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SELECTION OF THE BEST SEM MODEL TO IDENTIFY FACTORS AFFECTING MARKETING PERFORMANCE IN THE ICT INDUSTRY

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ABSTRACT

The digital revolution in society and the advances in marketing practices create tremendous challenges for companies and even more so for Information and Communication Technology (ICT) service providers. They are faced with increasingly complex and rapidly changing market competition, and knowing these problems can use SEM to form a research model and find out the relationship between latent variables and their indicators. The purpose of this study is to identify the best structural equation model that can describe Marketing Performance in the ICT Industry in Indonesia. The data used in this study are primary data obtained from distributing offline and online questionnaires to 300 management levels working in the ICT Industry. The methods compared in this study are Covariance Based Structural Equation Modeling and Partial Least Square Structural Equation Modeling. The results showed that the best model to determine the factors that influence Marketing Performance in the ICT Industry in Indonesia is PLS-SEM, with the goodness-of-fit model R2 for the latent variable Marketing Performance being 0.436. This shows that the accuracy of the variables CEM, DBI, and DOE together in predicting MP variables is relatively weak. Based on the PLS-SEM model, it is found that Digital Operational Excellence is a mediator that can increase the influence of Customer Experience Management on Marketing Performance. Meanwhile, Digital Business Innovation has no significant effect in increasing the influence of Customer Experience Management on Marketing Performance. The novelty of this research is the development of the best SEM models (CB-SEM and PLS-SEM) in the field of Information and Communication Technology in Indonesia.

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1. INTRODUCTION

The digital revolution in society and the development of marketing implementation have created extraordinary challenges for companies or organizations, especially Information and Communication Technology (ICT) service providers. Companies are faced with increasingly complex and rapidly changing market competition that is beyond the company's control. The phenomenon of changing this technological era is marked by the emergence of the evolution of the internet provided by companies that are not internet network providers or non-Internet Service Providers (ISPs) called Over The Top (OTT) services. This OTT platform provider utilizes network infrastructure built by telecommunications operators or often called telcos to provide added value services with the attraction of free services. The OTT platform was formed as a push for changes in customer preferences, technology changes, and convenience that offers a better customer experience than that offered by conventional services [1].

The main players in the ICT industry are telecommunications operators such as Telkom Indonesia, Singtel, and British Telecomm (BT) as telephone service providers, short messaging service (SMS) and 3G/4G/5G optical and mobile cable infrastructure dealing with competing OTT service providers that provide a variety of services: digital content, search engines, social media, and others. The various services provided by these OTT providers, for example, Whatsapp and Facebook Messenger, have had a huge impact on the ICT sector, including a decrease in revenue from calls and SMS, which were originally the main revenue for telecommunication operators.

According to [2], factors such as cost, convenience, features, content availability, and Customer Experience are utilized effectively by OTT players to offer substitutes for better offerings in the ICT industry without having to invest heavily in network infrastructure. The services provided to implement this OTT also significantly increase internet traffic so that it can affect the increase in Capital Expenditure (CAPEX) investments that can be implemented by ICT users without being accompanied by a balanced increase in income [3].

Poor and declining marketing performance was also marked by a decrease in revenue growth and also a decrease in Return on Invested Capex (ROIC) in 2009-2021 [4]. This was due to a significant increase in internet traffic which required investment in additional international bandwidth, without being followed by an equivalent increase in revenue which, of course, impacted on decreasing profitability.

From the data and explanation above, in general, the researchers concluded that the problems in the ICT industry in Indonesia are related to competition which has an impact on decreasing customer satisfaction so that customers switch to competitors and increase churn in companies. This resulted in a decrease in sales and, of course, pushed down the income of ICT industry players. In connection with the increasing intensity of competition from OTT players, which threatens the business continuity of ICT players, a special method is needed to improve the Marketing Performance of every company in the ICT industry [5].

Marketing performance is a latent variable that cannot be measured directly but can be measured through its indicator variables. One way to find out the relationship between variables and the relationship between variables and indicator variables is to use Structural Equation Modeling (SEM) [6]. SEM is an analytical method used to describe the pattern of a linear relationship between indicators and their variables [7].

