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Influential Factors Adoption Intention to Use Electric Vehicle in Indonesia: Extended Theory of Planned Behaviour

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Abstract – *The primary goal of the thesis was to examine the factors that affect the willingness of people in Indonesia to adopt Electric Vehicles (EVs). Given the pressing need in Indonesia to address energy shortages and reduce greenhouse gas emissions, this research aimed to investigate the elements that influence people's inclination to use EVs. In this study, questionnaires were used as a means of measurement. Respondents were provided with a brief explanation before completing the survey. Using an extended TPB (Theory of Planned Behavior) model, the research analyzed the adoption intentions of 310 respondents from Indonesia, following a minimum sample guideline of 200. The collected data was analyzed using smartPLS4 to extract insights. The empirical analysis of the research focused on five key factors: attitude, subjective norms, perceived behavioral control, environmental concern, and moral norms. Notably, the empirical results showed that while attitude had an insignificant impact on the adoption intention of EVs in Indonesia, the other factors subjective norms, perceived behavioral control, environmental concern, and moral norms had a significant and positive influence on the intention to embrace electric vehicles in the country. Based on these findings, it can be concluded that the extended TPB model is suitable for predicting the adoption intention of electric vehicles. It mentioned by successful results of extended TPB in India by Shalender & Sharma (2021). Considering these results, the study explores the implications for EV adoption in Indonesia, offering valuable insights and recommendations for future research and for the Indonesian government's decision-making process regarding the factors that influence EV adoption.*

Keywords: *Electric Vehicle (EVs); Greenhouse gas emission (GHG); EV Adoption; Sustainability*

I. INTRODUCTION

Electric vehicles are to solve emerging social and transportation problems to aim of technological development (Oelschlaeger, 2019), as well as reduce pollution level (Ajanovic, 2018). As a largest country, Indonesia has a big contribution of the region's energy consumption. Population growth is a main factor of the demands of the energy always increase every year, with 1,25% rate rise population its slightly lower compare period 2000-2010 with 1,49% rate (BPS, 2020). Indonesia has 143,797 million vehicles (BPS, 2021) with a 6.13% increase in number of vehicles each year (BPS, 2020). Indonesia is 20 of biggest country contribution for pollution with 34.3µg/m³ (IQAir, 2021). With high contribution in pollution Indonesia needs attention to be concern to this significant rise in usage. Large cities with a high population such as Jakarta, Surabaya, Medan, contribute more than 50% of air pollution from vehicles (Santoso et al, 2020). According to air quality index Indonesia have 126 values of index which means its unhealthy for sensitive group that may experience health effects (AQI, 2022). Increasing number of vehicles affect air pollution that can cause various disorders in the human respiratory system (Zhong, 2019).

The declining oil production and increasing consumption have resulted in Indonesia being a net oil importer since 2004 (PWC, 2020). Gas production for 2018 was 1.14 million barrels of oil equivalent per day which decreased slightly, 0.01 mboped from previous year (Trade, 2021). Over last decade, transportation-related diesel consumption grew by 10% and gasoline consumption grew 15%, according to the Indonesia Ministry of Energy and Mineral Resources (MEMR).

This led the government to gradually but substantially scale-back the domestic fuel subsidy during 2009-2014 (PWC, 2020). Potential of nickel has been considered due the energy demand in Indonesia, more 72 million of tons nickel are expected as a resource of a new energy, nickel resource in Indonesia have 52% contribute of nickel resource of the world. For future industry nickel can be develop into battery industry which is a solution for oil and gas transition to fulfill energy demand consumption in Indonesia (ESDM, 2021). Economic growth in 2019 decreased slightly to 5% compared to the previous year at 5.2%. Indonesia is unhealthy for state finance (BI, 2020), According to Bank Indonesia data collected from 2008-2019, the government average burden of fuel subsidies was 9,67% (OECD, 2019). Nickel industry will help to economic growth for Indonesia, data shown nickel industry give 13% of employment opportunities, Program Pengembangan, dan Pemberdayaan Masyarakat (PPM) reach 100-billion-rupiah, royalty from tax of nickel four times bigger past 5 year, and huge amount of investment from other country with value of US$ 814 million (ESDM, 2021).

An alternative method was given to reduce emission and lower dependability on fossil-based fuel (FF) with switching oil-fueled vehicles to switch to electric motorized one. The international energy agency predicted that electric vehicles could be vital for more sustainable transportation. (Maghfifiroh, 2021). Regarding the acceleration program for Battery Electric Vehicles for Road Transportation was enacted in Presidential Regulation Number 55-year 2019 to legal umbrella for Indonesian electric vehicle development and creates a domino effect for several ministries to start electric vehicle (EV) projects in Indonesia (PP no 55, 2019). In addition, to stimulate people willingness to switch, buy, and use electric vehicle the Indonesian government gives approximately 75% discount to electric motorcycle owners in tax incentives on transfer of name for motorized vehicles (BBN-KB) (Wirabrata, 2019).

