

Analysis of Factors Influencing User Satisfaction and Loyalty in MyPertamina based on Structural Equation Modeling using Partial Least Square Approach (A Case Study of MyPertamina Users in East Java)

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Abstract: *The increase in the price of Fuel (BBM) affects the economy of oil-exporting and oil-importing countries, including Indonesia. The Indonesian government must ensure that fuel subsidies are targeted correctly and not misused by unauthorized parties. MyPertamina is one of the solutions chosen by the government to facilitate the control of the distribution of subsidized fuel. User satisfaction is crucial for maintaining and improving application services. This study aims to determine the factors influencing user satisfaction and loyalty to MyPertamina. The research was conducted using Structural Equation Modeling-Partial Least Square (SEM-PLS). The sample was taken using purposive sampling technique, with a total of 110 respondents as MyPertamina users in East Java, Indonesia. The results show that the variables Efficiency, Trust, Reliability, and Citizen Support influence user satisfaction with MyPertamina. Meanwhile, user loyalty is influenced by the variables Efficiency, Reliability, and Satisfaction. The R-Square values for the endogenous latent variable Satisfaction are 0,886, and for the endogenous latent variable Loyalty, it is 0,896. The overall model test using the Goodness of Fit Index produces a value of 0,83431, indicating that the model has a high ability to explain the data overall, and it can be said that the formed model is valid. Recommendations are given to developers to continuously improve the performance of the MyPertamina application to enhance user satisfaction and loyalty. The government can impose strict sanctions on those who misuse subsidized fuel.*

Keywords: *MyPertamina, Satisfaction, Loyalty, SEM-PLS*

1. INTRODUCTION

The global economy is currently in an unstable and uncertain condition due to the impact of Covid-19 and the Russia-Ukraine war. One sector affected by this is the increase in the price of Oil. The rise in fuel prices will impose a greater burden on the government in providing subsidies to the public. The government must ensure that the subsidies provided are targeted correctly and not misused by unauthorized parties. MyPertamina is one of the solutions to control the distribution of subsidized fuel to those who are eligible. Understanding user satisfaction with MyPertamina is crucial for developers to improve application services. Higher customer satisfaction leads to benefits because satisfied customers will continue to subscribe to the company's services or products in the future, using them continuously. Therefore, high customer satisfaction is often followed by increased customer loyalty (Musanto, 2004).

The success of the application can be measured based on user evaluations. Until now, there have been many complaints from MyPertamina users. If the service provided is unsatisfactory, it can lead to dissatisfaction and

disappointment for users (Kotler, 2009). These complaints need to be promptly addressed by Pertamina by improving the quality of MyPertamina, so users feel satisfied with the application, and customer loyalty will increase. Hence, this study aims to identify the factors influencing user satisfaction and loyalty to MyPertamina.

The analysis is conducted based on Structural Equation Modeling with a Partial Least Square approach (SEM-PLS). SEM-PLS is a multivariate analysis technique that can simultaneously test and estimate relationships between one or more dependent variables that have many factors (Wang et al., 2020). PLS is an alternative approach different from covariance-based SEM. In SEM-PLS, there are two models: the structural model (inner model) that illustrates the relationships between latent variables, and the measurement model (outer model) that explains the relationships between latent variables and their indicators (manifest variables).

This study is conducted with the aim of identifying the factors influencing user satisfaction and loyalty to MyPertamina. The analysis is carried out using Structural Equation Modeling with a Partial Least Square approach. This

research is expected to provide recommendations for MyPertamina developers to further improve the quality of the services provided.

2. LITERATURE REVIEW

2.1 MyPertamina

MyPertamina is one of the e-Government applications that serves as a digital financial service developed by PT Pertamina. Initially, MyPertamina functioned as a digital payment tool and has now evolved into a control tool for the distribution of subsidized fuel. Through MyPertamina, users can purchase Pertamina products, and non-cash payments can be made due to the collaboration with LinkAja. The LinkAja balance automatically decreases after making a fuel purchase payment through MyPertamina. MyPertamina also provides various benefits to customers, offering opportunities to earn points that can be redeemed and access to a variety of rewards available in the MyPertamina application. To obtain the MyPertamina application, users can download it from the App Store (for iPhone) or Google Play Store (for Android phones) (Syamsir et al., 2022).

