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Identification of Determining Factors for Electric Vehicle Use in Indonesia from User Perspective

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Abstract: ***The use of electric-powered vehicles is considered as one of the steps that can be taken to reduce the use of fossil-fueled vehicles, but efforts to use electric-powered vehicle technology have encountered many obstacles, especially in developing countries. Indonesia as a developing country also experiences various obstacles from the cost of ownership of electric vehicles which are still considered high, inadequate facilities, and electric vehicle technology that does not meet user expectations. The purpose of this research is to study the determinants that must be met by electric vehicles to be used as an alternative to fossil fuel vehicles. This study uses the TAM, UTAUT-2 and Perceived Risk to develop a model that can describe the relationship between the criteria variables for selecting electric vehicles as an alternative to fossil fuel vehicles, the data will be collected using a questionnaire and will be analyzed using the Structural Equation Model. The results obtained from the study are expected to provide a better description of the factors that determine users choosing electricity as an alternative transportation.***

Keywords: TAM, UTAUT-2, PLS-SEM, Technology Usage and User Perspective

1. Introduction

One of the efforts made to stop the increase in greenhouse gas emissions is to replace the use of fossil fuel vehicles with electric vehicles. Various countries have taken steps to accelerate the development of electric vehicle technology with the main objective of reducing greenhouse gas emissions. Various policies and incentives are provided by policy makers to encourage faster growth in the use of electric vehicles. Starting from developed countries to developing countries began to develop strategies to encourage the use of electric vehicles. It was noted by the IEA (International Energy Agency) that countries such as America, China, Japan, Korea, New Zealand, and various European Union member countries have targeted to reach 100 percent of vehicle sales by 2050 (IEA, 2017). Countries that are included in the category of countries developing countries are also developing strategies to encourage the use of electric vehicles in their countries. Indonesia, which belongs to the category of developing countries, has also launched a policy package and roadmap to accelerate the use of electric vehicles.

In order to achieve the target in the roadmap, policies that support the development of electric vehicles in Indonesia have also begun to be rolled out by the Indonesia government, including the government setting a special tariff of zero percent import duty for motorized vehicles that are imported in incomplete and incomplete conditions (Incompletely Knocked Down / IKD) through Regulation of the Minister of Finance Number PMK-13/PMK.010/22 concerning Fourth Amendment to Regulation of the Minister of Finance Number 6/PMK.010/2017 concerning Stipulation of Goods Classification System and Imposition of Import Duty Tariffs on Imported Goods which is set on 22 February 2022.

However, the realization of the use of electric vehicles in Indonesia is still far from the very high portion of vehicle sales in Indonesia. Sales of electric vehicles in Indonesia were recorded in the first half of 2021 reaching 1900 units consisting of 1378 hybrid vehicles, 34 PHEV units and 488 BEV units. Sales of electric vehicles in 2021 have increased from data in 2019 which showed sales of only 705 units of which 680 hybrid vehicles, 25 PHEV units and 0 BEV units, although this figure is still considered low when compared to the target disclosed by the ministry of industry in Indonesia which in 2025 the use of electric cars is targeted at more than 500, 000 thousand units or has a market share of more than 20% of car sales in Indonesia (CNBC. 2022).

Many factors can affect the low use of electric vehicles by the Indonesian people, ranging from the lack of energy charging facilities for electric cars, the high operating costs of electric cars and the purchase price of electric cars which are still relatively high (Damayanti et al, 2020). With the many factors that influence the use of electric vehicles by the Indonesian people, a study is needed to better explain the factors that influence the use of electric cars in Indonesia.

Therefore, this study is intended to observe from the user's point of view the priority of the user's tendency in choosing alternative vehicles used so that it can be observed the factors that cause electric vehicles to be less attractive in Indonesia.

1.1 Objectives

The purpose of this study is to identify the factors that make electric vehicle technology less attractive to the people of Indonesia. So that a model can be developed that can show the correlation between the factors that cause user decisions in choosing to use electric cars as an alternative to fossil fuel cars. The model developed is expected to provide an overview of the factors that drive interest in adopting electric vehicles in Indonesia.

