American Journal of Humanities and Social Sciences Research (AJHSSR)
e-ISSN :2378-703X
Volume-08, Issue-02, pp-215-224
www.ajhssr.com
Research Paper Open Access

Implementation of SEM Partial Least Square in Analyzing the UTAUT Model

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ABSTRACT: Partial Least Squares (PLS) Structural Equation Modeling (PLS-SEM) is a statistical technique used to analyze the expected connections between constructs by evaluating the existence of correlations or impacts among these constructs. The objective of this work is to employ the Structural Equation Modeling (SEM) technique, specifically Partial Least Squares (PLS), to investigate the Unified Theory of Acceptance and Use of Technology (UTAUT) model in the specific domain of payment technology acceptance and utilization. The UTAUT model encompasses latent variables classified into independent, mediator, moderator, and dependent categories. Hence, the appropriate approach, the partial least squares structural equation modeling (PLS-SEM) method, was chosen. The rationale behind this decision is the capability of PLS-SEM to assess models with a relatively limited dataset, as demonstrated in this study, which included a sample of 50 participants. This study employs a quantitative methodology utilizing a survey-based approach to gather data via questionnaires. The UTAUT model in the technology acceptance and use domain was accurately assessed by PLS-SEM, as evidenced by the findings. The findings have substantial implications for comprehending the factors that influence the adoption of payment technology, specifically focusing on the linkages between constructs in the UTAUT model. This research validates the model and establishes a foundation for a more profound comprehension of user behavior in accepting and utilizing payment technologies. Ultimately, using PLS-SEM demonstrated its efficacy in examining the UTAUT model.

KEYWORDS :*Structural Equation Model, Partial Least Square, UTAUT*

I. INTRODUCTION

Along with advancing the business landscape and technology, research in various fields, including management programs, is increasing. Management research is not only confirmatory but also leads to predictive analysis. One method that is often used is Structural Equation Modeling.

Structural Equation Modeling, also known as covariance structure analysis, latent variable analysis, confirmatory factor analysis, and Linear Structural Relations (Lisrel) analysis, is recognized by several names [2\4]. SEM can be defined as an analytical method that integrates the methodologies of factor analysis, structural model, and path analysis. SEM is a statistical analytic technique that deals with several variables. The procedure for processing SEM data differs from regression data processing or path analysis. SEM data analysis is fundamentally complex, encompassing both measurement and structural models inside the SEM framework. Structural Equation Modeling (SEM) is a collection of statistical methods that examine intricate relationships that cannot be sufficiently explored using linear regression equations. SEM can be seen as an amalgamation of regression analysis and factor analysis. Alternatively, it is known as Path Analysis or Confirmatory Factor Analysis, as both are distinct versions of Structural Equation Modeling (SEM). A relationship between variables influenced by other factors and one or more variables that impact the former can be established.

According to [6], Structural Equation Modeling (SEM) is an influential technique for conducting comprehensive investigations of hypotheses and concepts. The outer/measurement model facilitates the assessment of latent variables at the observational level. In contrast, the inner/structural model enables the examination of the relationship between latent variables at the theoretical level. Structural equation modeling (SEM) techniques offer analytical advantages by elucidating the intricate connections between variables and the direct and indirect impacts of one or more variables on others [12]. Presently, two prevalent types of SEM are frequently employed in research, particularly in management: covariance-based SEM (CB-SEM) and component-based SEM.

[6] argues that the difference between CB-SEM and PLS-SEM is based on the contrasting objectives of the research. If the study aims to confirm and strengthen the hypothesis, then covariance-based structural equation modeling (CB-SEM) is the appropriate methodology. Conversely, if the objective of the research is to generate forecasts and develop theories, then the proper method would be Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is a statistical method used for causal modeling to maximize the explained variance in the dependent construct. Additionally, it evaluates the data's quality by analyzing the characteristics of the measurement model.