2.2 Validity Test

Validity is the ability of a measuring instrument to accurately and precisely measure the intended variable. Validity testing is commonly conducted on questionnaires or other measuring instruments to determine whether the instrument can be relied upon and is accurate in measuring the intended variable (Sugiyono, 2019). The Pearson Product Moment correlation test is used to assess validity in this research, with the formula as follows:

$$r_{xy} = \frac{n \sum_{i=1}^n (x_i y_i) - \sum_{i=1}^n x_i \sum_{i=1}^n y_i}{\sqrt{\{n \sum_{i=1}^n x_i^2 - (\sum_{i=1}^n x_i)^2\} \{n \sum_{i=1}^n y_i^2 - (\sum_{i=1}^n y_i)^2\}}} \tag{1}$$

with :

r_{xy} : Correlation coefficient for each item

n : Number of samples

x : Question item score

y : Total score of the question

$\sum x$: Total score of question items

$\sum y$: Total number of question scores

$\sum x^2$: Sum of squared scores of question items

$\sum y^2$: Total squared score of questions

2.3 Reliability Test

According to Ghozali (2018), reliability testing is a tool used to evaluate the consistency and stability of a questionnaire as an indicator of the construct or variable being measured. A questionnaire is considered reliable if the responses given to each statement in the questionnaire remain consistent and stable across different survey implementations.

One way to measure the reliability of the questionnaire items is by using Cronbach's Alpha value. The value of Cronbach's Alpha reliability level is shown in Table 1 below.

Table 1: Level of Reliability Coefficient Cronbach's Alpha

Cronbach's Alpha Value	Reliability Level
$0,00 \leq r_a < 0,20$	Very Low
$0,20 \leq r_a < 0,40$	Low
$0,40 \leq r_a < 0,60$	Medium or Fair
$0,60 \leq r_a < 0,80$	High
$0,80 \leq r_a < 1,00$	Very High

Source : (Guilford, 1956)

An instrument is declared reliable if the Cronbach's Alpha value is $\geq 0,60$. The Cronbach's Alpha reliability coefficient formula can be seen in the following equation.

$$r_{\alpha} = \frac{k}{(k-1)} \left\{ 1 - \frac{\sum_{i=1}^k \sigma_i^2}{\sigma_t^2} \right\} \tag{2}$$

with :

r_{α} : Cronbach's alpha value

k : Number of question items

σ_i^2 : Variance of question items

σ_t^2 : Variance of the total score of all questions

2.4 Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is an analysis technique used to evaluate the relationships between exogenous and endogenous variables with multiple indicators. By using SEM, researchers can effectively estimate and test complex models (Latan, 2013). SEM emphasizes confirmatory testing rather than exploratory testing, making it more suitable for testing theories rather than developing them. Additionally, SEM allows the measurement of variables that cannot be directly measured through their indicators. In SEM, the estimated model is assumed to have causal relationships between latent variables and their indicators (Hair et al., 2010).

SEM can be considered an effective statistical method for revealing the relationships between latent variables and their multiple indicators. SEM has several advantages, such as its ability to address various research problems more systematically and comprehensively, providing high flexibility to researchers to link theory and data, and explaining complex relationships between variables, including direct and indirect effects of one or more variables on other variables.

2.5 Partial Least Square (PLS)

Partial Least Squares (PLS) is a multivariate statistical technique used to analyze the relationships between one or more dependent variables and one or more independent variables. According to Ghozali (2014), PLS is an alternative approach different from covariance-based SEM. While covariance-based SEM is often used to test causality and

theory, PLS focuses more on predictive modeling. PLS is a powerful method because it does not heavily rely on many assumptions.