Various environmental issues due to high number of motorized vehicle users, thereby causing climate change, global warming, scarcity regarding Indonesian oil resources, and pollution that is harmful to health, that make electric vehicle use become important in Indonesia. The challenge to get intension of people in Indonesia are they preference or expectations regarding electric vehicles, considering the electric vehicles are new in Indonesia. Price, maintenance, durability, and supporting infrastructure are considered for customers as a factor in assessing electric vehicles (Wibrata, 2019). Indonesia electric vehicle programs still contra due to perceptions of the limited mileage factor for batteries cause people still skepticism towards it, limited of public electric charging station (SPKLU), production cost, and prolonged charging time comparing to using conventional oil-fueled vehicles (Subekti, 2014). Study in Singapore show important factor to consider beside the other is charging behaviour. A full estimation model (FEM) is suggested to be implemented beside two other two behaviour models due to the lack of data. Charging stations for EV is relatively low cost compared to fossil fuel, this price sensitivity can be an important factor to shift the charging demand to avoid bottle necks in the system. Compared to study in Singapore, Indonesia have study about charging station, the results of the study show the main reason is supply and demand, policy dividends, relative abundance of social capital, and technological advances that affect for constructing a suitable charging infrastructure. The government should provide legitimate support and adopt relevant policies from the five-factor perspective of politics, culture, society, ecological civilization, and economy, particularly in the fiscal area. The government should develop standards for the charging infrastructure as soon as possible because we far away from the other country that have been applied charging station since last 5 years like a Singapore, as well as providing specific suggestion in terms of subsidies, direct investment, government procurement, various tax-related privileges, and budgetary arrangements for fiscal expenditure, such as increasing financial support for scientific research into the charging infrastructure (Yang, et all, 2016). Due to high numbers of users is a parameter showing that demand of electric vehicles is still high and studied that several factors need government support. The government is optimistic, and support Indonesian market will gradually accept electric vehicles according to PERMEN ESDM Number 13-year 2020.

This research is concern in Theory of Planned Behavior (TPB) models, with Attitude (ATT), Subjective Norm (SN), Perceived Behavior Control (PBC), Environmental Concern (EC), and Moral Norm (MN) capable of influencing an intention individual behavior in use the EVs that researchers learn by previous research (Shalender and Sharma, 2020). The process of analyzing the theoretical approach, model framework, and the hypothesis will be described in chapter 2. The method will be described in chapter 3 including preparing the instrument for design questioner and model of the ETPB.

II. METHODS

2.1 Model

Figure 1 provides an overview of the Extended Theory of Planned Behavior (ETPB), which had been previously established in Shalender and Sharma's (2020) research on the intention to adopt electric vehicles in India. Shalender and Sharma's (2020) study delved into the adoption intention of electric vehicles within the Indian context. In this current study, the ETPB developed by Shalender and Sharma (2020) demonstrated its efficacy as a valuable tool for predicting the intention to adopt electric vehicles. This success prompted the adaptation of the ETPB framework for the present investigation into Indonesian consumers' adoption intentions regarding electric vehicles.

Figure 1. Extended theory of planned behaviour (own illustration based on the model of Ajzen (1991), adapted from Shalender & Sharma's (2020) model of EV adoption intention)

2.2 Methodology

This chapter outlines the methodological process employed to address the research questions and test the hypotheses. Initially, the samples and research design of the online study are introduced. This is followed by an explanation of the research material and the measurement tools utilized, along with a description of the structure and execution of the empirical study.

This study uses a survey questionnaire for testing the hypotheses. To examine non-response bias, the study followed the guidelines outlined by Armstrong and Overton (1977). During the questionnaire distribution process, respondents were asked to provide information on their demographic and social factors, allowing for the identification of those who had responded and those who had not. The collected responses were categorized into three groups: (1) accurate respondents who completed the entire questionnaire, (2) inaccurate respondents who returned incomplete questionnaires, and (3) non-respondents who did not return the questionnaire at all. The test results indicated no significant differences between the demographic and social characteristics of these groups and their corresponding variables. Therefore, it can be inferred that the study is not affected by any bias associated with non-response.

2.3 Research Hypothesis

Individual behaviour discussed through the TPB approach based on information analysis results and logical judgments to reduce negative consequences due to poor decisions.

Hypothesis 1 (H1). Attitude (ATT) positively affects an adoption intention to use using electric vehicles in Indonesia.
Hypothesis 2 (H2). Subjective Norm (SN) positively affects an adoption intention to use using electric vehicles in Indonesia.
Hypothesis 3 (H3). Perceived behaviour control (PBC) positively affects an adoption intention to use using electric vehicles in Indonesia.
Hypothesis 4 (H4). Environmental concern (EC) positively affects an adoption intention to use using electric vehicles in Indonesia.
Hypothesis 5 (H5). Moral norms (MN) positively affect an adoption intention to use using electric vehicles in Indonesia.

2.4 Population and Sample

2.4.1 Design

In this research, an inquiry was distributed to individuals residing in Indonesia. The survey gathered data by having the participants evaluate themselves. A specific question was included to apply purposive sampling judgment technique. Respondents were required to be at least 17 years old, in accordance with Indonesian driver's license regulations. The questionnaire was exclusively distributed online through a link generated by Google Forms.

2.4.2 Data Collection

The survey link was disseminated through various channels, including the author's personal network on platforms like WhatsApp and Facebook, as well as via email. It was accompanied by a concise introductory statement presented under the survey title "Intensi Masyarakat Dalam Penggunaan Kendaraan Listrik (Electric Vehicle) di Indonesia." Participants were also encouraged to share the study with others.

To initiate the study, participants were provided with a brief explanation of the survey's background and an introductory overview of the procedure. Subsequently, they were informed about the measures taken to ensure the confidentiality and anonymity of their data. Following this, participants provided their consent to participate in the study.

2.4.3 Sample

The sample is the population who understand electric vehicles, research design the question of the questioner that answers an acknowledgement about electric vehicles. The minimum sample target of this research is 90 samples. This model is prediction model with statistic nonparametric using PLS-SEM, according to (Hair, 2017) minimum of sample is 10 multiply total of the indicators. This research consists of 20 indicators which means the minimum sample is 200 samples.