2. Literature Review

In previous research studies to explain the relationship of factors that influence the use of electric vehicles, several methods are used to model the influence of several variables in determining the use of electric vehicles by users. The study uses various theories to explain the determination of the use of electric vehicles from the user's point of view, Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM). Sonja Haustein et al (2019) uses TPB to describe the determination of the use of electric vehicles by users and then uses the variables in theory to create a questionnaire. Wang Shanyong (2018) uses TAM as a model to describe the relationship of factors that influence the use of electric vehicles. From these two studies, the results show how the relationship between variables in the model uses the Partial Least Square Structural Equation Model (PLS-SEM) methodology. Jain Kumar et al (2022) uses a model compiled with other theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and Perceived Risk and then uses the Covariance Based Structural Equation Model to show the relationship between variables.

The use of theory in forming a model of the relationship between variables is not only used exclusively but can also be used together, Gunawan Indra et al (2022) uses TPB, UTAUT, and Perceived Risk together to describe the relationship between the determinants of the use of electric vehicles by users. Gunawan Indra et al (2022) uses PLS SEM to show the relationship between variables in the TPB, UTAUT, and Perceived Risk integration models.

The results of the research by Gunawan Indra et al (2022) have a fairly high bias and show that the construct of TPB has a small effect on the intention to use electric vehicles.

This study was proposed to fill the gap of previous research by using the Technology Acceptance Model which uses the constructs of perceived usefulness and perceived ease of use as the main model, UTAUT-2, and Perceived Risk as variables to complete the description. the intention to use electric vehicles in Indonesia. The use of TAM compared to TPB is expected to avoid bias from previous studies.

3. Methods

The theoretical approach in this study uses the integration of several theories, including the Theory of Acceptance Model and Perceived Risk to predict the interest in the adoption of electric vehicles in Indonesia. The process of consumer judgment to use technology based on the benefits obtained, environmental influences, experience, and knowledge, has a close relationship with the conception of interest that leads to interest in adopting electric vehicles.

The Theory of Acceptance Model (TAM) by Davis et al (2003) explains that Attitude Toward Usage (ATU) is influenced by Perceived Usefulness (PU) and Perceived Ease of Use (PEU), the relationship between PU and PEU towards ATU is a positive relationship where PEU and PU will positively affect ATU. ATU will positively affect the Intention to Use or Desire to Use. This study also integrates Perceived Risk(PR) by Mitchell et al (1992) by consumers as a factor that affects ATU. The relationship between several aspects of PR such as Perceived Finance Risk or Perceived Financial Risk (PFR), Perceived Physical Risk (PPR), Perceived Functional Risk (PfuR), Perceived Social Risk (PSR), and Perceived Time Risk (PTR) will negatively affect against consumer ATU.Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) by Venkatesh et al (2003) also used by involving a few variables such as Hedonic Motivation (HM), Habit (H), Price Value (PV) and Facilitating Conditions (FC) also involved in model to accommodate more variable to draw a clearer picture of Indonesian user behaviours. Other variable such as Performance Expectancy (PE) and Effort Expectancy (EE) is not used due to similarity with PEU and PU from TAM.

By using a pre - existing theories, the questionnaire was made by taking into account the conceptual framework as the model used in this study. The questionnaire will be divided into three parts namely, the first part of the questionnaire model is divided into two parts, the second one collects their demographic data objectives. Third, the question instrument regarding the research intention variable uses three question indicators. These include all thirteen Variable mentioned before, culminating in 39 constructs. A Likert scale of 1-5 was used in this study, where scores of 1 and 5 indicated the opinion of "strongly disagree" and "strongly agree".

After general data processing has been carried out, it is continued with analysis using Smart PLS software version 3.2.9 which aims to identify the factors in the use of electric vehicles in Indonesia. There are two stages of testing in using PLS-SEM. The two stages are external construct model testing and structural model testing.

There are several things that are done in testing the measurement model in the form of reflective models. The first is to test composite reliability to evaluate internal consistency, the second is to test the reliability of individual indicators, the third is to calculate the average variance extracted (AVE) value to evaluate convergent validity, and the last is to calculate the Fornell-Larcker criteria and cross loadings to test the discriminant validity. In performing the test, the variables will be represented by code for easy reading.