The PLS method has several advantages, such as the PLS algorithm that can be used to link manifest variables with latent variables in both reflective and formative formats. Additionally, PLS is suitable for use with relatively small samples, can handle very complex models, and can be used with data that does not follow a normal distribution. The PLS algorithm has the ability to estimate complex models with hundreds of latent variables and thousands of indicators. On the other hand, PLS also has limitations, such as not being able to assess statistical significance because it does not know the distribution of the data used. According to Ghozali (2014), the limitations of the PLS method can be overcome by using bootstrapping or resampling methods.

2.6 Formation of SEM-PLS Model

The path analysis model in SEM consists of three sets of different relationships, namely the inner model that explains the relationships between latent variables, the outer model that explains the relationships between latent variables and indicators, and weight relations that can be used to estimate the values of latent variable cases (Ghozali, 2014). The measurement model or outer model shows the relationship between latent variables and manifest variables (indicators). There are two types of models in the outer model, namely reflective indicator models and formative indicator models. A reflective model occurs when indicators are influenced by latent variables. The equation for the reflective indicator model is as follows:

$$x = \lambda_x \xi + \delta_x \quad (3)$$

$$y = \lambda_y \eta + \varepsilon_y \quad (4)$$

while the formative indicator from model is as follows:

$$\xi = \Pi_\xi x + \delta_\xi \quad (5)$$

$$\eta = \Pi_\eta y + \varepsilon_\eta \quad (6)$$

where:

- x : vector of exogenous indicator variables (ξ)
- y : vector of endogenous indicator variable (η)
- λ_x, λ_y : loading matrix
- δ, ε : measurement error or noise
- Π_ξ, Π_η : such as multiple regression coefficients on latent variables on indicators

The second model is the structural model (inner model). The inner model describes the specification of the relationship between latent variables. The model of the Inner equation model can be written as follows:

$$\eta = \beta \eta + \Gamma \xi + \zeta \quad (7)$$

Where η is the vector of endogenous indicator variables, ξ is the vector of exogenous latent variables, ζ is the vector of residual variables. While β is the coefficient matrix indicating

the influence of endogenous latent variables on other variables and Γ is the path coefficient matrix that relates the endogenous latent variable to the exogenous latent variable.

The third model is the Connection Weight, which is a weight connecting the structural model (inner model) and the measurement model (outer model) that aims to form estimates of endogenous and exogenous latent variables. The estimation of latent variable scores can be formulated as follows:

$$\hat{\xi}_i = \sum_{k_g} w_{k_g i} x_{k_g i} \quad (8)$$

$$\eta_i = \sum_{k_d} w_{k_d i} x_{k_d i} \quad (9)$$

$\hat{\xi}_i$: exogenous latent variable

η_i : endogenous latent variable

$w_{k_g i}$: the weight used to estimate exogenous latent variable

$w_{k_d i}$: the weight used to estimate endogenous latent variable

k : the number of exogenous latent variables

m : the number of endogenous latent variables

2.7 Parameter Estimation with PLS

PLS uses the least squares method to estimate or predict parameters (Ghozali, 2014). Through the PLS algorithm, estimation of latent variables and parameters can be performed. This estimation consists of three stages. The first stage involves an iterative procedure of simple or multiple regression, considering relationships in the structural model, measurement model, and weight estimation. A set of estimated weights is used to calculate latent variable scores. These scores are the result of a linear combination of indicator or manifest variables. In the second stage, the estimation of coefficients for the structural model and coefficients for each measurement model is conducted. The third stage determines the average estimate and the location of the parameters for the indicators and latent variables.