2.5 Validity and Reliability

Composite reliability is to measure the validity and reliability. By using composite reliability, PLS-SEM is able to accommodate different indicator reliability, while also avoiding the underestimation associated with Cronbach's alpha. The value of Cronbach is 0.7 or higher. To evaluate reflect indicators is the assessment of validity (Hair et al, 2019). Support is provided for convergent validity when each item has outer loading above 0.7 and when each construct average variance extracted (AVE) is 0.5 or higher. The AVE is the grand mean value of the squared loadings of a set of indicators (Hair et al, 2014) and is equivalent to the communality of a construct. AVE of 0.50 shows that the construct explains more than half of the variance of its indicators (Hair et al, 2019).

Once the reliability and validity of the outer models is established, several steps need to be taken to evaluate the hypothesized relationship within the inner model. Instead, the assessment of the model quality is based on its ability to predict the endogenous constructs. The following criteria facilitate this assessment: Coefficient of determination (R^2), cross-validated redundancy (Q^2), path coefficient, and the effect size (f^2) (Hair et al, 2019).

2.6 Analysis Method

This research uses linear regression to explain systematic or statistical model. Linear regression analysis is used to predict the value of a variable based on the value of another variable. The variable you want to predict is called the dependent variable. The variable you are using to predict the other variable's value is called the independent variable (Ghozali, 2018). As the inner model estimates result from sets of regression analyses, their values and significances can be subject to biases if constructs are highly correlated (Hair et al, 2019).

Coefficient of determination (R^2). The R^2 is a measure of the model's predictive accuracy. Another way to view R^2 is that it represents the exogenous variable's combined effect on the endogenous variables. This effect ranges from 0 to 1 with 1 representing complete predictive accuracy. Because R^2 is embraced by a variety of disciplines, scholars must rely on a "rough" rule of thumb regarding an acceptable R^2, with 0.75, 0.50, 0.25, respectively, describing substantial, moderate, or weak levels of predictive accuracy (Hair et al., 2011; Henseler et al., 2009).

Path coefficients. After running a PLS model, estimates are provided for the path coefficients, which represent the hypothesized relationships linking the constructs. Path coefficient values are standardized on a range from -1 to +1, with coefficients closer to +1 representing strong positive relationships and coefficients closer to -1 indicating strong negative relationships. Based on the f^2 value, the effect size of the omitted construct for a particular endogenous construct can be determined such that 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively, (Cohen, 1988)

III. RESULTS AND DISCUSSION

3.1 Result of Data Collecting and Processing

3.1.1 Collecting and Processing of Respondent Data

The preliminary data collection phase involved a meticulously curated sample of 310 respondents. Utilizing the power of modern technology, we distributed the well-crafted questionnaires via Google Form, reaching out through various social media platforms. Our aim was to capture a diverse demographic representation from Indonesia, ensuring a comprehensive representation of its diverse population. Our intent was to examine thoroughly their intentions to adopt electric vehicles, uncovering the driving forces behind their choices. Through meticulous data collection efforts during this initial phase, we have amassed a wealth of invaluable information, laying a firm and unyielding foundation for our research. The rich insights gained from this diverse dataset will illuminate the myriad factors influencing electric vehicle usage in this vibrant and forward-thinking nation, opening doors to sustainable transportation solutions that align with Indonesia's dynamic landscape.

The data collected could be transferred to PLS-SEM and processed there with the help of an automatic data export from the online tool Google Form. The scales used to measure attitude, subjective norm, perceived behavioral control, moral norm, environmental concerns, and intention electric vehicle adoption were assumed to be at the interval scale level. This assumption was based on the five-point Likert-scale used, where response options were assigned numerical values from one to five. The difference between these values can be interpreted to gauge the respondents' perceptions accurately. Following the reverse coding of negatively worded items, the numerical values of each item within a scale were summed. Subsequently, the mean value was computed for each respective scale. The resulting mean or total scores of each scale serve, akin to the original study, as the operationalization of the variables being investigated.

3.1.2 Demographic Data Processing Results

This research has 310 respondents with results on attachment. This demographic data collection was conducted to determine the intention to use electric vehicle in Indonesia, with the data used being respondent's responses to the EVA1 indicator, "I am willing to adopt an electric vehicle when I adopt a vehicle in the future". Table I This represents the data on electric vehicle intention behavior among individuals in Indonesia collected from 310 respondents in this study.

Table 1. Scale data of Intention to Adopt EV in Indonesia

Scale	Description	Number of Respondents	Percentage
Scale 1	Strongly Disagree	4	1,3%
Scale 2	Disagree	11	3,5%
Scale 3	Neutral	78	25,2%
Scale 4	Agree	118	38,1%
Scale 5	Strongly Agree	99	31,9%
TOTAL		310	100%

Table II This is the result of the demographic data processing for the 310 sample respondents in the study related to the percentage of purchase intention electric vehicle in each category factor within the demographic data.

Tabel II. Demographic Profile Recapitulation of Respondents

Demographic Data	Respondent Percentage (N=310)
In General	100%
Male	51.9%
Female	48.1%
17 – 25 years	35.8%
26 – 34 years	33.9%
35 – 43 years	18.1%
44 – 50 years	5.2%
More than 50 years	7%
Marital Status	

Married	36.5%
Unmarried	63.5%
Working Status	
Government employee	10.32%
Private sector employee	35.8%
Entrepreneur	14.84%
College student	10%
Student	1.94%
Retired	4.84%
Freelance	10.65%
Not working	7.42%
BUMN	1.29%
Doctor	2.9%
Education	
Master's degree	3.55%
Bachelor's degree	59.68%
Undergraduate	19.03%
Highschool	17.74%
Driving License	
Have	84.8%
Don't Have	15.2%
Domicile	
Jakarta	25.5%
Banten	17.4%
Jawa Barat	14.2%
Jawa Tengah	5.2%
Jawa Timur	4.8%
Bali	5.2%
Sulawesi	5.2%
Papua	5.5%
Sumatera	8.4%
Kalimantan	7.7%
Kepulauan Riau	0.3%
NTT	0.3%
Batam	0.3%