The testing phase carried out on the measurement model is testing the validity and reliability of the latent variable indicators. The first criterion that is evaluated is internal consistency reliability. The traditional criterion for testing internal consistency is to use Cronbach's Alpha. Cronbach's Alpha assumes that all indicators are reliable (all indicators have the same outer loading on the latent variable). However, PLS-SEM prioritizes indicators based on the reliability of each individual. Thus, it would be more appropriate to use a different measure of internal consistency reliability, namely composite reliability (Hair et al, 2016). Table 4.7 displays the results of the composite reliability test. The value of good composite reliability is in the range of 0.7 – 0.9. However, a value above 0.95 is considered undesired because it indicates that the indicator on the latent variable calculates the same phenomenon so that it is probably not a valid measure for measuring the latent variable (Hair et al, 2016).

The next step for testing the outer model is discriminant validity testing. Discriminant validity is the degree to which a construct is completely different from another construct by empirical standards. Thus, establishing discriminant validity implies that a construct is unique and captures phenomena that are not represented by other constructs in the model. Traditionally, researchers have relied on two measures of discriminant validity. Cross-loadings are usually the first approach to assessing the discriminant validity of an indicator. In particular, the outer loadings indicator on the associated construct must be greater than the cross-loadings on the other constructs.

After the measurement model testing has been met, then the structural model testing is carried out. The results of testing the structural model determine how well the empirical data support the theory that can be used to decide whether the theory can be confirmed empirically. Structural model testing is related to testing the predictive ability of the model and the relationship between latent variables. The first step that must be done is to test for collinearity on the structural model. In doing collinearity testing, the value used is the Variance Inflation Factor (VIF) value. When the VIF value is above 5.00 on the latent predictor variable, then there is an indication of collinearity (Hair et al, 2016).

The next step is to test the value of the coefficient of determination (R2) to evaluate the structural model. The coefficient of determination is a measure of the model's prediction accuracy and is calculated as the squared correlation between the actual and predicted values of certain endogenous latent variables. The coefficient of determination represents the effect of the combination of exogenous latent variables on endogenous latent variables. The value of R2 ranges from 0 to 1 and the higher the value, the higher the prediction accuracy. The R2 value of 0.75 is included in the high category, the R2 value of 0.5 indicates moderate and the R2 value of 0.25 indicates weak (Hair et al, 2016).

The next step is to test the blindfolding and predictive relevance of Q2. The value of Q2 is obtained by using the blindfolding procedure to calculate the omission distance. The value of Q2 is an indicator of the relevance of the model's predictions. When PLS-SEM has predictive relevance, the model can accurately predict data points on indicators in the reflective measurement model of endogenous latent variables. In the structural model, a Q2 value greater than 0 for certain endogenous latent variables indicates the relevance of the predictive path model for these latent variables (Hair et al, 2016).

After all of the testing has been done, the results and discussion of the model implication will be made by using appropriate statistical standards.

4. Data Collection

Sources of data used in this study can generally be divided into two, namely secondary data through a literature review from previous studies and primary data conducted with questionnaires distributed to respondents.

Secondary data is carried out by reviewing the literature on similar research studies that have been carried out in the past. The purpose of conducting a literature review is to get an overview of the factors that influence the interest in adopting electric vehicles. The results of this literature review will then be used as a basis for developing a model that can better explain the relationship between the factors that influence the interest in adopting electric vehicles.

Primary data obtained by questionnaires addressed to respondents as potential users of electric vehicles. The questionnaire will cover factors that can influence the interest in adopting electric vehicles, user knowledge about electric vehicles, and the risks from the user's perspective on the use of electric vehicles. The data obtained from this questionnaire will be used as a basis for hypothesizing the relationship between the factors that influence the interest in adopting electric vehicles. Selection of respondents aims to obtain a more accurate sample of data so that the research results can be more accurate. In this study, the main object of research is the interest of the Indonesian people in using electric vehicles and the factors that influence it. To obtain accurate data, respondents are selected from users with age > 17, adjusted for the minimum age for drivers in Indonesia to have a driving license. Respondents are not separated by gender and profession because data collection is expected to represent all groups of vehicle users in Indonesia. By using these criteria in selecting respondents, it is hoped that the results of the study can obtain data that is as accurate as possible, and can better describe the factors that influence the interest in adopting electric vehicles from the perspective of drivers in Indonesia.