Meanwhile, [3]states that SEM, based on components or variance, is called Partial Least Square (PLS). This analysis tests the causality/theory model and makes predictions. PLS is utilized for doing causal-predictive research in scenarios characterized by high complexity and limited theoretical support. It is a powerful method based on only a few assumptions. Another opinion is that Partial Least Square (PLS) is another approach of the Structural Equation Modeling (SEM) method that can address conflicts where the interaction between variations is very complicated. Still, the sample size is relatively small [8]. PLS-SEM aims to examine the predicted association between constructs by assessing the presence of a relationship or influence between them [3].

In addition, [6] present a detailed table that outlines specific criteria (Rules of Thumb) for choosing between CB-SEM or PLS-SEM. One of the objectives is to articulate the research objectives unambiguously. One of the tasks is to define the research goals clearly. Apply Partial Least Squares Structural Equation Modeling (PLS-SEM) when the research aims to forecast important target constructs or uncover influential 'driving' constructs and when the study is either exploratory or an expansion of an already established structural theory. CB-SEM is utilized when the research aims to scrutinize, authenticate, or compare various approaches.

The discussion of SEM categorizes the model's qualities into three distinct groups: focused, unfocused, and balanced [6]. The concentrated model has limited internal variables, which are elucidated by a more extensive set of external factors (with a minimum ratio of twice as many external variables to internal variables). The model lacks clarity and includes multiple hidden variables and intermediary effects, in contrast to a small number of external variables (where the number of hidden variables is at least twice the number of external variables). Equilibrium models lie between concentrated and diffuse. The concentrated and balanced models align with the predictive objective of PLS-SEM. CB-SEM is more suited for models that lack concentration.

[15] elucidated in their scholarly publication that biased outcomes in structural equation modeling (SEM) occur when researchers lack knowledge of the underlying nature of the population data, whether common factors, covariances, composites, or components characterize it. This issue is prevalent in social science research, thus making partial least squares (PLS) the method of choice in such circumstances. In this study, [15]examine the contrast between utilizing Partial Least Squares (PLS) for estimating standard factor models and Covariance-Based Structural Equation Modeling (CBSEM) for evaluating composite models. Multiple investigations using Partial Least Squares (PLS) have demonstrated that the bias resulting from PLS estimation of standard component models is negligible, and the measurement models satisfy the minimum suggested criteria. Furthermore, when the specific model type and population data are unknown, employing Partial Least Squares (PLS) is the most dependable option to avoid any potential bias in the parameters.

The validity test assesses whether the measuring instrument effectively fulfills its measuring function in alignment with the measurement objectives, ensuring that each instrument component can accurately measure the research variable. The reliability test is conducted to assess the internal consistency of an indicator for a latent variable and its capacity to accurately measure a constructed variable (a variable that cannot be directly observed). A measuring equipment is deemed reliable if it continuously yields identical outcomes when employed repetitiously.

Creating a latent variable score component is contingent upon the specification of the inner model, which connects latent variables and represents the substantive theory, and the outer model establishes the relationship between indicators and constructs in the measurement model. The reference is from Ghozali's work, precisely on page 19 of the 2006 publication.

II. LITERATURE REVIEW

In the Partial Least Squares (PLS) context, evaluating the measurement model involves analyzing the convergent and discriminant validity of the reflective indicators in the outer model and the composite reliability for the indicator block. The coefficient of determination (R2) is the primary metric used to assess the accuracy of the internal model. It measures the amount of variability explained by each endogenous latent variable. Aside from the R2 value, evaluating the construct model also involves assessing the Q2 predictive relevance. This statistic measures the degree to which the model and its parameter guesses accurately produce the observed results.