3.2 Hypothesis Testing

3.2.1 Data Processing Using PLS-SEM Method

During this phase, the data obtained from respondents will undergo processing using the PLS-SEM approach. The data processing using PLS-SEM consists of various stages, including examining the indicator loadings (loading above 0,708 are recommended, as they indicate that the construct explains more than 50% of the indicator variance, thus providing acceptable item reliability), assessing internal consistency reliability (higher values generally indicate higher levels of reliability), reflective measurement model assessment addresses the convergent validity of each construct measure, and assess discriminant validity. (Hair et al, 2019). Furthermore, an outer loading value > 0.5 can also be considered indicative of a strong relationship with the construct (Chin, 1998; Hulland, 1999).

3.2.1.1 Assessment of Validity

Table III shows the data of Composite Reliability (CR) values for each construct after the improvement (eliminating data does not meet the evaluation criteria of theory of hair the CR and outer loading value < 0,7).

The results presented in Table III indicate that all constructs have Composite Reliability values ≥ 0.7. Therefore, it can be concluded that all constructs are reliable. Table III shows the data of outer loadings values for each indicator after the improvement.

Table III. Assessment of Vaidity Improvement Model

Behavioural Model	Construct	Indicator Code	Outer Loadings Value	AVE	CR
Theory of Planned Behaviour (TPB)	Intention to Adopt EV	EVA1	0,783	0,612	0,759
		EVA3	0,782		
	Attitude	ATT1	0,792	0,717	0,834
		ATT2	0,898		
	Perceived Behavioural Control	PBC2	0,924	0,768	0,868
		PBC3	0,826		
		EC1	0,771	0,626	0,869
		EC2	0,706		
	Environmental concern	EC3	0,856		
		EC4	0,823		
Extended Theory of Planned Behaviour	Moral Norms	MN1	0,728	0,534	0,774
		MN2	0,7		
		MN3	0,763		

The results from Table III reveal that each indicator has an outer loading value of at least 0.7, indicating their validity. Therefore, we can confidently state that all the indicators are valid and reliable measures for their respective constructs. These findings support the suitability of our measurement model in capturing the intended constructs accurately and effectively. The validity of the indicators ensures that the data collected from respondents provides meaningful insights into the factors influencing the intention to use electric vehicles in Indonesia. With reliable indicators in place, we can proceed with more confidence in our subsequent analyses and interpretations, contributing to the robustness of our research findings.

In addition, the convergent validity test also considers the Average Variance Extracted (AVE) values, where constructs are considered valid if the AVE value is ≥ 0.5 (Hair et al., 2019). Table 3 presents the AVE values for each construct after the necessary improvements were made. These AVE values play a crucial role in assessing the convergence of indicators within their respective constructs. The results show that all constructs have AVE values that meet the validity criteria, reinforcing the reliability and validity of the measurement model. This further strengthens the confidence in the research model's ability to accurately measure the intended constructs and provides a solid foundation for the subsequent structural model evaluation.

According to the AVE values presented in Table 3, it can be concluded that all constructs have AVE values of ≥ 0.5, signifying their validity.

3.2.1.2 Discriminant Validity Test

The assessment of discriminant validity has become a widely acknowledged prerequisite for exploring relationships among latent variables. In variance-based structural equation modelling, like partial least squares, the Fornell-Larcker criterion and cross-loading analysis are the prevailing methods for evaluating discriminant validity. However, a simulation study conducted by Henseler, Ringle, and Sarstedt (2015) demonstrates that these approaches might not consistently detect the absence of discriminant validity in common research scenarios. Considering this, the authors propose an alternative method for assessing discriminant validity based on the multitrait-multimethod matrix: the heterotrait-monotrait ratio of correlations (HTMT). If the HTMT value is below 0.90, it indicates that discriminant validity is established between two reflective constructs.

In the initial cross-loading evaluation, certain indicators exhibit values lower than their corresponding latent variables. Consequently, adjustments are necessary. The findings of data processing for HTMT, Cross Loading and Fornell Lacker values after refinement are presented in Table IV and Table V respectively.

Table IV. HTMT Value Improvement Model

	Heterotrait-monotrait ratio (HTMT)
Environmental Concern <-> Attitude	0.517
Intention to adopt EV <-> Attitude	0.657
Intention to adopt EV <-> Environmental Concern	0.791
Moral Norms <-> Attitude	0.468
Moral Norms <-> Environmental Concern	0.700
Moral Norms <-> Intention to adopt EV	0.869
Perceived Behaviour Control <-> Attitude	0.568
Perceived Behaviour Control <-> Environmental Concern	0.658
Perceived Behaviour Control <-> Intention to adopt EV	0.707
Perceived Behaviour Control <-> Moral Norms	0.466
Subjective Norms <-> Attitude	0.188
Subjective Norms <-> Environmental Concern	0.178
Subjective Norms <-> Intention to adopt EV	0.448
Subjective Norms <-> Moral Norms	0.237
Subjective Norms <-> Perceived Behaviour Control	0.122

Table V. Fornell Lacker Value Improvement Model

	ATT	EC	EVA	MN	PBC	SN
Attitude	**0.847**					
Environmental Concern	0.364	**0.791**				
Intention to adopt EV	0.318	0.430	**0.782**			
Moral Norms	0.279	0.469	0.395	**0.731**		
Perceived Behaviour Control	0.369	0.483	0.371	0.300	**0.876**	
Subjective Norms	0.161	0.157	0.271	0.178	0.115	**1.000**

Based on the results of the Cross Loading and Fornell Lacker values, it is evident that all indicators and constructs have correlations higher than their corresponding latent variables. Furthermore, the results of HTMT shown all indicator have value < 0.9 it indicates discriminant validity has been established between two reflective constructs. Therefore, based on the discriminant validity test, all indicators and constructs can be considered valid.