5. Results and Discussion

5.1 SMART PLS Outer Model Testing Results

The testing phase carried out on the measurement model is testing the validity and reliability of the latent variable indicators. The first criterion that is evaluated is internal consistency reliability. The traditional criterion for testing internal consistency is to use Cronbach's Alpha. Cronbach's Alpha assumes that all indicators are reliable (all indicators have the same outer loading on the latent variable). However, PLS-SEM prioritizes indicators based on the reliability of each individual. Thus, it would be more appropriate to use a different measure of internal consistency reliability, namely composite reliability (Hair et al, 2016). Table 5.1 displays the results of the composite reliability test. The value of good composite reliability is in the range of 0.7 – 0.9. However, a value above 0.95 is considered undesired because it indicates that the indicator on the latent variable calculates the same phenomenon so that it is probably not a valid measure for measuring the latent variable (Hair et al, 2016).

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Table 5.1: Composite Reliability Test

Variable	Composite Reliability	AVE
ATU	0.864	0.681
FC	0.892	0.733
HM	0.754	0.532
H	0.879	0.710
ITU	0.725	0.525
PEU	0.439	0.566
PFR	0.846	0.651
PFuR	0.809	0.587
PPR	0.848	0.651
PSR	0.896	0.743
PTR	0.895	0.740
PU	0.808	0.584
PV	0.764	0.528

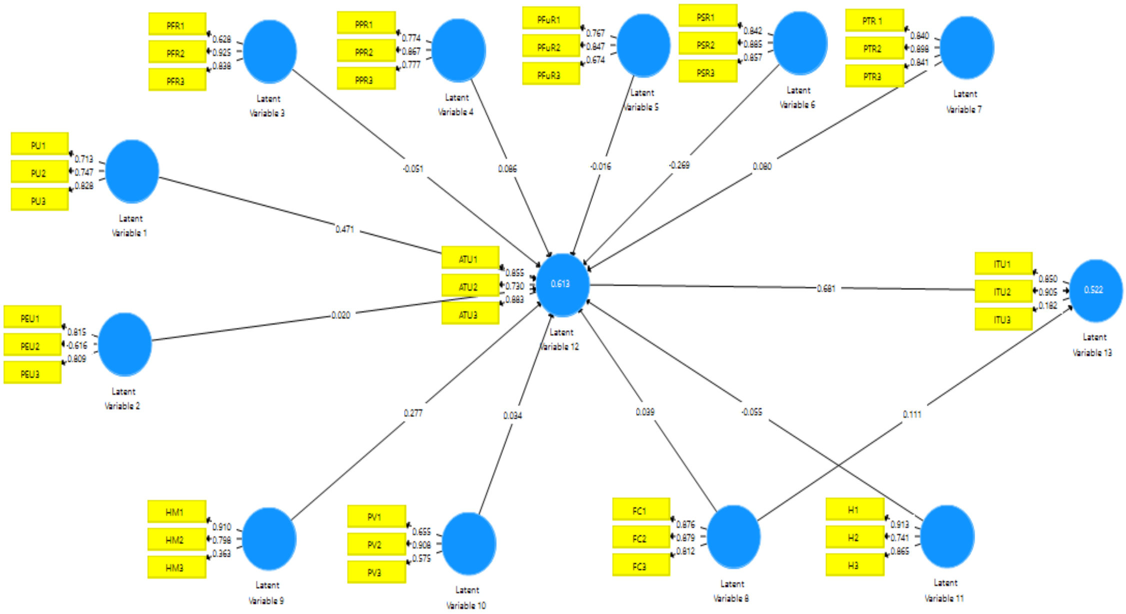

Figure 5.1: Initial model design

In the initial model testing, the results showed that the composite reliability value was not good in the PEU construct where the composite reliability value showed a value below 0.7. Therefore, in the PEU construct, the elimination of one item with a poor outer loadings value is carried out. The high value of outer loadings on the latent variable indicates that the indicators on the latent variable have similarities. The value of outer loadings must be above 0.708. The value of 0.7 is considered close enough and acceptable. If the outer loading value is in the range of 0.4 – 0.7, it is necessary to calculate the composite reliability and average variance extracted (AVE) values further if these indicators are removed. If by removing the indicator, the composite reliability and AVE values can be increased, then the indicator can be deleted. However, when the outer loadings are below 0.4, the indicator must be removed (Hair et al, 2016).

After eliminating items with poor outer loadings, the model is obtained as shown in Figure xx below. By eliminating construct items with less significant loading values, all variables already have a composite reliability value above 0.7 and do not have a composite reliability value above 0.95. Therefore, it can be concluded that the seven variables have met the requirements for testing composite reliability.