2.8 SEM-PLS Model Evaluation

Evaluation of the SEM-PLS model on the measurement model (outer model) is evaluated by looking at the validity and reliability. If the measurement model is valid and reliable, the next step can be carried out, namely the evaluation of the structural model. If the measurement model is not valid and reliable, so the path diagram should be re-constructed. A validity test is conducted with convergent validity. Convergent validity of the measurement model with reflexive indicators is seen from the Average Variance Extraction (AVE). Convergent validity is said to be sufficient if the AVE value is greater than 0.5. This shows that the latent variable explains more than half of the indicator variance (Hair et al., 2010). The AVE value is calculated based on the following formula:

$$AVE = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum \text{var}(\varepsilon_i)} \quad (10)$$

where λ_i is the factor loading and $\text{var}(\varepsilon_i) = 1 - \lambda_i^2$.

Composite reliability measures the reliability of the variable. a variable is said to be reliable if it has composite

reliability of ≥ 0.7 . Composite reliability can be calculated by the following formula:

$$\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum_i \text{var}(\epsilon_i)} \quad (11)$$

While the evaluation of the inner model is done by looking at the value of the R^2 model. The value of R^2 ranging from 0 to 1. The closer to 1, the better the model in explaining the relationship between exogenous latent variables and endogenous latent variables.

3. METHODOLOGY

3.1 Data

The data used in this research are primary data obtained from a survey of MyPertamina users in East Java, Indonesia are primary data obtained from a survey of MyPertamina users in East Java, Indonesia.

3.2 Data Collection Techniques

The data collection technique in this research involves using purposive sampling by selecting respondents based on criteria, namely those who have used the MyPertamina application, are at least 17 years old, and reside in East Java. According to Hair et al. (2010), if the sample size is too large, it will be difficult to obtain a suitable model, so it is recommended to use an appropriate sample size, typically between 100-200 respondents, to enable estimation and interpretation with Structural Equation Model (SEM). The sample size will be determined based on the calculation of the minimum sample for SEM according to Ferdinand (2014), who suggests that the ideal minimum sample size is 5 to 10 times the number of indicators. In this study, there are 22 indicators, so based on this guideline, the required sample size is 110 respondents.

3.1 Research Variable

Table 2: Satisfaction Variable

Variable	Indicator
Exogenous Variable	
Efficiency (x_1)	The application is clear and easy to follow (x_{11})
	The scanning machine is effective and responsive (x_{12})
	The menu and icons are in accordance with their functions (x_{13})
	Complete and accurate information (x_{14})
	Latest information (x_{15})
Trust (x_2)	Ensuring the security of usernames and passwords (x_{21})
	Authentication using the required data (x_{22})
	Data is securely archived (x_{23})
	Data is used according to needs (x_{24})
Reliability	Accessible anytime when needed (x_{31})

Variable	Indicator
(x_3)	The application is not prone to errors (x_{32})
	The reload menu takes a short amount of time (x_{33})
	Functions well on the device used (x_{34})
Citizent Support (x_4)	The administrator is interested in resolving user issues (x_{41})
	The administrator responds to questions quickly and accurately (x_{42})
	The administrator can answer user questions (x_{43})
Endogenous Variable	
Satisfaction (y_1)	The application is easy to operate (y_{11})
	The application is effective when used (y_{12})
	The application system is efficient (timely) when used (y_{13})
Loyalty (y_2)	Will use the MyPertamina application again (y_{21})
	Will inform others about the advantages of MyPertamina (y_{22})
	Will recommend MyPertamina to others (y_{23})

4. RESULTS

4.1 Validity Test

Table 3: Validity Test on the Dimensions of Tangible

Attribute	P-value	Decision	Conclusion
x_{11}	0,000	Reject H_0	Valid
x_{12}	0,000	Reject H_0	Valid
x_{13}	0,000	Reject H_0	Valid
x_{14}	0,000	Reject H_0	Valid
x_{15}	0,000	Reject H_0	Valid
x_{21}	0,000	Reject H_0	Valid
x_{22}	0,000	Reject H_0	Valid
x_{23}	0,000	Reject H_0	Valid
x_{24}	0,000	Reject H_0	Valid
x_{31}	0,000	Reject H_0	Valid
x_{32}	0,000	Reject H_0	Valid
x_{33}	0,000	Reject H_0	Valid
x_{34}	0,000	Reject H_0	Valid
x_{41}	0,000	Reject H_0	Valid
x_{42}	0,000	Reject H_0	Valid
x_{43}	0,000	Reject H_0	Valid
y_{11}	0,000	Reject H_0	Valid
y_{12}	0,000	Reject H_0	Valid
y_{13}	0,000	Reject H_0	Valid
y_{21}	0,000	Reject H_0	Valid
y_{22}	0,000	Reject H_0	Valid
y_{23}	0,000	Reject H_0	Valid