3.3 Path Modelling

Figure 2 displays the outcomes of path modelling conducted on the measurement model (Outer Model) and the structural model (Inner Model) using SMART PLS software after refinement, with the exclusion of all invalid and unreliable indicators.

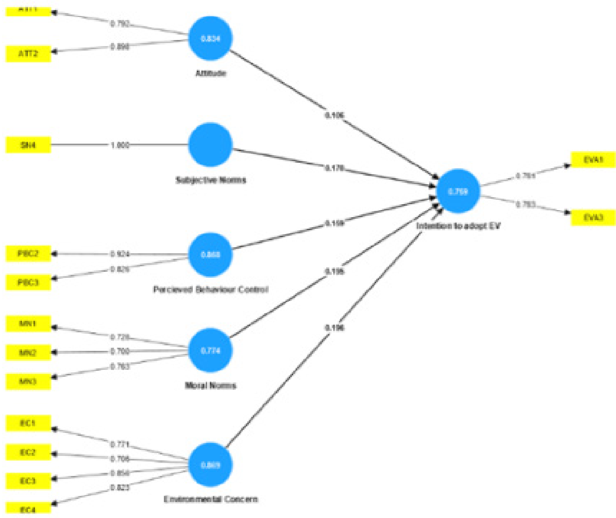

Figure 2. Path Modelling After Improvement

3.4 Evaluation of The Structural Model (Inner Model) After Improvement

During the evaluation of the structural model or inner model, multiple testing stages are involved, including Coefficient of determination (R2), Cross-validated redundancy (Q2), Effect size (f2), and Path Coefficient, which collectively address all research hypotheses.

- **Coefficient of Determination (R^2)**

The R2 square and adjusted R2 tests are used to measure the predictive accuracy of a model, where the R2 square and adjusted R2 values represent the amount of variance in the dependent variable explained by the independent variables. Many researchers interpret the R2 statistic as a measure of their model's predictive power. This interpretation is not entirely correct, however, as the R2 only indicates the model's in-sample explanatory power - it says nothing about the model's out-of-sample predictive power (Hair et al, 2019). It must be supported by Q2, SRMR, PLS Predict, Index GoF, and Robustness Check. Table 10 shows the results of processing the R2 square and adjusted R2 tests on the dependent variables in this study.

Furthermore, to assess the predictive accuracy of the model, the PLS Predict test is executed, which involves comparing the RMSE and MAE values of the PLS model with those of the linear regression model.

Researchers can evaluate the predictive power of a model by utilizing various prediction statistics that measure the extent of prediction error in the indicators of a specific endogenous construct.

The term "error" in this context doesn't refer to a mistake, but rather to residuals. A lower value is preferred, as it represents the disparity between actual values and predicted values.

When assessing prediction errors, it's crucial to consider their distribution. If the errors follow a normal distribution, Root Mean Square Error (RMSE) should be used to gauge a model's predictive effectiveness. However, when the prediction errors exhibit significant asymmetry, noticeable by an extended tail to the left or right in the error distribution (as described by Danks & Ray, 2018), the Mean Absolute Error (MAE) becomes a more suitable prediction metric, as emphasized by Shmueli et al. (2019).

Table VI. Results of PLS Predict Test Processing

Dependent Variable	Q^2	PLS-SEM RMSE	PLS-SEM MAE	LM_ RMSE	LM_ MAE	RMSE PLS-LM
EVA1	0,155	0.839	0,658	0,858	0,682	-0,019
EVA3	0,157	0,875	0,730	0,892	0,740	-0,017

The data presented in Table VI reveals that the majority of measurement items in the proposed PLS model demonstrate lower RMSE and MAE values when compared to the linear regression model (LM). This suggests that the research model possesses a high level of predictive strength.

- **Cross-Validated Redundancy (Q^2)**

In this stage, it is essential to evaluate the predictive relevance of the structural model (outer model). As a rule of thumb, Q2 values higher than 0, 0.25 and 0.50 depict small, medium, and large predictive relevance of the PLS-path model. (Hair et al, 2019). The outcomes of the Outer Cross-Validated Redundancy (Q2) test are displayed in Table VII.

Table VII. Results of Outer Cross-Validated Redundancy

Dependent Variable	Q^2	Explanation
EVA1	0,155	Small
EVA3	0,157	Small

- **Effect Size (f^2)**

Effect Size values are determined by examining the variations resulting from the coefficient of determination (R^2) test. Table 8 presents the Effect Size (f^2) values corresponding to each independent variable.

Path Coefficient

The significance test is carried out to ascertain the significance of each coefficient. Moreover, path coefficient testing is conducted to address all research hypotheses. Table VIII displays the significant values of the influence of each construct.