In light of the prevailing conditions, we employed Structural Equation Modeling (SEM) with Partial Least Squares (PLS) to examine the Unified Theory of Acceptance and Use of Technology (UTAUT) model as the primary subject of this investigation. The UTAUT model, also known as the Unified Theory of Acceptance and Use of Technology, is well recognized as a fundamental theoretical framework used to assess the acceptability and usage of technology. The model in question was established in 2003 by Venkatesh, Morris, Davis, and Davis, who integrated various preexisting theoretical models, including TAM (Technology Acceptance Model), TPB (Theory of Planned Behavior), and IDT (Model of Innovation Diffusion).

The UTAUT model posits that an individual's propensity to adopt new technology is influenced by four primary factors: Performance Expectations, Effort Expectations, Social Influence, and Facilitating Conditions. Performance expectations are to the anticipated benefits and advantages of using technology. Effort expectation refers to utilizing and acquiring proficiency in a particular technology. Social influence refers to the perceived pressure or support exerted by colleagues and social networks to adopt technology. Facilitating conditions encompass vital resources and infrastructure for enabling technology usage [24].

The UTAUT model includes both mediating and moderating variables. The association between exogenous and endogenous dimensions in model construction frequently necessitates elucidation through connecting or mediating factors. In SEM, aspects that establish a connection between other variables are known as intervening variables. An intervening variable, as defined by [22], is a mediating variable that acts as an intermediary between the independent variable (predictor) and the dependent variable (predictor). However, it is widely recognized that Moderate Regression Analysis (MRA) is a frequently employed technique in multiple linear regression analysis. It involves incorporating a third variable as the product of two independent variables (exogenous) as a moderating variable [3]. Using latent variables in MRA estimation leads to an inconsistent and biased measurement error of the estimation coefficient, resulting in a non-linear relationship. One possible method to address this measurement inaccuracy is to utilize the SEM (Structural Equation Model) and incorporate the interaction effect into the model [3]. Hence, the more compelling the need for employing SEM PLS Analysis for testing in this study.

The study utilizes Smart PLS 3.0 software designed explicitly for Structural Equation Modeling (SEM) PLS analysis. This software provides many tools that simplify user investigation of complex theoretical models. PLS-SEM and Smart PLS 3.0 software to analyze the UTAUT model offers numerous advantages. Firstly, it enables testing intricate theoretical models, including those with causal connections between latent variables. Secondly, it does not necessitate data normality assumptions, allowing for examining models with abnormal data and a limited number of samples. Lastly, it provides various features that facilitate the analysis of theoretical models, such as bootstrapping and power analysis capabilities.

III. METHOD

General Background

The author of this paper used a quantitative methodology to examine and assess data, specifically focusing on causal links. This analysis additionally encompasses statistical computations. The study will utilize associative-causality research, a quantitative research method to establish the causal relationship between the independent and dependent variables [15]. This study examines the impacts of utilizing digital payment methods within the UTAUT framework, considering demographic variables as moderators. Additionally, there are several techniques employed to gather data.

Data Collection Method

The authors gathered data from the source for this investigation. [22]identifies two categories of data collecting based on the source:

1. Primary data refers to information collected directly from respondents through the completion of surveys.
2. Secondary data refers to additional information acquired from sources such as books, journals, or other relevant materials that support this research.

The data collection was conducted utilizing the sample survey methodology. The method described involves collecting data from a natural environment through administering a questionnaire [1]. This technique is implemented because the chosen sample accurately represents the members of the population at the research site. The data-gathering process will employ the questionnaire technique, which involves providing respondents with questions or written statements to answer [21].

Population and Sample

The population encompasses the complete set of individuals, instances, or objects to whom the research findings will be generalized [23]. The study focuses on MSME practitioners in Lombok, Indonesia. The sample consists of individuals selected from the population and can serve as a representative sample [17]. The sampling methodology employed in this study utilized a convenience sampling strategy. The study's sample size is selected based on the parameters outlined by [6], which recommend that the number of samples should be 5-10 times greater than the indicator of the entire latent variable. The study's sample size comprised 50 participants.