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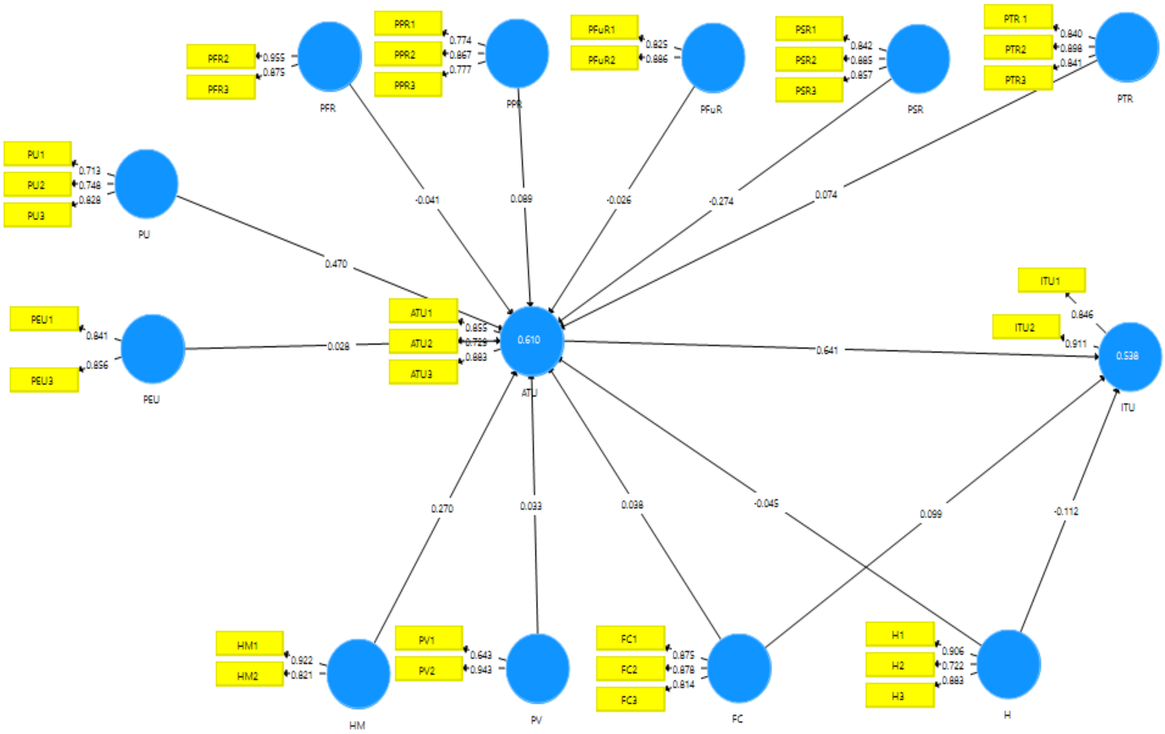

Figure 5.2: Model after elimination of low loading factor construct

Table 5.2: Composite Reliability Test after Elimination

Variable	Composite Reliability	AVE
ATU	0.864	0.681
FC	0.891	0.733
H	0.878	0.707
HM	0.865	0.762
ITU	0.872	0.773
PEU	0.837	0.720
PFR	0.912	0.839
PFuR	0.846	0.733
PPR	0.848	0.651
PSR	0.896	0.743
PTR	0.895	0.740
PU	0.808	0.584
PV	0.783	0.652

The next step for testing the outer model is discriminant validity testing. Discriminant validity is the degree to which a construct is completely different from another construct by empirical standards. Thus, establishing discriminant validity implies that a construct is unique and captures phenomena that are not represented by other constructs in the model. Traditionally, researchers have relied on two measures of discriminant validity.