Table VIII. Result of the hypothesis testing from the Path Coefficient

Hypothesis	*P Values* (<0,05)	Explanation		R^2	Criteria	f^2	Criteria
Attitude -> Intention to Adopt EV	0,091	*H0 Not Accepted*	*Not Significant*			0,013	*Small*
Environmental Concern -> Intention to Adopt EV	*0,012*	*H0 Accepted*	*Significant*			0,039	Small
Moral Norms -> Intention to Adopt EV	*0,001*	*H0 Accepted*	*Significant*	0,288	*Low*	0,026	*Small*
Perceived Behavioural Control -> Intention to Adopt EV	0,017	*H0 Accepted*	Significant			0,035	*Small*
Subjective Norms -> Intention to Adopt EV	*0,001*	*H0 Accepted*	*Significant*			0,041	*Small*

- **Goodness-of-Fit**

During this stage, a fitness assessment is conducted using the Standardized Root Mean Square Residual (SRMR) to evaluate how well the research model fits the data and to prevent model misspecification (Henseler, Hubona, & Ray, 2016). A SRMR value between 0.08 - 0.10, according to the more conservative approach (Hu & Bentler, 1999), is considered acceptable. Table IX presents the SRMR values obtained from the research model fit test.

Table IX. The SRMR value for the goodness-of-fit testing of the research model.

Fit Summary	Saturated Model	Estimated Model
SRMR	0,088	0,088

3.5 Research Findings Discussion

3.5.1 Discussion of Reliability Test Result

The first test is reliability test, The initial assessment of respondent reliability was conducted to gauge the questionnaire's consistency in this study. Hinton et al. (2004) recommended a minimum Cronbach's Alpha (α) value of 0.5. According to Chin (1998), rho_c provides a more accurate estimate of reliability when assuming precise parameter estimates. Table 3 displays the results of the reliability test, showing that each indicator's rho_c value is greater than 0.50.

This suggests that all indicators are reliable, and the questionnaire exhibits consistency, making it a suitable measurement tool for this research.

3.5.2 Discussion of Measurement Model Evaluation Results

The measurement model demonstrates how observable variables collectively represent their latent constructs, and this measurement model is assessed by testing the validity and reliability of each construct. The validity testing is performed in two stages: convergent validity test and discriminant validity test. Meanwhile, the construct's reliability is evaluated based on the internal consistency reliability values.

3.5.2.1 Internal Consistency Reliability

Hair et al. (2019) suggested that the Composite Reliability (CR) values are more suitable for assessing internal consistency reliability as they avoid assuming the same bootstrap for indicators. Indicators are deemed reliable if their CR values fall within the 0.6 to 0.7 range, which is considered "acceptable in exploratory research". CR values ranging from 0.7 to 0.9 are regarded as "satisfactory to good", while values equal to or above 0.95 are problematic as they imply redundancy, potentially compromising construct validity.

The data analysis results presented above indicate that during the initial testing phase, one of the indicators, specifically Intention to Adopt EV (EVA), lacked reliability due to its CR value < 0.7, at 0.630. Following model refinement, all constructs were found to have CR values ≥ 0.7, providing evidence that all indicators are reliable.

3.5.2.2 Assessment of Convergent Validity

The convergent validity test examines the outer loadings, which indicates the correlation between indicators and the measured construct. According to Hair et al. (2019), an indicator is considered valid if its outer loading is > 0.708, and a construct is valid if it has an AVE value ≥ 0.5. Additionally, the value of Outer Loading > 0.5 (Chin, 1998; Hulland, 1999) can also be considered as an indicator of good consistency.

In this study, two tests were conducted based on the criteria by Hair (2019) and Chin (1998). The initial measurement model evaluation revealed that, according to the Hair's theory, some indicators had outer loadings < 0.708, specifically EVA2 (0.182), ATT3 (0.480), SN1 (0.598), SN2 (0.606), SN3 (0.674), and PBC1 (0.669). These six indicators showed insufficient correlation with the construct being measured and were deemed inappropriate or invalid for measuring that construct. Moreover, the AVE values of the constructs "Intention to Adopt EV" and "Subjective Norms" were below 0.5, specifically 0.412 and 0.465, respectively, indicating that these constructs were not valid.

Therefore, improvements were necessary by eliminating the invalid indicators. After the necessary adjustments, it was found that all indicators had outer loadings > 0.5, indicating that all indicators were now valid.

Furthermore, based on the improvement results through the elimination of indicators that did not meet the minimum threshold, it was also found that all constructs had AVE values ≥ 0.5. Previously, the construct "Perceived Behavioral Control" (PBC) had AVE values < 0.5, specifically 0.412 and 0.465. However, after eliminating some indicators, namely EVA2, SN1, SN2, and SN3, the AVE value for PBC increased to 0.612. Therefore, based on the improvement results from the convergent validity test, it can be concluded that all constructs are now considered valid.

3.5.2.3 Assessment of Discriminant Validity

This testing was conducted by considering the Cross Loading and Fornell Lacker values, where according to Hair et al. (2019), the correlation values of each indicator with its respective latent variable should be higher. Based on the results of the discriminant validity test, considering the Cross Loading values, it can be shown that the Cross Loading and Fornell Lacker values indicate that the indicators and constructs have higher correlations with their latent variables. Therefore, based on the discriminant validity test, all indicators and constructs can be considered valid.

Furthermore, based on the evaluation results of the measurement model (outer model) with testing for internal consistency reliability, convergent validity, and discriminant validity, it can be stated that all the involved indicators and constructs are considered valid and reliable. Henseler et al. (2015) suggest a threshold value of 0.90 for structural models in cases where constructs are highly conceptually similar, like cognitive satisfaction, affective satisfaction, and loyalty. In this scenario, an HTMT value exceeding 0.90 would imply a lack of discriminant validity. However, when constructs possess clearer conceptual differences, a more conservative threshold value, such as 0.85, is recommended by Henseler et al. (2015). Alongside these guidelines, bootstrapping can be employed to assess whether the HTMT value significantly deviates from 1.00 (Henseler et al., 2015), or from a lower threshold like 0.85 or 0.90, contingent upon the specific research context (Franke and Sarstedt, 2019). More precisely, researchers can investigate whether the upper limit of the 95 percent confidence interval of HTMT falls below 0.90 or 0.85. the results of Moral Norms <-> Intention to Adopt EV is 0,869.