Data Analysis Technique

This study utilizes the Partial Least Squares (PLS) approach with the SmartPLS 3 software package. Partial Least Squares (PLS) is a suitable method for doing Structural Equation Modeling. It is beneficial when dealing with complex variables, data that does not follow a Gaussian distribution, and small sample sizes (less than 100 samples). Partial Least Squares (PLS) is a statistical technique used to reveal the relationship between many variables and analyze structural equations. Furthermore, PLS offers the capability to do concurrent measurement model testing and structural model testing. Measurement models are utilized to assess the precision and reliability of tests, whereas structural models are employed for hypothesis testing to prove causality [18].

Performing the model evaluation stage is essential in "PLS analysis." This assessment follows a two-step methodology. Firstly, it assesses the measurement model to determine its compliance with the specified standards. Secondly, it analyzes the structural framework and then evaluates the overall excellence of the model [25].

Evaluation of the Measurement Model

The measuring methodology employed in this work utilizes reflective indicators, as the latent variable indicators influence the observed indicators. The assessment of the measuring model by examining the value in (Yamin, 2022):

a. The Loading Factor (LF) or outer loading represents the degree of correlation between each measurement item and the variable. This metric measures the extent to which the item precisely represents or characterizes the measurement of the variable. Based on the research conducted [11,12], it is considered appropriate to have a latent factor (LF) value of 0.70 or higher. However, according to [2], an LF value greater than 0.50 is considered acceptable or legitimate.

b. Composite reliability (CR) is a metric that assesses a variable's internal consistency, indicating its reliability level. The CR value should be at least 0.6 or higher, according to [12]. According to the research conducted by [6], a Composite Reliability score of more than 0.70 is deemed acceptable. Values within the range of 0.60 to 0.70 are considered suitable in this study.

c. The Average Variance Extracted (AVE) is a statistical metric that quantifies the average amount of variance accounted for by each measurement item within a variable. How much can the overarching variable explain the differences in measurement items? This metric also illustrates the strong convergent validity displayed by the variable. According to Hair et al., in 2021, the AVE value is more than or equivalent to 0.50.

Discriminant validity refers to the extent to which variables or constructs are distinct from other variables/constructs and are subjected to statistical analysis. Discriminant validity testing is conducted at both the variable and indicator levels. The cross-loadings measure is employed at the indicator level. At the same time, the Fornell-Lacker Criterion is used at the variable level to compare the AVE root with the correlation between variables. Another measure used to test discriminant validity is HTMT (HeterotraitMonotrait Ratio). It evaluates the validity by checking if the HTMT value is less than 0.9 [11,12].

Structural Model Evaluation

This structural model evaluation aims to perform hypothesis testing to determine causation. Hypothesis testing utilizes the bootstrapping technique, explicitly employing the percentile approach. The t-test is the statistical test used in this approach. The t-values obtained from the two-way test (two-tailed test) suggest a significance level of 5% and have a value of 1.96. The test conditions for the t-test comprise evaluating whether the t-statistic value exceeds the critical t-value or if the significance value is below 0.05. If any of these conditions are satisfied, it can be inferred that there is a substantial impact on the relationship between variables [25].

Evaluation of Model Quality and Fit

Assessing the model's quality involves analyzing the model. The model's acceptability can be evaluated by many measures, including R square, Q square, F square, and SRMR [25].

1. R Square

The R square value quantifies the collective impact of exogenous and endogenous variables on the remaining endogenous variables in the model. [2] found that the R square value is 0.67, which suggests a significant correlation. Additionally, the value of 0.33 indicates a moderate link, while the value of 0.19 suggests a weak association.

2. Q Square

Q Square assesses the predictive importance of the model by evaluating its accuracy in making predictions and its capacity to forecast endogenous variables based on changes in external variables. A positive value of Q square suggests that the exogenous factors have predictive relevance for the endogenous variables. Q square values of 0, 0.25, and 0.50 correspond to low, moderate, and good predictive accuracy, respectively [9]. Calculation of the area of a square

3. F Square

The F square measures the extent of the impact that the variables in the structural model or the exogenous latent variables have on the endogenous variables. This measure is determined by comparing the R square value achieved when variables are added or removed from the structural model. The F square value in [6] study can be interpreted as follows: 0.02 indicates a little impact size, 0.15 indicates a moderate effect size, and 0.35 indicates a big effect size.