The results of the validity test in Table 4 show that all statement variables have a $p\text{-value} = 0,000 < \alpha (0,05)$. Therefore, the conclusion is that all statements in the questionnaire are able to measure the same aspect, so they can be considered valid.

4.2 Reliability Test

Table 4: Reliability Test

Variable	Cronbach's alpha	Conclusion
Efficiency (ξ_1)	0,918	Very high reliability
Trust (ξ_2)	0,900	Very high reliability
Reliability (ξ_3)	0,888	Very high reliability
Citizen Support (ξ_4)	0,887	Very high reliability
Satisfaction (η_1)	0,875	Very high reliability
Loyalty (η_2)	0,884	Very high reliability

The results of the reliability test in Table 5 indicate that all variables have Cronbach's Alpha values of more than 0,800. Therefore, it can be concluded that all variables have a very high level of reliability.

4.3 Evaluation of the Measurement Model

The relationship between latent variables and their indicators can be determined by evaluating the measurement model. To conduct the evaluation, assessments of convergent validity and composite reliability are performed. Convergent validity is measured based on the Average Variance Extracted (AVE) values.

Table 5: Average Variance Extracted

Attribute	AVE	Conclusion
Efficiency (ξ_1)	0,753	Valid
Trust (ξ_2)	0,771	Valid
Reliability (ξ_3)	0,748	Valid
Citizen Support (ξ_4)	0,803	Valid
Satisfaction (η_1)	0,803	Valid
Loyalty (η_2)	0,815	Valid

Based on Table 5, each variable has an AVE value $> 0,5$. Therefore, it can be concluded that all variables in this study have acceptable convergent validity. Meanwhile, composite reliability is used to measure the consistency of a respondent in answering the research instrument and to measure the consistency of the measuring instrument in measuring the concept. The composite values can be seen in Table 6.

Table 6: Composite Reliability

Attribute	Composite Reliability	Conclusion
Efficiency (ξ_1)	0,938	Reliable
Trust (ξ_2)	0,931	Reliable
Reliability (ξ_3)	0,922	Reliable

Attribute	Composite Reliability	Conclusion
Citizen Support (ξ_4)	0,924	Reliable
Satisfaction (η_1)	0,925	Reliable
Loyalty (η_2)	0,929	Reliable

It can be observed from Table 6 that all latent variables in this study have composite reliability values $> 0,7$, indicating that each indicator is considered reliable. Additionally, each indicator also exhibits accuracy, consistency, and precision in measuring latent variables.

4.4 Evaluation of the Structural Model

The structural model evaluation is conducted to assess the relationships between latent variables. Two analyses used in this evaluation are the coefficient of determination and prediction relevance. The calculation using the coefficient of determination is based on the R-Square values (R^2). The influence of exogenous latent variables on endogenous variables will be greater as the obtained R^2 value increases. The R^2 values are only possessed by endogenous variables and can be found in Table 7.

Table 7: R-Square

Attribute	R-Square
Satisfaction (η_1)	0,886
Loyalty (η_2)	0,896

R^2 values greater than 0,67 can be interpreted as the influence of exogenous variables on endogenous variables falling into the good or substantial category (Chin, 1998). The variables Satisfaction (η_1) and Loyalty (η_2) have R^2 values of 0,886 and 0,896, respectively. This means that the variable Satisfaction (η_1) can be well-explained by the variables Efficiency (ξ_1), Trust (ξ_2), Reliability (ξ_3), dan Citizen Support (ξ_4) at 88,6%, while 11,4% is explained by other factors outside the study. Similarly, the variable Loyalty (η_2) can be well-explained by the variables Efficiency (ξ_1), Trust (ξ_2), Reliability (ξ_3), dan Citizen Support (ξ_4) at 89,6% while 10,4% explained by other factors outside the study.