Structural Equation Modeling has two approaches, namely Covariance Based Structural Equation Modeling (CB-SEM) and Component Based Structural Equation Modeling (VB-SEM), which includes Partial Least Square Structural Equation Modeling (PLS-SEM) and Generalized Structural Component Analysis (GSCA) [8]. The difference in previous research is that previous research only explained that there were two SEM approaches, while the research conducted proved differences in the SEM approach, which model is better to use. CB-SEM was first developed by [9], which aims to test a theory or confirm a theory. In addition, CB-SEM still depends on fulfilling the double normal assumption and is limited to reflective indicator variables. In 1982, Wold developed a PLS approach. PLS-SEM does not require double normal assumptions, data does not have to be of a certain scale, is effective on small sample sizes, and can be used for indicators that are both reflective and formative [10]. GSCA was developed by [11], which does not require multivariate normality data assumptions and can be tested without a strong theoretical basis with a small number of samples. Joreskog's research only focused on the CB-SEM approach, while research that only focused on PLS-SEM was conducted by Haenlein & Kaplan. Previous studies focused only on one SEM model approach, so there was a research gap comparing the two SEM models, namely the comparison between the CB-SEM and PLS-SEM models. The comparison of this model is a novelty in research applied to the information and communication technology industry in Indonesia.

The data used in this study is primary data derived from a survey with an ordinal scale, so it is not relevant to test the normality of the data. Besides the variables used are variables, the researcher wants to confirm the theory regarding the factors that influence marketing performance with a large enough sample size. These data conditions and variables are the basis for researchers to compare CB-SEM and PLS-SEM to obtain the best model that can describe the value of marketing performance in the ICT industry in Indonesia.

2. RESEARCH METHOD

2.1. Covariance Based Structural Equation Modelling (CB-SEM)

Structural Equation Modeling was developed by [9] with a covariance approach, hereinafter referred to as covariance-based SEM (CBSEM). Structural Equation Modeling (SEM) is a multivariate analysis that combines factor analysis and path analysis [12]. [13] states that there are two component models in SEM analysis, namely, the measurement model and the structural model. The measurement model explains the relationship between indicator variables and variables, while the structural model explains the relationship between variables. The following is Figure 1 of the path diagram between variables [14].

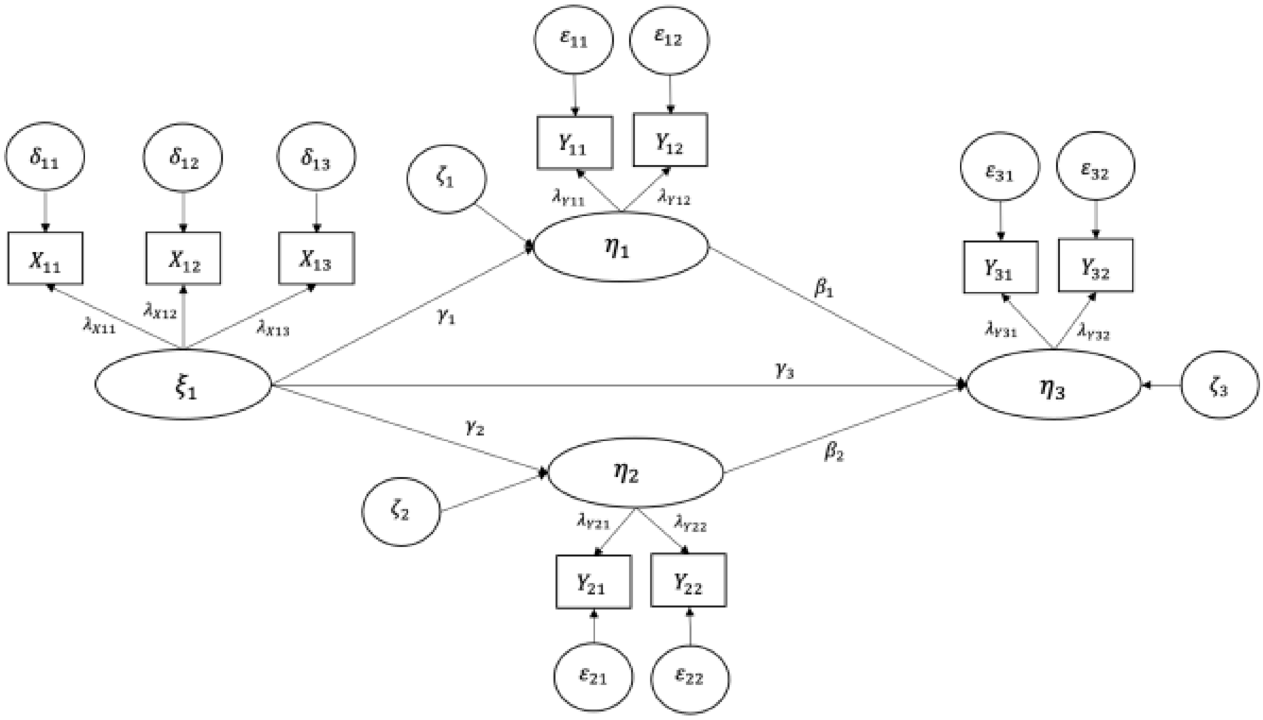

Figure 1. Path Diagram of Latent Variable Relationships

Where:

X_{bm} : The m-th indicator of the b-th exogenous latent variable, m=1,2,3 (for b=1 and b=2)
Y_{jn} : The nth indicator of the j-th endogenous latent variable, n=1,2 (for j=1 and j=2)
λ_{Xbm} : Loading factor of the b-th exogenous latent variable for the m-th indicator
λ_{Ybm} : Loading factor of the j-th endogenous latent variable for the nth indicator
ξ_b : b-th exogenous latent variable, b=1,2
η_j : j-th endogenous latent variable, j=1,2
β_j : Coefficient of influence of the endogenous variable on the j-th endogenous variable
γ_{jb} : Coefficient of influence of the b-th exogenous variable on the j-th endogenous latent variable
δ_{bm} : Measurement error on the m-th indicator for the b-th exogenous latent variable
ε_{jn} : Measurement error on the n-th indicator of the j-th endogenous latent variable
ζ_j : Measurement error of the j-th latent variable

2.2. CB-SEM Structural Model

CB-SEM is an approach to the SEM model, according to [13] generally defines the CB-SEM Structural model in Equation (1)

$$\eta = \beta_{\eta} + \Gamma\xi + \zeta \tag{1}$$

Where:
B : Matrix of endogenous latent variable coefficients of size m × m
Γ : Coefficient matrix of exogenous variables of size m × n
η : Vector of m × 1 endogenous variable
ξ : Vector of exogenous variables of size n × 1
ζ : Random error vector of relationship between η and ξ of size m × 1

2.3. CB-SEM Model Estimation

Methods that can be used to estimate the coefficients in SEM are Maximum Likelihood, Unweighted Least Square, Weighted Least Square and Generalized Least Square.

1. Maximum Likelihood (ML) Method ML is the most widely used estimation method [15]. This method produces the best (unbiased) parameter estimator if the data meets the assumption of multivariate normality. According to [16], the recommended sample size for the ML method ranges from 100-200 samples.
2. The ULS Unweighted Least Square (ULS) method is an estimation method that does not require the assumption of normality of the data as long as the parameters are identified. The ULS estimation method is consistent and relatively fast in its process, but it is not efficient for large data [17].
3. The WLS Weighted Least Square (WLS) method does not require data normality assumptions, but the number of constructs that can be estimated is very limited. In addition, this method requires a very large number of samples, namely between 2000-2500 [18].
4. Generalized Least Square (GLS) method GLS is a special case of WLS. The use of this method is based on the same assumptions as the ML method, namely that it must meet the assumption of multivariate normality. However, the performance of this method is not good at small sample sizes [19].

2.4. Partial Least Squares Structural Equation Modelling (PLS-SEM)

PLS-SEM was developed by Herman World since 1974. The characteristics of PLS-SEM in estimating the coefficients and testing the feasibility of the model do not require assumptions about the normal distribution of variables and can be applied to relatively small samples [12]. PLS-SEM can be applied to all data scales and can also be used to build relationships that have no theoretical basis [6]. PLS-SEM can be used for structural modeling with indicators that are reflective or formative. Evaluation of the PLS model is carried out by assessing the measurement model (outer model) and structural model (inner model) [20].

2.5. PLS-SEM Structural Model

PLS-SEM is an approach to the SEM model, according to [21] generally defines the PLS-SEM Structural model in Equation (2).

$$\eta_j = \beta_{j0} + \sum \beta_{j1}\eta_i + \zeta_j \tag{2}$$

For j = 1, 2, …, p and i = 1, 2, …, q
Where:
p : Many variables
q : Many paths from endogenous variables to exogenous variables
β_{ji} : Path coefficient of the jth and ith variables
β_{j0} : Constant
η_j : The jth exogenous latent variable
η_i : Endogenous latency i for j ≠ 1
ζ_j : Error of the jth structural model

2.6. PLS-SEM Model Estimation

The stages in the PLS-SEM estimation process, according to [22] are as follows:

1. Each latent variable is grouped with each indicator [23]
2. Outer approximation or estimation of the measurement model of the variable score is calculated as a linear combination of the indicators associated with each latent variable [24].
3. Inner weight (w) is calculated to illustrate the strength of the relationship between the variable and other variables in the model. There are 3 methods for estimating inner weights: centroid, factor weighting, and path weighting [25].
   a. The centroid method is estimated based on the inner weights of the sign of the relationship between variables and adjacent variables.
   b. The factor weighting method is presumably based on the inner weights of a combination of correlations between variables and adjacent variables.
   c. The path weighting method is estimated based on the inner weights of the latent variable relationship arrows in the model.
4. The inner approximation or estimation of the structural model of the latent variable score is calculated as a combination of the outer approximation of the latent variable score (the value obtained in step 2).
5. Measurement model weighting [26].
6. The next stage is the estimation of the path coefficient connecting the variables and the estimation of the loading factor between the variables and their indicators using the Ordinary Least Squares (OLS) estimation method [27].