IV. RESULTS

The process of data analysis in PLS-SEM involves splitting the test into two distinct sections: the Evaluation of the Measurement Model and the Evaluation of the Structural Model.

1. Evaluation of the Measurement Model

The Measurement Model refers to a framework used to quantify and assess various aspects or variables of interest systematically and precisely. Evaluation elucidates the connection between the construct and its indicators. The measurement model assesses data to ascertain its validity and reliability. When evaluating the measurement model, two validity tests are conducted: Convergent validity pertains to the extent to which two measures, intended to assess the same concept, exhibit a meaningful relationship with each other. Discriminant validity pertains to the extent to which two measures, intended to assess distinct variables, exhibit no correlation.

Convergent Validity Test

The assessment of the measurement model's convergent validity is established by examining the values of the outer loadings and applying the AVE parameter. The threshold value employed for outer loadings in confirmatory research is 0.5. For explanatory research, the maximum limit for outside loadings is set at 0.6. The upper threshold for outside loadings in development studies is 0.5. The maximum threshold for the outer loadings in this investigation is set at 0.7.

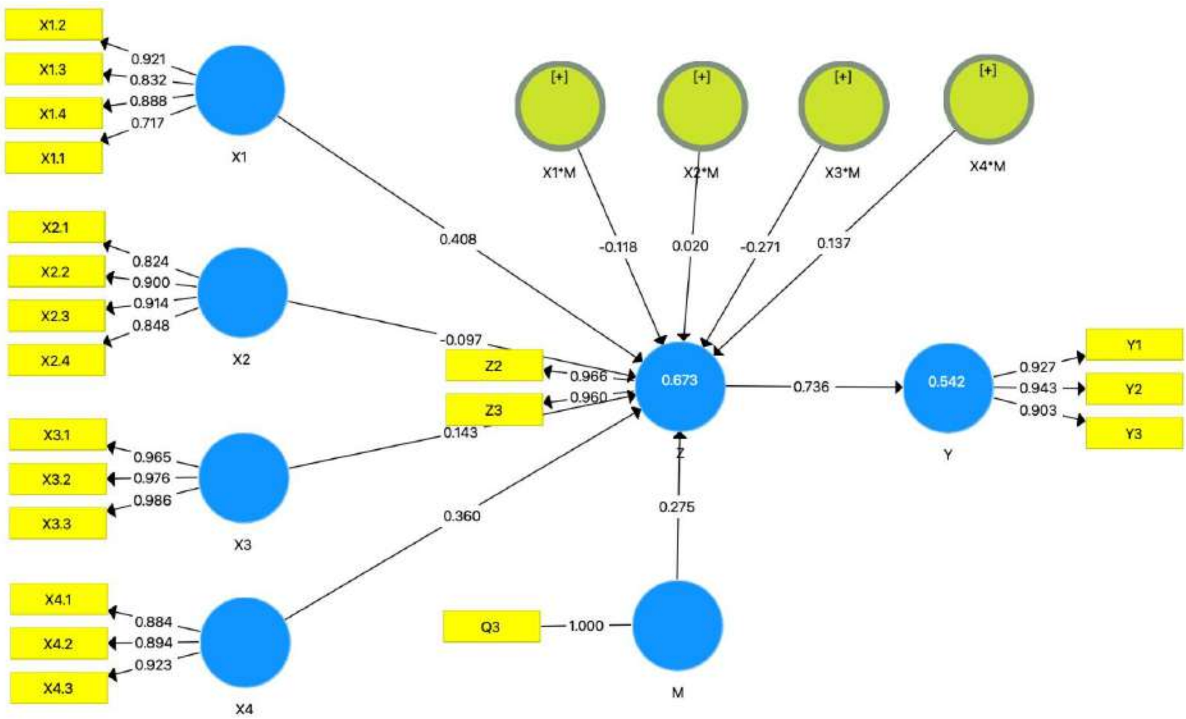

Figure 1. Overall Model Estimation Results

According to the data analysis, there are certain indicators with outer loading values below 0.7, which makes them invalid and necessitates their removal from the model. The estimation results obtained after excluding several indicators from the model are as follows:

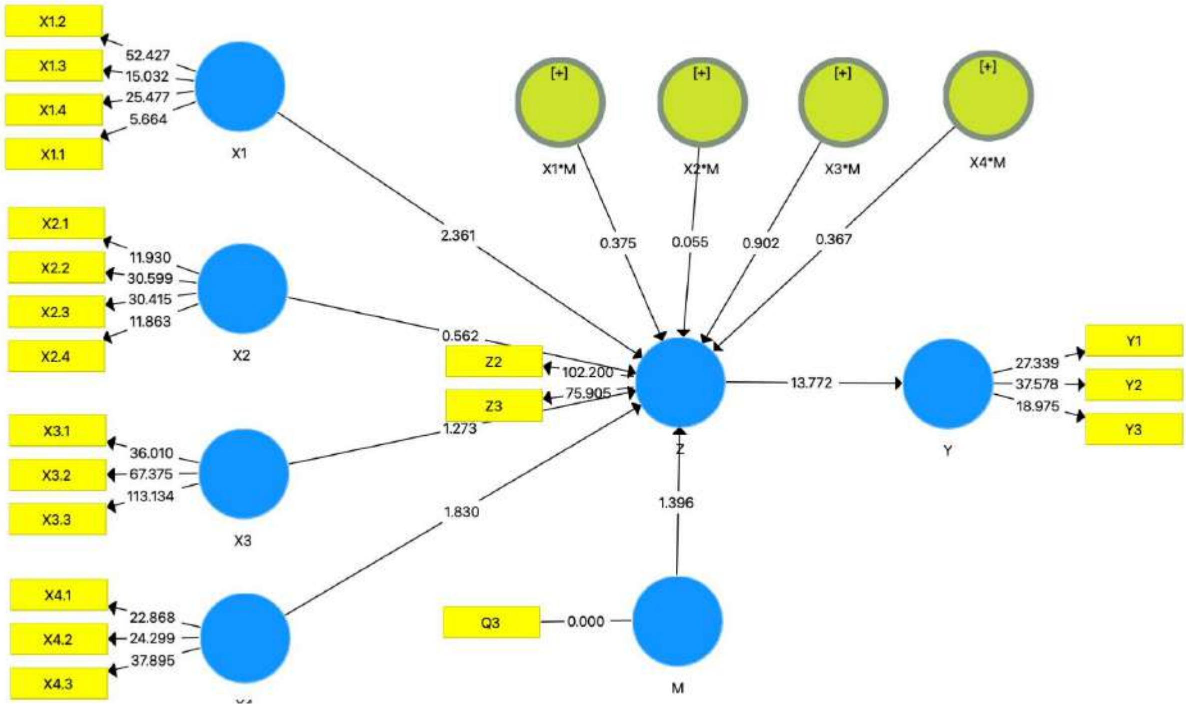

Figure 2. Valid Model Estimation Results

The model's estimated findings, as depicted in the figure above, indicate that all indicators have outer loading values over 0.7, satisfying the convergent validity condition. Convergent validity is assessed by examining the external loadings of each indicator and the average variance extracted (AVE) value of each construct. Convergent validity is attained in a model when each construct's average variance extracted (AVE) value exceeds 0.5.