3.6 Discussion of Structural Model Evaluation Results

In the study conducted by Hair et al. (2020), the assessment of the structural model or inner model consists of various testing phases, such as Coefficient of determination (R2), Cross-validated redundancy (Q2), Effect size (f2), and PLSPredict.

3.6.1 Coefficient of Determination Test (R^2)

This test is conducted to determine the proportion of the variation in the dependent variable that can be explained by the independent variable. In this study, the Coefficient of Determination, represented by R2 square, for the construct "Intention to Adopt EV" is 0.300, while the adjusted R2 for this model is 0.288. The R^2 value ranges from 0 to 1, with higher values indicating a stronger explanatory power of the model. As a general guideline, R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively (Henseler et al., 2009; Hair et al., 2011). However, acceptable R^2 values can vary depending on the context and discipline. In some cases, an R^2 value as low as 0.10 can be considered satisfactory, for instance, when predicting stock returns (Raithel et al., 2012). Moreover, the R^2 is influenced by the number of predictor constructs used in the model – the more predictor constructs there are, the higher the R^2 tends to be. Numerous researchers mistakenly interpret the R^2 statistic as a measure of their model's predictive ability. However, this interpretation is not entirely accurate because R2 only reflects the model's explanatory power within the observed data (in-sample). It does not provide any insights into the model's predictive performance on new, unseen data (out-of-sample) (Shmueli, 2010; Shmueli and Koppius, 2011; Dolce et al., 2017).

Moreover, in this study, the PLS Predict test is performed to evaluate the model's predictive accuracy. This test aims to validate the robustness of the proposed PLS model, assessing whether changes in exogenous variables can accurately predict changes in the endogenous variable.

The PLS Predict test is conducted by comparing the RMSE and MAE values between the PLS model and the linear regression model. A PLS model is considered to have good predictive strength if it has lower RMSE and MAE values compared to the linear regression model. In the results of the PLS Predict test in this study, it is evident that almost all measurement items in the proposed PLS model have lower RMSE and MAE values than the linear regression model. For the dependent variable EVA1, the PLS model has an RMSE of 0.839 and MAE of 0.658, while the linear regression model has an RMSE of 0.858 and MAE of 0.740. As for the dependent variable EVA3, the PLS model has an RMSE of 0.875 and MAE of 0.730, whereas the linear regression model has an RMSE of 0.892 and MAE of 0.740.

The proposed PLS research model falls into the high predictive power category, indicating that the predictive accuracy of the research model can be considered high predictive power.

3.6.2 Cross-validated Redundancy Test (Q^2)

Cross-validated redundancy (Q^2) is utilized to assess the predictive significance of the structural model. As a guideline, Q^2 values should surpass zero for a specific endogenous construct, indicating the predictive accuracy of the structural model for that construct. Following a general rule, Q^2 values above 0, 0.25, and 0.50 signify small, medium, and large predictive relevance of the PLS-path model. Similar to the f^2 effect sizes, Q^2 effect sizes can also be calculated and interpreted (Hair et al., 2019). In this study, it is evident that the Q^2 value for the dependent construct is 0.155. Consequently, the predictive accuracy of the model falls into the "small" category, similar to the results of the Coefficient of Determination test. Therefore, based on the Q^2 value, it can be concluded that the predictive capability of this research model demonstrates small predictive relevance.

3.6.3 Effect Size Test (f^2)

The f^2 value is calculated based on the change in the R^2 value when an independent variable is removed from the model to assess its impact on each path of the model. Following a general rule, values greater than 0.02, 0.15, and 0.35 represent small, medium, and large f^2 effect sizes (Cohen, 1988). In this study, all independent constructs exhibit small effect sizes with f^2 values lower than 0.15 on their dependent construct, namely "Intention to Adopt Electric Vehicle." Nevertheless, all independent constructs still exert an influence on their dependent construct.

As a result, the evaluation of the structural model (inner model) in this study indicates that the predictive ability of the research model in forecasting the dependent construct, "Intention to Adopt Electric Vehicle," is considered quite effective.

3.6.4 Goodness-of-Fit (GoF)

During this stage, a fitness assessment is conducted using the Standardized Root Mean Square Residual (SRMR) to evaluate how well the research model fits the data and to prevent model misspecification (Henseler, Hubona, & Ray, 2016). A SRMR value between 0.08 - 0.10, according to the more conservative approach (Hu & Bentler, 1999), is considered acceptable. This research presents the SRMR values obtained from the research model fit test is 0,088 which is acceptable fit. In other words, all empirical data could explain the influence between the involved variables within the model. However, according to the research conducted by Hair et al. (2014), PLS SEM employs sample data to obtain accurate parameters for predicting constructs. As a result, PLS SEM lacks a distinct goodness-of-fit standard compared to SEM methods that rely on covariance. Therefore, based on this study, it can be identified that factors with a significant positive relationship, as determined through statistical tests, with the intention to adopt the use of electric vehicles are the constructs of Subjective Norms, Perceived Behavioral Control, Environmental Concern, and Moral Norms. On the other hand, the construct of Attitude in this study was not found to have any relationship or influence on the intention to adopt the use of electric vehicles.

In this study, the utilized model serves the purpose of facilitating an understanding of the intention to adopt the use of electric vehicles by modelling the Extended Theory of Planned Behavior. This research draws upon the recommendations of a previous study conducted by Shalender and Sharma (2020).