2.7. Bootstrap method

The bootstrap method is takes random samples from existing samples with replacement [28]. Bootstrap can be used to solve problems in statistics, both the problem of small data, data that deviates from its assumptions, and data that has no assumptions in its distribution [29].

The bootstrap method is carried out by taking samples from the original sample and carried out a replacement. The position of the original sample in the bootstrap method is seen as a population. In the structural equation modeling calculation algorithm, the bootstrap method is used to generate t-count values that are used to evaluate the inner model. The bootstrap method is the right method because it can estimate the distribution in data populations that do not have a distribution, and from this method the standard error value is also obtained, which will later be useful for t-count calculations [30]. By using the standard error values generated from the bootstrap distribution, we can test the hypothesis or whether the path coefficient is significant with the t-count obtained from Equation (3):

$$t = \frac{\hat{\rho}}{se\hat{\rho}} \tag{3}$$

The symbol $\hat{\rho}$ is the path coefficient obtained from the model and $se\hat{\rho}$ is the standard error value obtained from the bootstrap method.

2.8. Data

This study used a questionnaire with a Likert measurement scale. The Likert scale is used to measure attitudes, opinions, and perceptions of a person or group of people about social phenomena. The research variables will be translated into variable indicators. These variable items are used as the basis as a starting point for preparing instruments which can be in the form of questions or statements.

The answer to each instrument that uses a Likert scale has a gradation from very positive to negative. As a basis for quantitative analysis, these statements can be given a score. For example, a score of 1 is given to strongly disagree statements, a score of 2 is given to disagree statements, a score of 3 is given to a neutral statement, a score of 4 is given to a statement that agrees, and a score of 5 is given to a statement that strongly agrees.

2.9. Research Model

The research variables consisted of 1 exogenous variable, 2 mediating endogenous variables, and 1 pure endogenous variable. Customer Experience Management (CEM) (X1), Digital Business Innovation

(DBI) (Y1), Digital Operational Excellence (DOE) (Y2), and Marketing Performance (MP) (Y3). The research model can be seen in Figure 2.

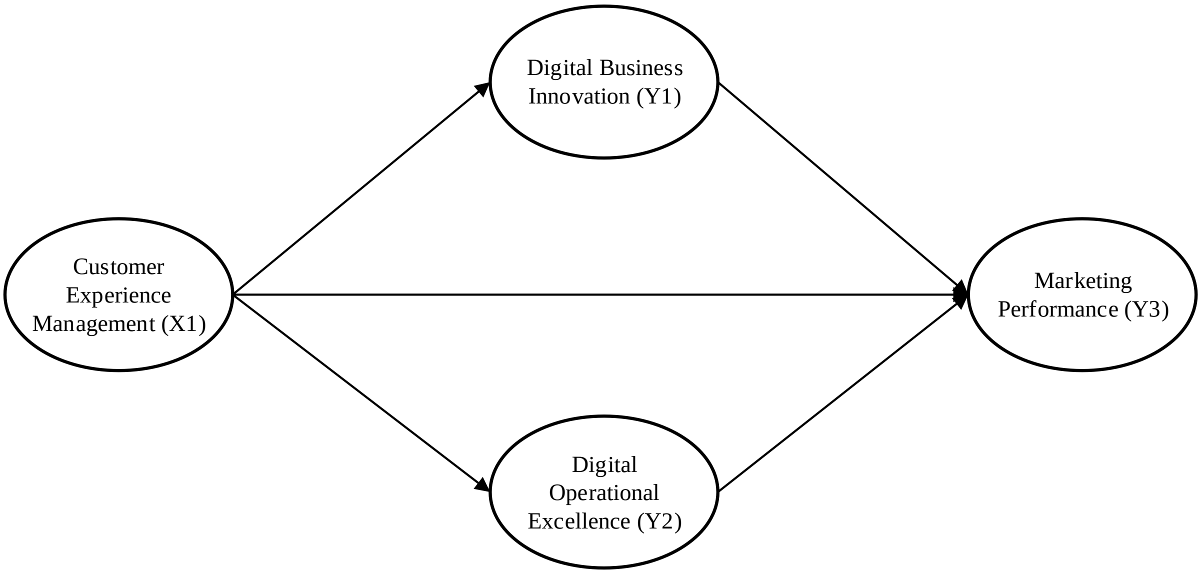

Figure 2. Path analysis model

2.10. Data Analysis

The data analysis procedure performed is as follows:

1. Develop a path diagram that explains the relationship between variables and indicators as shown in Figure 3 below:

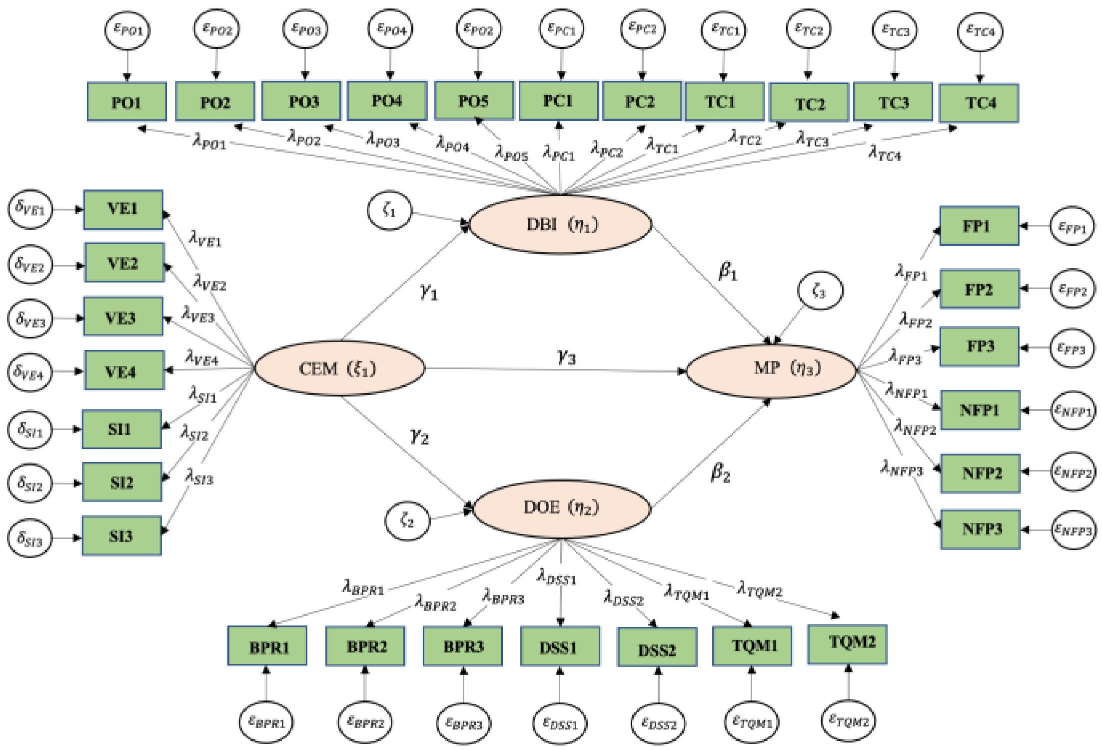

Figure 3. Path diagram of latent variable relationships

2. Develop a Measurement Model (outer model) and Structural (inner model)
3. Exploring and cleaning data
4. Evaluate the measurement model and structural model in Table 1 below:

Table 1. Criteria for the Goodness of the Model in CB-SEM and PLS-SEM

Category	CB-SEM	PLS-SEM
Evaluation of Measurement Models	a. Loading factor value ≥ 0.7 b. Average Variance Extracted ≥ 0.5	a. Loading factor value ≥ 0.7 b. Average Variance Extracted ≥ 0.5
Structural Model Evaluation	a. Chi-square is expected to be small (p-value ≥ 0.05) b. Coefficient direction $\gamma_i,\ \beta_i(+)$ c. The relationship between variables is significant	a. The coefficient of determination b. Coefficient direction $\gamma_i,\ \beta_i(+)$ c. The t-statistic value of the relationship between variables is significant

5. Selection of the best model
6. Doing hypothesis testing to see the significance of the influence between variables. The results of hypothesis testing will be significant when the t-statistic value is > 1.96 or the p-value is <0.05
7. Draw conclusions

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

Descriptive analysis is used as an initial stage of data exploration to get an overview of the data used. A histogram presentation is done to see the distribution of data on each latent variable. The distribution of data that is symmetrical or close to symmetrical indicates that the data follows a normal distribution, while the distribution of data that is skewed to the left or skewed to the right indicates that the data does not follow a normal distribution. The following shows a histogram of variables of Customer Experience Management (X1), Digital Business Innovation (Y1), Digital Operational Excellence (Y2), and Marketing Performance (Y3). The results of the descriptive analysis are presented in **Figure 4**.