Table 5.3: Fornell Lacker test

	ATU	FC	H	HM	ITU	PEU	PFR	PFuR	PPR	PSR	PTR	PU	PV
ATU	0.825												
FC	0.303	0.856											
H	-0.416	-0.272	0.841										
HM	0.509	0.330	-0.223	0.873									
ITU	0.718	0.324	-0.406	0.423	0.879								
PEU	0.495	0.296	-0.354	0.390	0.474	0.848							
PFR	-0.298	-0.310	0.464	-0.189	-0.300	-0.291	0.916						
PFuR	-0.339	-0.236	0.428	-0.247	-0.314	-0.310	0.402	0.856					
PPR	-0.373	-0.200	0.530	-0.272	-0.335	-0.277	0.610	0.581	0.807				
PSR	-0.482	-0.083	0.489	-0.190	-0.386	-0.304	0.424	0.353	0.522	0.862			
PTR	-0.334	-0.245	0.529	-0.199	-0.245	-0.333	0.626	0.463	0.661	0.536	0.860		
PU	0.678	0.288	-0.444	0.343	0.592	0.575	-0.281	-0.370	-0.438	-0.370	-0.379	0.764	
PV	0.449	0.451	-0.152	0.520	0.388	0.320	-0.235	-0.262	-0.306	-0.289	-0.259	0.413	0.807

Based on the test results using the Fornell-Larcker criteria, it can be seen that the square root of the AVE value in each latent variable has a greater value than the highest correlation with other latent variables. So it can be concluded that the test using the Fornell-Larcker criteria has been met.

The path model has been tested for internal consistency, indicator reliability, convergent validity and discriminant validity. Therefore, it can be said that the path model is valid and reliable.

5.2 SMART PLS Inner Model Testing Results

Inner model testing is related to testing the predictive ability of the model and the relationship between latent variables. The first step that must be done is to test for collinearity on the structural model. In doing collinearity testing, the value used is the Variance Inflation Factor (VIF) value. When the VIF value is above 5.00 on the latent predictor variable, then there is an indication of collinearity (Hair et al, 2016). Table 4.14 shows the VIF value in collinearity testing.

Table 5.4: VIF Test Results

	ATU	FC	H	HM	ITU	PEU	PFR	PFuR	PPR	PSR	PTR	PU	PV
ATU					1.269								
FC	1.482				1.133								
H	1.856				1.245								
HM	1.526												
ITU													
PEU	1.702												
PFR	1.993												
PFuR	1.619												
PPR	2.676												
PSR	1.728												
PTR	2.321												
PU	1.917												
PV	1.817												

Based on the results of collinearity testing, it was found that the overall VIF value of the predictor latent variable had a value below 5.00. This shows that the path model has no indication of collinearity.

Table 5.4: Significance Test

	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Conclusion
ATU -> ITU	0.048	13.456	0.000	Hypotheses Accepted
FC -> ATU	0.048	0.794	0.428	Hypotheses Rejected
FC -> ITU	0.048	2.082	0.038	Hypotheses Accepted
H -> ATU	0.070	0.634	0.526	Hypotheses Rejected
H -> ITU	0.047	2.373	0.018	Hypotheses Accepted
HM -> ATU	0.069	3.906	0.000	Hypotheses Accepted
PEU -> ATU	0.076	0.365	0.715	Hypotheses Rejected
PFR -> ATU	0.069	0.592	0.554	Hypotheses Rejected
PFuR -> ATU	0.064	0.401	0.689	Hypotheses Rejected
PPR -> ATU	0.067	1.331	0.184	Hypotheses Rejected
PSR -> ATU	0.057	4.772	0.000	Hypotheses Accepted
PTR -> ATU	0.068	1.091	0.276	Hypotheses Rejected
PU -> ATU	0.071	6.606	0.000	Hypotheses Accepted
PV -> ATU	0.076	0.432	0.666	Hypotheses Rejected

After VIF test then comes significance test to determine each construct significance toward ATU and ITU However, if the estimated coefficient is closer to 0, then the relationship will be weaker. The standard error obtained from bootstrapping determines whether the coefficient is significant or not. Bootstrap standard error makes it possible to calculate empirical t-values. The significance value used in this study is 5%, so the t value is 1.96 (Hair et al, 2016). Table 4.15 displays the results of the significance test (path coefficient).

Based on the results of the significance test, it was found that the six initial hypotheses were not rejected and the eight initial hypotheses were rejected. Attitude Towards Use, Habit, Hedonic Motivation, Perceived Social Risk and Perceived Usefulness have been proven to have a significant effect on Intention to use. On the other hand, the other 7 constructs are considered to have less effect on Intention to use.

