicates that the model has a large Goodness of Fit, indicating an excellent model fit. This value is well above the 0.36 threshold used to categorize large GoF (Hair et al., 2017). Thus, it can be concluded that the tested model is not only valid for each construct, but also shows good performance in describing the relationships between constructs in the model as a whole.

Hypothesis Test Analysis

This study uses path coefficients and t-values to test hypotheses about the factors that affect consumers' intention to buy electric cars. The results show that government incentives and easy access to charging infrastructure have a significant positive influence on consumer attitudes towards electric car purchases. However, the perception of purchase prices and product diversification has no significant effect. In contrast, perception of resale prices, social influence, environmental concerns, and consumer attitudes towards electric cars all have a significant positive influence on purchase intentions. It emphasizes the importance of government incentives, easily accessible charging infrastructure, as well as factors such as resale prices, social influence, and environmental concerns in increasing consumer adoption of electric vehicles.

CONCLUSION

This study highlights the factors that affect consumer purchase intentions for electric cars in the Greater Jakarta area. The findings show that government incentives, ease of access to charging infrastructure, perception of resale prices, product diversification, social influence, and concern for the environment play an important role in shaping consumer attitudes and intentions. The managerial implications of this study emphasize the need for strong government incentive strategies, improved charging infrastructure, product diversification, social influence through marketing campaigns, environmental awareness, and competitive pricing. However, this study has limitations such as limited geographical coverage and uneven samples. Suggestions for further research include expanding geographic coverage, using more varied measurement scales, and more representative sampling. It is hoped that future research can provide more comprehensive and accurate insights to support strategies for promoting the adoption of electric vehicles in various regions.

SUGGESTION

Based on the article's content, here are suggestions to improve the research or discussion on factors influencing consumer purchase intentions for electric cars in Greater Jakarta:

1. Expanding Geographical Scope: The study focuses on Greater Jakarta, but consumer behavior might vary across Indonesia. Expanding the research to include other regions could provide a more comprehensive understanding of electric vehicle (EV) adoption in the country.
2. Incorporate More Variables: While the study already covers a broad range of factors (government incentives, infrastructure, prices, etc.), future research could include additional variables such as consumer knowledge of electric vehicle technology, perceived risks (such as battery life or maintenance issues), and brand loyalty.
3. Longitudinal Study: A follow-up study over a longer period could track changes in consumer behavior as government policies evolve and as the market for electric vehicles in Indonesia matures. This would provide insights into whether factors like government incentives or infrastructure improvements lead to sustained changes in purchase behavior.
4. Behavioral and Psychological Analysis: Incorporating theories from behavioral economics or psychology, such as loss aversion (fear of losing out by not adopting new technology) or social proof (influence of others' decisions on one’s purchase), could enrich the analysis of consumer attitudes.
5. Comparative Analysis: Comparing the factors influencing consumer behavior in Indonesia with those in other emerging markets or more developed markets could reveal unique aspects of the Indonesian market and provide lessons for other countries at similar stages of EV adoption.

These suggestions could offer a deeper, more nuanced understanding of the factors that drive or hinder the adoption of electric vehicles in Indonesia.

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