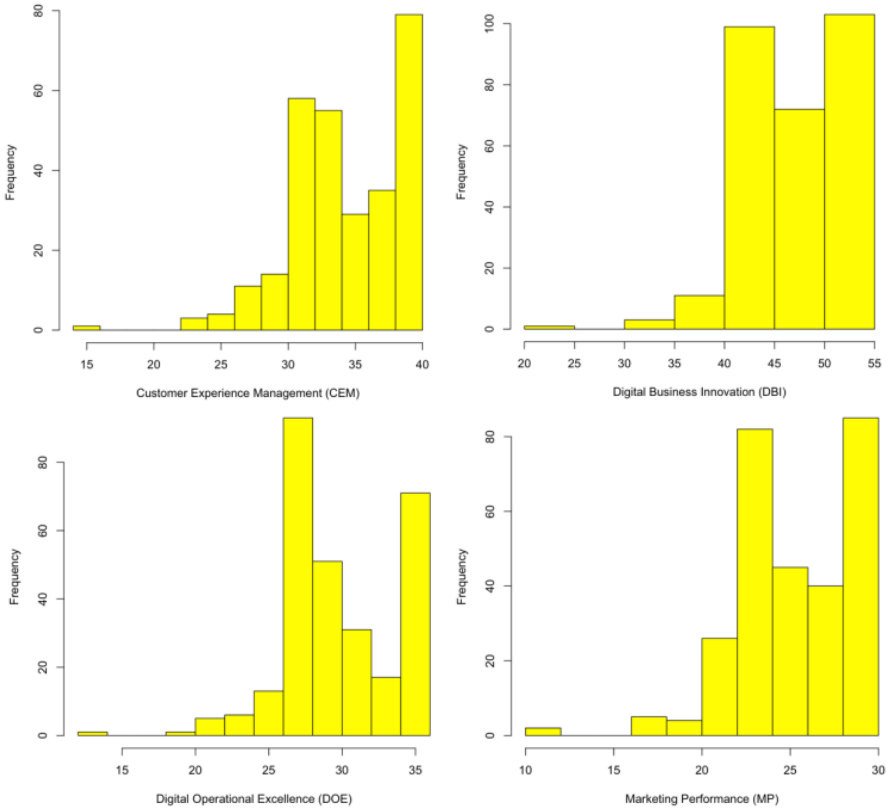

Figure 4. Testing Process Flowchart

Based on the histogram from **Figure 4**, it can be observed that the data distribution of the variables CEM, BDI, DOE, and MP tends to be skewed to the left, indicating that the data is suspected to not follow a normal distribution.

3.2. Evaluation of Measurement Models

Evaluation of the Measurement Model is carried out to see whether the measurement indicators used are feasible or not to be used as a measuring tool. The measurement model models the relationship between variables and observed variables. The measurement model aims to confirm whether the observed variables are a measure or reflection of a latent variable obtained through model validity and reliability analysis.

Evaluation of the CB-SEM Measurement Model

a. Validity Level

The validity level of the observed variables in the model can be seen from the factor loading score. An indicator can be said to be able to measure a latent variable if the loading factor score is ≥ 0.7. The results of measuring the validity of the model can be presented in **Figure 5** below:

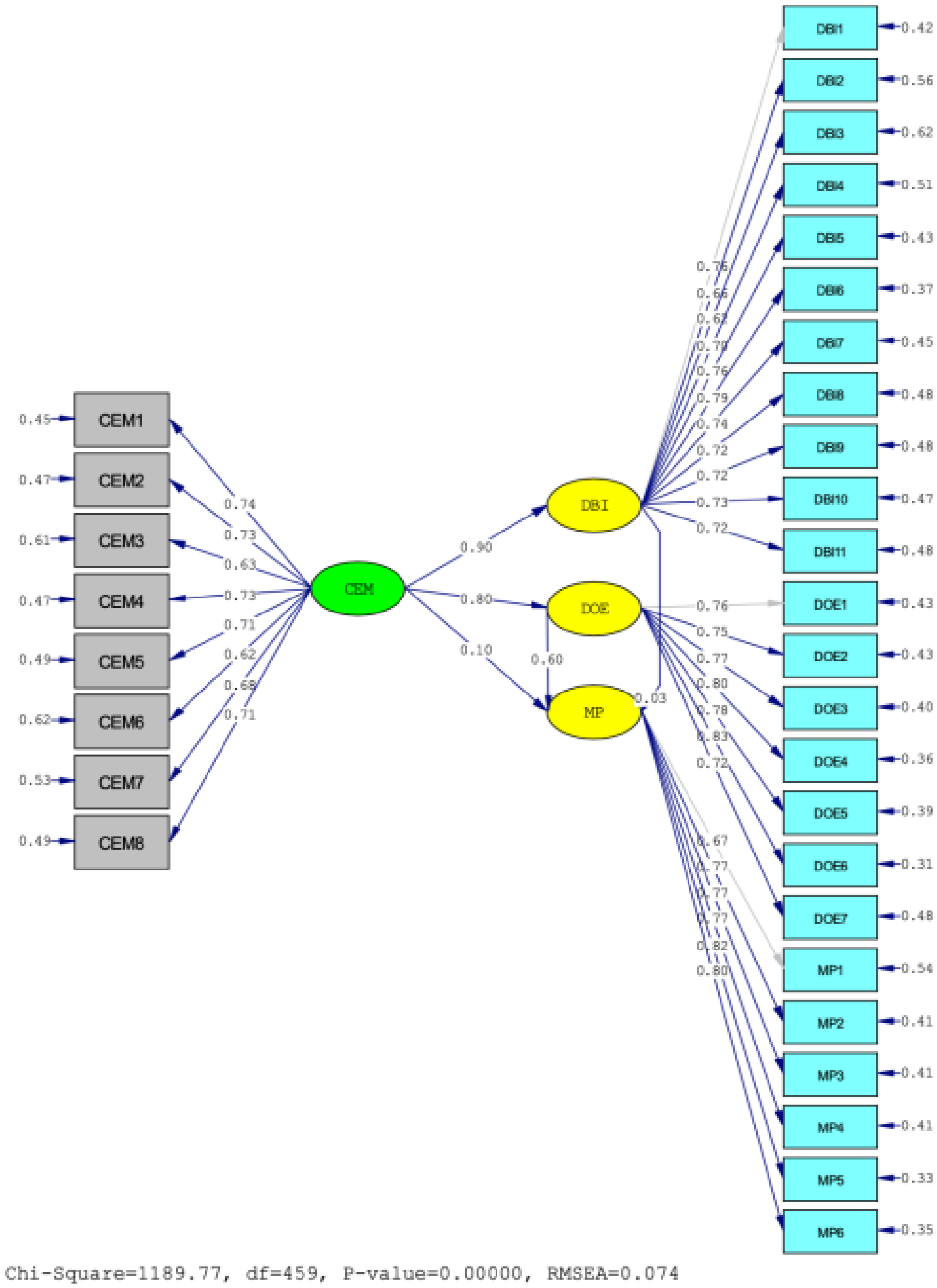

Figure 5. Estimating Results of the Loading Factor Score

In **Figure 5**, it can be seen that the loading factor score of the variables observed in the model is greater than 0.7 so that the indicators built are good at measuring variables.

b. Reliability Level

The reliability of each latent variable can be seen from the Average Variance Extracted (AVE) value. A latent variable can be declared reliable if the AVE value ≥ 0.5 [12]. The reliability results are presented in Table 2.

Table 2. Ave Reliability Results of Variables

Latent Variable	AVE	Information
CEM	0.82	Reliable
DBI	0.83	Reliable
DOE	0.65	Reliable
MP	0.63	Reliable

Based on Table 2, it can be seen that the reliability values of the CEM, DBI, DOE, and MP constructs have an AVE value ≥ 0.5. This indicates that the indicators developed are good at explaining the four variables. AVE 0.50 indicates that the construct explains more than half of the indicator variance.

Evaluation of the PLS-SEM Measurement Model

a. Validity Level

As with CB-SEM, the level of validity in PLS-SEM is measured by the value of the loading factor on the variables and the indicators. An indicator of a variable is valid if the loading factor is ≥ 0.7. However, for research in the early stages of developing a measurement scale, a loading value of 0.5 to 0.6 is considered sufficient. The results of the validity of the PLS-SEM measurement model are presented in Figure 6.