Prediction relevance is used to validate the ability of a model and is assessed based on Q^2 . If the Q^2 value approaches 1, then the structural model fits the data well and has relevant predictions (Ghozali, 2011). The Q^2 values in this study are as follows:

$$Q^2 = 1 - (1 - R_1^2)(1 - R_2^2) = 0,988144$$

The obtained Q^2 value in this study is 0,988144 which is close to 1. Therefore, it can be stated that the structural model fits the data well and has relevant predictions.

4.5 Goodness of Fit Model

The overall model is validated based on the Goodness of Fit Index (GoF). The GoF value is obtained through the

calculation of the average values of communalities (AVE) and the average values of R^2 .

$$GoF = \sqrt{\text{com} \times R^2} \quad (12)$$

The obtained GoF value in this study is 0,83431. This GoF value falls into the 'large' category (Trujillo, 2009). Therefore, it is known that the model has a high ability to explain the data, and overall, it can be considered that the formed model is valid.

4.6 Hypothesis Test

Following the stages of model evaluation and obtaining the results of statistical hypothesis testing in the structural model (partial tests), hypothesis testing is carried out for the measurement model and structural model. In this study, hypothesis testing for the measurement model is conducted using t-statistic and p-value. The hypotheses for the measurement model are as follows:

$H_0: \lambda_i = 0$ (there is no influence)

$H_1: \lambda_i \neq 0$ (there is the influence)

With a significance level of $\alpha = 0,05$ and the criterion that if the $|t_{\text{statistics}}| \geq 1,98$ then reject H_0 indicating that the parameter used is significant.

Table 8: Significance Test of Measurement Model

Variable	T-Statistics	P-Value
x_{11}	43,103	0,000
x_{12}	49,009	0,000
x_{13}	31,059	0,000
x_{14}	31,082	0,000
x_{15}	45,665	0,000
x_{21}	40,931	0,000
x_{22}	42,859	0,000
x_{23}	47,662	0,000
x_{24}	35,434	0,000
x_{31}	37,994	0,000
x_{32}	52,828	0,000
x_{33}	38,134	0,000
x_{34}	33,439	0,000
x_{41}	51,132	0,000
x_{42}	55,560	0,000
x_{43}	55,276	0,000
y_{11}	43,804	0,000
y_{12}	62,051	0,000
y_{13}	67,153	0,000
y_{21}	53,077	0,000
y_{22}	50,418	0,000
y_{23}	84,630	0,000

From Table 8, it can be seen that each indicator has a $|t_{\text{statistics}}| \geq t_{\alpha/2, n-2} = 1,98$ and $p\text{-value} < \alpha(0,05)$. Therefore, it is concluded that all indicators are significant and capable of measuring their latent variables.

Meanwhile, the hypotheses for the estimation of structural model parameters are as follows:

$H_0: \gamma_i = 0$ (there is no influence)

$H_1: \gamma_i \neq 0$ (there is the influence)

The results of the significance test for the structural model can be seen in Table 9.

Table 9: Significance Test of Structural Model

Variable	T-Statistics	P-Value
$x_1 \rightarrow y_1$	2,128	0,033
$x_1 \rightarrow y_2$	3,061	0,002
$x_2 \rightarrow y_1$	2,777	0,006
$x_2 \rightarrow y_2$	1,177	0,239
$x_3 \rightarrow y_1$	2,508	0,012
$x_3 \rightarrow y_2$	2,536	0,011
$x_4 \rightarrow y_1$	2,396	0,017
$x_4 \rightarrow y_2$	0,277	0,782
$y_1 \rightarrow y_2$	2,027	0,043

The statistical hypothesis testing was conducted using a significance level of $\alpha = 0,05$ and $t_{\alpha/2, n-2} = 1,98$. The conclusion drawn is that only the latent variables Trust and Citizen Support do not significantly influence the latent variable Loyalty, so they need to be rejected.