Table 1. Average Variance Extracted (AVE) Value

Variable	**Average Variance Extracted (AVE)**
M	**1,000**
X1	**0,711**
X1*M	**1,000**
X2	**0,761**
X2*M	**1,000**
X3	**0,952**
X3*M	**1,000**
X4	**0,811**
X4*M	**1,000**
Y	**0,854**
Z	**0,927**

Based on the analysis results presented in the table above, it can be observed that the AVE value for all variable constructs exceeds 0.5. This suggests that all indicators within each construct meet the required criteria for convergent validity.

Discriminant Validity Test

The discriminant validity test assesses the degree to which the variables or constructs being studied are distinct from other variables or constructs, and this is assessed by statistical analysis. One can assess this test by examining the HTMT (HeterotraitMonotrait Ratio) value.

Table 2. HTMT Value

Variable	M	X1	X1*M	X2	X2*M	X3	X3*M	X4	X4*M	Y
M										
X1	0,402									
X1*M	0,400	0,130								
X2	0,465	0,722	0,106							
X2*M	0,046	0,069	0,660	0,052						
X3	0,353	0,419	0,174	0,158	0,050					
X3*M	0,315	0,202	0,642	0,044	0,612	0,048				
X4	0,381	0,820	0,085	0,861	0,074	0,260	0,134			
X4*M	0,179	0,087	0,782	0,077	0,860	0,120	0,683	0,051		
Y	0,328	0,855	0,129	0,703	0,141	0,198	0,187	0,886	0,128	
Z	0,494	0,791	0,058	0,612	0,080	0,475	0,023	0,766	0,007	0,799

The table indicates that the HTMT value for all variable pairs is below 0.9, therefore confirming the presence of discriminant validity. This implies that the correlation between measurement items within the same variable is more robust compared to the correlation between items from different variables. In simpler terms, the measurement items are more closely related to the construct being assessed than to other constructs.

Reliability Test

Cronbach's alpha and composite reliability values serve as benchmarks for assessing the reliability testing needs. It is advisable to have a minimum value of 0.7 for both Cronbach's alpha and composite dependability.

Table 3. Reliability Test Results

Variable	Cronbach's Alpha	Composite Reliability
M	1,000	1,000
X1	0,864	0,907
X1*M	1,000	1,000
X2	0,897	0,927
X2*M	1,000	1,000
X3	0,975	0,984
X3*M	1,000	1,000
X4	0,883	0,928
X4*M	1,000	1,000
Y	0,915	0,946
Z	0,921	0,962

The provided table displays the outcomes of the reliability test, indicating that all constructions exhibit a composite reliability value over 0.7 and Cronbach's alpha surpassing 0.7. This indicates that all structures have achieved the necessary degree of dependability.

2. Evaluation of Structural Model

The inner model test evaluates the structural model. An inner model is a visual depiction that showcases the relationships between variables in a research model. The testing phases on the inner model are carried out utilizing the Path Value, R Square, and T-Statistic Test as the foundation. Conclusions on the hypothesis are drawn by comparing the observed error rate in this study with the p-value. The analysis demonstrates a 5%

margin of error. The hypothesis is considered accepted when the p-value is below the predetermined error rate (p-value <0.05). The T-statistic value serves as an additional signal for hypothesis testing alongside the p-value. A positive correlation exists between the independent variable and the dependent variable when the T-statistic value exceeds 1.96 (T-Statistic > 1.96).

Table 4. Inner Model Test Results

Correlation between variables	T-Statistics	P-Value	Conclusion
X1 -> Z	2,361	**0,019**	Accepted
X2 -> Z	0,562	**0,575**	Rejected
X3-> Z	1,273	**0,204**	Rejected
X4 -> Z	1,830	**0,068**	Rejected
Z -> Y	13,772	**0,000**	Accepted
X1 -> Z -> Y	2,224	**0,027**	Accepted
X2 -> Z -> Y	0,560	**0,576**	Rejected
X3-> Z -> Y	1,309	**0,191**	Rejected
X4 -> Z -> Y	1,826	**0,068**	Rejected
X1*M -> Z	0,375	**0,708**	Rejected
X2*M -> Z	0,055	**0,956**	Rejected
X3*M -> Z	0,902	**0,368**	Rejected
X4*M -> Z	0,367	**0,714**	Rejected

Table 4 indicates that 3 hypotheses have been accepted, and 10 hypotheses have been rejected. The prevailing hypothesis suggests that the independent variable exerts a positive and substantial impact on the dependent variable. However, a hypothesis that has been disproven suggests that the relationship between variables is not statistically significant.