Table 5.5: R Square Determination Test

	R Square	R Square Adjusted
ATU	0.610	0.587
ITU	0.538	0.531

Next is R^2 Test to determine the model predictive ability. Based on the test results, it can be seen that the latent variable Intention to Use has an R^2 value of 0.538. This value falls into the moderate category. It can be concluded that the Intention to Use can be explained by 0.538 by the predictor variable. Another test such as Q2 blindfolding and predictive relevance test. The value of Q2 is obtained by using the blindfolding procedure to calculate the omission distance. The value of Q2 is an indicator of the relevance of the model's predictions. When PLS-SEM has predictive relevance, the model can accurately predict data points on indicators in the reflective measurement model of endogenous latent variables. In the structural model, a Q2 value greater than 0 for certain endogenous latent variables indicates the relevance of the predictive path model for these latent variables (Hair et al, 2016).

Table 5.6: Q Square Blindfolding and Predictive Relevance Test

	SSO	SSE	Q^2 (=1-SSE/SSO)
ATU	600.000	365.066	0.392
FC	600.000	600.000	
H	600.000	600.000	
HM	400.000	400.000	
ITU	400.000	244.795	0.388
PEU	400.000	400.000	
PFR	400.000	400.000	
PFuR	400.000	400.000	
PPR	600.000	600.000	
PSR	600.000	600.000	
PTR	600.000	600.000	
PU	600.000	600.000	
PV	400.000	400.000	

6. Discussion

In the external construct testing, which was carried out through three stages, namely the Composite reliability test to test the reliability of the external construct used in the study. The requirement that must be met by the construct is that a good minimum composite reliability value is in the range of 0.7 – 0.9. However, a value above 0.95 is considered undesireable because it indicates that the indicator on the latent variable calculates the same phenomenon so that it is probably not a valid measure for measuring the latent variable. (Hair et al, 2016). The value of the initial model there are several constructs that do not meet the requirements of composite reliability so it is necessary to eliminate constructs that have low loading values to improve composite reliability of the data. In this case, table xx shows that the value of the PEU2 construct has a poor loading value of 0.434 which makes the composite reliability value of the PEU variable less good so that the PEU2 construct is removed from the model to improve the reliability value of the PEU variable. In addition, other variables that have constructs with unfavorable loading factors are also removed at this stage, provided that if the outer loading value is in the range of 0.4 – 0.7, it is necessary to calculate the composite reliability and average variance extracted (AVE) values more continue if the indicator is removed. If by removing the indicator, the composite reliability and AVE values can increase, then the indicator can be deleted. However, when the outer loadings are below 0.4, the indicator must be removed

After obtaining external variables and constructs that have good composite reliability values, the test continues to the Discriminant Validity test which is carried out using the Fornell method. Based on the test results using the Fornell-Larcker criteria, it can be seen that the square root of the AVE value in each latent variable has a greater than the highest correlation with other latent variables. So it can be concluded that the test using the Fornell-Larcker criteria has been met

The first step in testing the inner construct is done with collinearity testing to show that each variable in the construct does not have any indication of collinearity. Based on the results of collinearity testing, it was found that the overall VIF value of the predictor latent variable had a value below 5.00. This shows that the path model has no indication of collinearity.

Based on the results of the significance test, it was found that the six initial hypotheses were not rejected and the eight initial hypotheses were rejected. Attitude Towards Use, Habit, Hedonic Motivation, Perceived Social Risk and Perceived Usefulness have been proven to have a significant effect on Intention to use. On the other hand, the other 7 constructs are considered to have less effect on Intention to use.

Perceived Usefulness or PU positively influences attitudes towards the use of electric vehicles. These results support studies by Yuen et al (2020), Thomas et al (2003) According to them, those who feel that electric vehicles have good benefits in their use include improving air quality and environmental conditions.

Perceived Ease of Use or PEU positively affects attitudes towards the use of electric vehicles. Venkatesh et al (2003). According to them, those who feel that electric vehicles are easy to understand, learn and benefit from, thus adopt a positive perception of their adaptation in Indonesia. they adapt in Indonesia. However, in this study found a very small effect of perceived ease. This shows that electric vehicles and their supporting technology are still poorly understood by the Indonesian people.

Hedonic motivation (HM) positively affects the ATU of electric vehicles. These results are consistent with the study of Yuen et al (2020). The higher the perception of happiness and pleasure obtained when using an electric vehicle, the greater the positive rating. Individuals with the perception of obtaining pleasure and comfort when using the product tend to have a positive attitude, which encourages future use.