4.7 Model Interpretation

Through the bootstrapping procedure, the measurement and structural models regarding the factors influencing user satisfaction and loyalty in MyPertamina were obtained. After evaluating the measurement and structural models, the final path diagram was generated, as depicted in Figure 1.

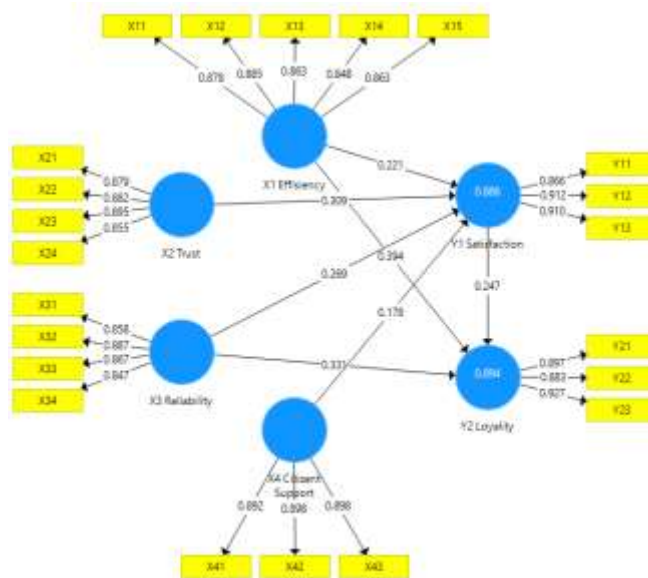


Fig. 1 Final Model Path Chart

Based on Figure 1, the final path diagram results in the measurement matrix of endogenous variables as follows:

- Efficiency

$$\begin{aligned}x_{11} &= 0,878\xi_1 \\x_{12} &= 0,885\xi_1 \\x_{13} &= 0,863\xi_1 \\x_{14} &= 0,848\xi_1 \\x_{15} &= 0,863\xi_1\end{aligned}\quad (13)$$

Based on Equation 13, there is a positive correlation between the latent variable Efficiency (ξ_1) and its indicators. According to Equation 13, it can be explained that indicator x_{11} can explain 87,8% of the latent variable Efficiency, indicator x_{12} can explain 88,5% dari variabel laten Efficiency, indicator x_{13} can explain 86,3% of the latent variable Efficiency, indicator x_{14} can explain 84,8% of the latent variable Efficiency, and indicator x_{15} can explain 86,3% of the latent variable Efficiency.

- Trust

$$\begin{aligned}x_{21} &= 0,879\xi_2 \\x_{22} &= 0,882\xi_2 \\(14) \\x_{23} &= 0,895\xi_2 \\x_{24} &= 0,855\xi_2\end{aligned}$$

Based on Equation 14, there is a positive correlation between the latent variable Trust (ξ_2) and its indicators. According to Equation 14, it can be explained that indicator x_{21} can explain 87,9% of the latent variable Trust, indicator x_{22} can explain 88,2% of the latent variable Trust, indicator x_{23} can explain 89,5% of the latent variable Trust and indicator x_{24} can explain 85,5% of the latent variable Trust.

- Reliability

$$\begin{aligned}x_{31} &= 0,858\xi_3 \\x_{32} &= 0,887\xi_3 \\(15) \\x_{33} &= 0,867\xi_3 \\x_{34} &= 0,847\xi_3\end{aligned}$$

Based on Equation 15, there is a positive correlation between the latent variable Reliability (ξ_3) and its indicators. The latent variable Reliability, it can be explained that indicator x_{31} can explain 85,8%, indicator x_{32} can explain 88,7%, indicator x_{33} can explain 86,7%, and indicator x_{34} can explain 84,7% of the latent variable Reliability.