The R Square test, also known as the Coefficient of Determination, may be used for analyzing the structural model. The coefficient of determination, often known as R Square, measures the extent to which the independent variable impacts the dependent variable. The coefficient of determination (R Square) for the dependent variable (Y) is 0.542, suggesting that the combined effect of X1, X2, X3, and X4 explains 54.2% of the variability in the dependent variable, with the remaining 45.8% being influenced by other variables. The mediating variable (Z) has an R-squared value of 0.673, suggesting that 67.3% of its impact can be elucidated by the variables X1, X2, X3, and X4. In comparison, the remaining 32.7% is ascribed to unaccounted factors in the model.

	R Square	**R Square Adjusted**
Y	0,542	0,532
Z	0,673	0,599

V. DISCUSSION

The decision to use Partial Least Squares (PLS) in Structural Equation Modeling (SEM) was wise, considering the study's small sample size of only 50 respondents, since it ensures the robustness of the analysis. SEM PLS is recognized for its resilience in managing smaller datasets. It is particularly suitable for exploratory research in new sectors such as technology adoption, where acquiring large samples may be difficult. The study's capacity to derive significant results with a limited sample size highlights the adaptability and dependability of Structural Equation Modeling (SEM) Partial Least Squares (PLS) in such circumstances.

The Unified Theory of Acceptance and Use of Technology (UTAUT) model was accurately calculated using SEM PLS. The ability of SEM PLS to manage intricate connections among latent variables was crucial in revealing the subtle interaction between X1, X2, X3, X4, Z, and Y. An accurate estimation is crucial for researchers and practitioners who aim to gain a thorough grasp of the elements that impact technology adoption.

The inclusion of Z as a mediating variable emphasizes the intricate mechanism by which users' intents transform favorable views into tangible usage (Y). SEM PLS successfully recorded this intermediary connection, offering valuable insights into the sequential process of decision-making in the adoption of technology. This discovery underscores the significance of focusing on users' objectives in order to achieve effective technology deployment techniques.

Although SEM PLS effectively mediated the impact of X1 on Y through Z, difficulties arose in mediating the effects of X2, X3, and X4. Furthermore, variable M did not exhibit any moderation effects.

These issues indicate that the connections within the UTAUT model are complex and impacted by elements that were not considered in this study. Subsequent investigations could examine supplementary factors or contextual intricacies to tackle these intricacies.

VI. CONCLUSION

This study effectively showcased the application of SEM-PLS analysis to examine the UTAUT model in the specific context of acceptance and utilization of payment technology. The utilization of SmartPLS 3 software enabled a thorough and unambiguous assessment of the measurement and structural models. This methodology can be utilized to assess the UTAUT model in many contexts, producing reliable and credible results. The findings of this study have significant ramifications for scholars and practitioners involved in the field of Structural Equation Modeling (SEM) using Partial Least Squares (PLS).

VII. ACKNOWLEDGEMENTS

This research is supported by Mataram University, where the author pursued education. We express our gratitude to Embun Suryani, SE., M.Si., Ph.D., and H. Akhmad Saufi, SE., M.Bus., Ph.D., the thesis adviser, for providing moral support, valuable advice, and consistent supervision, which are essential to the realization of the study. We thank the American Journal of Humanities and Social Sciences Research (AJHSSR) for allowing the author to share insights with the community through its scholarly journal. Our appreciation also goes to all parties who guided and assisted in completing this research.

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