3.7 Discussion of Hypothesis Testing Result

Hypotheses are validated when the specified criteria are met, and conversely, they are rejected if any of these conditions remain unfulfilled. Within the framework of the PLS-SEM methodology, the assessment of hypotheses is achieved through the execution of a Path Coefficient examination within the SMART-PLS model. This procedure is conducted to ascertain the influential variables on others in order to address the proposed hypotheses.

The Path Coefficient values encompass a range from -1 to +1, wherein a value approaching -1 indicates a notable negative correlation and nearing +1 signifies a substantial positive correlation. After scrutinizing the results of the Path Coefficient analysis in this investigation, it has been established that independent constructs displaying a significant association with the dependent construct are Subjective Norms, Perceived Behavioral Control, Environmental Concern, and Moral Norms. These findings have been determined through statistical evaluation employing the SEM-PLS methodology in SMART-PLS, showcasing P-Values below 0.05. Conversely, the Attitude construct showcases a non-significant association with a P-Value surpassing 0.05. The ensuing discussion provides a comprehensive exploration of each individual hypothesis.

- Hypothesis 1: The Attitude variable has an influence on the intention to adopt the use of electric vehicles.
- Hypothesis 2: The Subjective Norms variable has an influence on the intention to adopt the use of electric vehicles.
- Hypothesis 3: The Perceived Behavioural Control variable has an impact on the intention to adopt the use of electric vehicles.

- Hypothesis 4: The Environmental Concern variable has an impact on the intention to adopt the use of electric vehicles.
- Hypothesis 5: The Moral Norms variable influences the intention to adopt the use of electric vehicles.

IV. CONCLUSION

This research concludes that problem formulation about the factor influencing the intention to use electric vehicles in Indonesia are:

- Hypothesis 5 are the greatest factor that influence intention to use EV in Indonesia, results shown moral question is more influence the people to use EV in Indonesia. This suggests that people with a strong commitment to societal well-being, such as a sense of social responsibility, are more inclined to favor the use of electric vehicles.
- Hypothesis 1 suggests a lack of significant influence between the Attitude variable and the community's intention to adopt electric vehicles. This lack of influence may be attributed to barriers in Indonesia, including the relatively high price and the challenges in sourcing spare parts, which are perceived as obstacles.
- Hypothesis 2 shows a significant influence between the subjective norms and the community's intention to adopt electric vehicles.
- Hypothesis 3 shows a significant influence between the perceived behavioral control and the community's intention to adopt electric vehicles.
- Hypothesis 4 shows a significant influence between the environmental concern and the community's intention to adopt electric vehicles.
- Hypothesis 5 shows a significant influence between the moral norms and the community's intention to adopt electric vehicles.

The availability of electric vehicles (EVs) has experienced a substantial rise in Indonesia. One major driving force behind this trend is the growing concern over the environmental impact attributed to the transportation sector. In Indonesia, EVs have transitioned from being novel innovations to garnering significant attention and commitment from the political sphere, particularly the Indonesia government. The government recognizes the imperative to mitigate environmental harm and has therefore intensified its focus on promoting the shift from traditional combustion engines to electric vehicles. This study sought to comprehend the determinants influencing the decision to adopt an electric vehicle (EV). The primary objective was to unravel the underlying factors that drive the purchase decisions of electric vehicles within the Indonesia context. In pursuit of uncovering the causal factors behind the EV purchase decision spectrum in Indonesia, this research delved into the considerations that guide the Indonesia populace when choosing to invest in an electric vehicle. This purpose answer about the results of analysis factor impacting adoption intention to use EV in Indonesia.

This discovery enhances our comprehension of the ways in which societal norms and personal moral convictions can impact the adoption of groundbreaking technologies that offer environmental advantages. Irrespective of the outcomes and conclusions derived from this research, the subject of electric vehicle demand remains pertinent. Given that the commercialization of electric vehicles is still in its initial stages, this thesis addresses a relatively young and progressively significant area of study for the future.

Future Work

The academic significance of this study lies in its effort to address the research gap pertaining to Indonesian consumers' intention to adopt electric vehicles (EVs). It serves as an initial exploration, primarily examining purchase intention from a surface-level perspective, encompassing the investigation of the first five factors (Attitude, etc.). By validating the results of the conducted regression analysis, this study suggests that all five factors—Attitude, Subjective Norm, Perceived Behavioral Control, Moral Norm, and Environmental Concerns—play a role in influencing the purchase intention of Indonesian consumers, except for Attitude. This finding contrasts with existing literature, such as the work by Shalender and Sharma (2020).

In contrast to prior research, this study and its outcomes are specifically tailored to Indonesian consumers and their intentions to adopt EVs. While this study represents a modest step in addressing the research gap related to the growth of electric vehicles among Indonesian consumers, it contributes to a basic understanding of the behaviours that drive Indonesian consumers to consider purchasing an electric vehicle. Consequently, it paves the way for future research opportunities in this field of study.

However, it's important to acknowledge that there are numerous other factors that could potentially impact adoption to use EV decisions, which were not taken into account in this study. Beyond considerations related to environmental awareness and social responsibility, consumers also take into consideration additional factors when to adopt an electric vehicle. Aspects like practicality, user-friendliness, and the availability of supporting infrastructure are particularly significant for electric vehicles (EVs) and warrant further exploration within the context of Indonesian consumers.

Specifically, the adoption of EVs introduces new challenges, including the reliance on charging infrastructure and the facilitating conditions required for their successful use (Tu & Yang, 2019). Therefore, it is advisable to conduct a follow-up study that considers these variables and delves deeper into their impact on the purchasing behaviour of Indonesian consumers in the context of electric vehicles. This would provide a more comprehensive understanding of the factors influencing EV adoption in Indonesia.

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