Price Value (PV) has a positive effect on the ATU of electric vehicles. These results are consistent with the study by Yuen et al (2020), which states that an increase in positive perceptions. Individuals with the belief that the price of electric vehicles is directly proportional to product quality tend to behave positively and support the electric vehicle acceleration program, resulting in higher usage ratings. support the electric vehicle acceleration program, thereby generating interest in future use.

Habit (H) positively affects attitudes towards the use of electric vehicles at an insignificant level. This result is inconsistent with the study by Yuen et al (2020). but supports Ajzen's theory, which explains why past behavior does not directly control future behavior. It does not directly control future behavior.

Physical risk perception (PPR) does not have a negative effect on the ATU of electric vehicles. The results of this study contradict the study by Choi et al (2012). Sanayei and Bahmani but consistent with Majali. Perception of physical hazards when using electric vehicles does not cause individuals to perceive electric vehicles negatively.

Perception of performance/functional risk (PFR) has a negative effect on the ATU of electric vehicles. These results are consistent with the study by Majali et al (2020), which stated that the higher the possible functional risks that arise in electric vehicles, the lower the individual's positive perception of electric vehicles. Therefore, those who feel that electric vehicles tend to have problems with batteries, maintenance, and other constraints tend to have negative attitudes and are reluctant to adapt to use.

Perception of financial risk (PFN) has a negative effect on the ATU of electric vehicles. This result is consistent with the study by Majali et al (2020), which states that the higher the potential for financial loss, the more negative the individual's assessment of electric vehicles. financial loss, the more negative the individual's assessment of electric vehicles. For example, those who think that the purchase will lead to an increase in financial burdens, such as electricity, electricity, maintenance costs, and the purchase of spare batteries, tend to have negative attitudes towards the purchase and use of electric vehicles.

The perception of social risk (PSR) positively affects the ATU of electric vehicles. This is contrary to the study of Majali et al (2020), which states that the higher the social pressure to use electric vehicles, the higher the perceived social risk. Stated that the higher the social pressure to use electric vehicles, the greater the positives of electric vehicles. Therefore, individuals who are resistant to pressure from the social environment, such as the family environment and social environment, such as family and work environments, tend to be confident and have more positive attitudes towards electric vehicles.

Perceived time risk (PTR) has a negative effect on the ATU of electric vehicles at an insignificant level. This result is inconsistent with the study by Majali et al (2020), which stated that perceptions about the likelihood of individuals losing time when buying and using electric vehicles did not

7. Conclusion

Based on the results of the significance test, it was found that the six initial hypotheses were not rejected and the eight initial hypotheses were rejected. Attitude Towards Use, Habit, Hedonic Motivation, Perceived Social Risk and Perceived Usefulness have been proven to have a significant effect on Intention to use. On the other hand, the other 7 constructs are considered to have less effect on Intention to use.

Based on the results of the Loading Test, it was found that there are several variables that have a major influence on the Attitude towards Use variable such as Habit, Hedonic Motivation, Perceived Social Risk and Perceived Usefulness.

Theoretically, this study has developed a technology use model by combining several theories such as TAM, UTAUT-2, and Perceived Risks to describe user behavior in technology use. In previous studies, the same thing was done but by combining different theories. The results obtained from this study also illustrate something new, namely the influence of Hedonic Motivation and Habit which is quite high in influencing Intention to use on the consumer side.

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Biography

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Djoko Sihono Gabriel is the first person who introduced "Material Value Conservation" knowledge with plastic packaging as the first evident of the new paradigm phenomenon. In a context of material utilization, resources conservation and in a more specific, material resources conservation exists as an approach of saving natural resources in order to maintain long term supply of materials from its sources. But unfortunately, product designers and producers lack of interest in conserving the material since it used as raw material. Therefore intensive material value degradation in plastic packaging symptom reflected in the status of China and Indonesia as the top sources of plastic waste reaching the oceans in the year of 2010. Material Value Conservation proposed as a new paradigm with ability to maintain material value and will generate broader impact and more benefit if adopted for other type of materials, especially for region with high density population and high consumption rate of conserved products.

Farizalis a lecturer at of Industrial engineering master program at Universitas Indonesia Engineering Department. His main research focus including Engineering Economics, Linier Programming, Finance and Investments, Operations Research, and Advanced Operations Research.