- Citizen Support

$$\begin{aligned}x_{41} &= 0,892\xi_4 \\x_{42} &= 0,898\xi_4 \\(16) \\x_{43} &= 0,898\xi_4\end{aligned}$$

Based on Equation 16, there is a positive correlation between the latent variable Citizen Support (ξ_4) and its indicators. According to Equation 16, it can be explained that indicator x_{41} can explain 89,2%, indicator x_{42} can explain 88,8% and indicator x_{43} can explain 89,8% of the latent variable Citizen Support.

Based on Figure 1, the final path diagram of the research yields the measurement equations for the endogenous variables as follows:

- Satisfaction

$$\begin{aligned}y_{11} &= 0,866\eta_1 \\y_{12} &= 0,912\eta_1 \\(17) \\y_{13} &= 0,910\eta_1\end{aligned}$$

Based on Equation 17, there is a positive correlation between the latent variable Satisfaction (η_1) and its indicators. According to Equation 17, it can be explained that indicator y_{11} can explain 86,6% of the latent variable Satisfaction, indicator y_{12} can explain 91,2% of the latent variable Satisfaction, and indicator y_{13} can explain 91,0% of the latent variable Satisfaction.

- Loyalty

$$\begin{aligned}y_{21} &= 0,897\eta_2 \\y_{22} &= 0,883\eta_2 \\(18) \\y_{23} &= 0,927\eta_2\end{aligned}$$

Based on Equation 18, there is a positive correlation between the latent variable Loyalty (η_2) and its indicators. According to Equation 18, it can be explained that indicator y_{21} can explain 89,7% of the latent variable Loyalty, indicator y_{22} can explain 88,3% of the latent variable Loyalty, and indicator y_{23} can explain 92,7% of the latent variable Loyalty.

The structural model equation explains the factors influencing user satisfaction and loyalty in MyPertamina. The interpretation of the structural model equation is as follows:

- Satisfaction

$$\eta_1 = 0,221\xi_1 + 0,309\xi_2 + 0,269\xi_3 + 0,178\xi_4 \quad (19)$$

Equation 19 indicates that the variable Satisfaction is explained by the variable Efficiency at 22,1%, variable Trust at 30,9%, variable Reliability at 26,9% and variable Citizen Support at 17,8%. The four positive path coefficient values indicate a direct relationship between the four exogenous latent variables and the latent variable Satisfaction. It can be interpreted that the higher the efficiency level of the application, the trust level in the application, the reliability level of the application, and the level of community support provided by the MyPertamina application, the higher the satisfaction level of the community with the MyPertamina application.

- Loyalty

$$\eta_2 = 0,247\eta_1 + 0,394\xi_1 + 0,331\xi_3 \quad (20)$$

Equation 20 indicates that the latent variable Loyalty is explained by the latent variable Satisfaction at 24,7%, variable Efficiency at 39,4%, and variable Reliability at 33,1%. The three positive path coefficient values indicate a direct relationship between the three latent variables and the

endogenous latent variable Loyalty. It can be interpreted that the higher the efficiency level of the MyPertamina application, the reliability level of the MyPertamina application, and the satisfaction level of the community with the MyPertamina application, the higher the loyalty of the community towards the MyPertamina application.

5. CONCLUSION

The results showed that Goodness of Fit Test yields a value of 0,83431. This value falls into the 'large' category. It can be interpreted that the model has a high ability to explain the data, and, therefore, overall, it can be said that the formed model is valid.

The variables Efficiency, Trust, Reliability, and Citizen Support have a significant impact on user satisfaction in MyPertamina. Variables Efficiency, Reliability, and Satisfaction significantly influence user loyalty in MyPertamina. However, variables Trust and Citizen Support do not have a significant impact on user loyalty in MyPertamina.

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