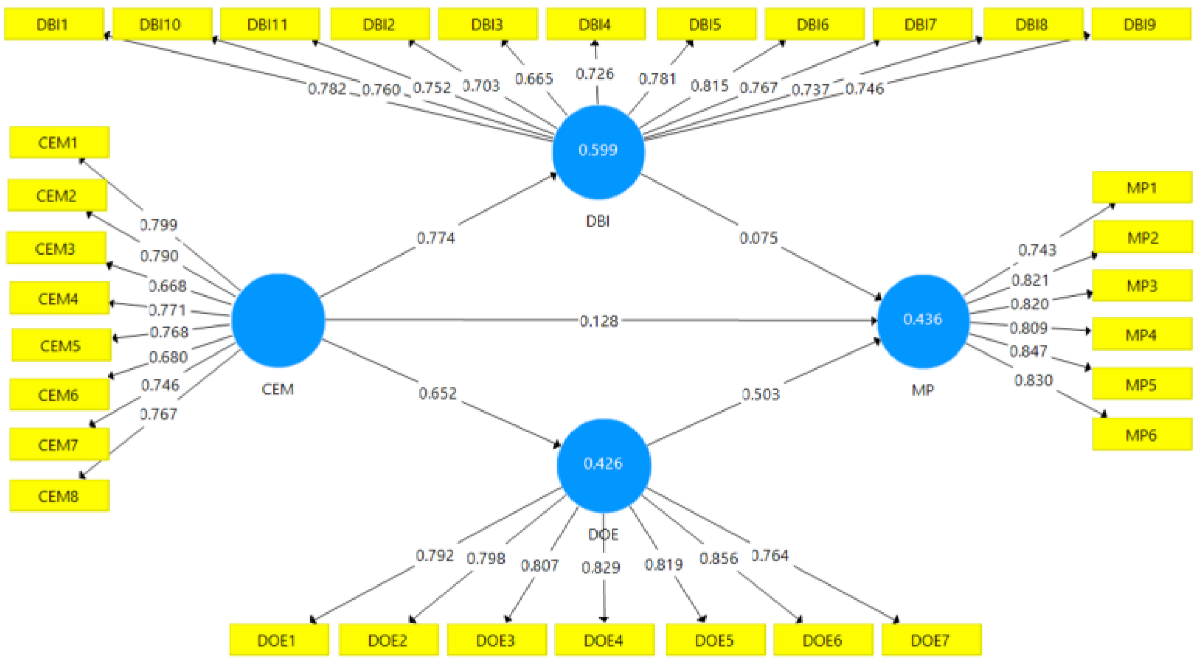

Figure 6. PLS-SEM Measurement Model

In Figure 6, it can be seen that each latent variable CEM, DBI, DOE, and MP has met the requirements because the loading factor value for each indicator is more than 0.6.

b. Reliability Level

The reliability of each latent variable can be seen from the Average Variance Extracted (AVE) value. A latent variable can be declared reliable if the value of AVE ≥ 0.5. The reliability results are presented in Table 3.

Table 3. Results of the Reliability of the PLS-SEM Measurement Model

Latent Variable	AVE
CEM	0.56
DBI	0.56
DBO	0.66
MP	0.66

In Table 3, it can be seen that the AVE value for each latent variable is greater than 0.5, so the latent variable can reflect the intended indicator well. This shows that the measurement tool built has measured the variables well, so that the measurement tool is considered appropriate.

3.3. Structural Model Evaluation

Evaluation of the suitability of the structural model is carried out to measure the goodness of the structural model that has been built. Things that are evaluated in the structural model include structural equation coefficients, t-statistics values, and goodness of fit in CB-SEM or the coefficient of determination in PLS-SEM. The structural equation coefficient value is good if the path coefficient (relationship direction) of each causal relationship between variables is positive. While the t-count value is said to be significant if the t-count ≥ 1.96 in each causal relationship between variables.

Evaluation of the CB-SEM Structural Model

The estimation results of the CB-SEM structural model are shown in Table 4.

Table 4. Path Coefficient and T-Statistics Values

Latent Variable	Path Coefficient	T-Ststistics	Conclusion
CEM → DBI	0.90	13.47	Significant
CEM → DOE	0.80	12.04	Significant
CEM → MP	0.10	0.55	Not Significant
DBI → MP	0.03	0.23	Not Significant
DOE → MP	0.06	5.51	Significant

Based on Table 4, the test statistic used is the chi-square value of 1189.77 with a p-value of 0.00 which means < 0.05. This can explain why the SEM model obtained is not fit because there are differences in the predicted input matrix with the actual.

Evaluation of the PLS-SEM Structural Model

The estimation results of the PLS-SEM structural model are shown in Table 5.

Table 5. Path Coefficient and T-Statistics Values

Latent Variable	Path Coefficient	T-Ststistics	Conclusion
CEM → DBI	0.90	13.47	Significant
CEM → DOE	0.80	12.04	Significant
CEM → MP	0.10	0.55	Not Significant
DBI → MP	0.03	0.23	Not Significant
DOE → MP	0.06	5.51	Significant
CEM → DBI → MP	0.06	0.76	Not Significant
CEM → DOE → MP	0.33	4.55	Significant

Based on Table 5, the size of the suitability of the PLS-SEM model is based on the results of the coefficient of determination. The results of the Coefficient of Determination indicate the level of prediction accuracy, where 0.25; 0.50; 0.75 respectively describe a strong, medium, or weak level of prediction accuracy. The results of the coefficient of determination are presented in Table 6.

Table 6. Results of the Coefficient of Determination

Latent Variable	R-Square	Level of accuracy
DBI	0.56	Currently
DOE	0.43	Weak
MP	0.44	Weak

Based on Table 6, it shows that the accuracy of the CEM variables in predicting DBI variables is moderate, while the accuracy of CEM variables in predicting DOE variables is relatively weak and the accuracy levels of CEM, DBI, and DOE together in predicting MP variables are relatively weak.

3.4. Best Model Selection

Comparison of the results of selecting the best model is presented in Table 7.

Table 7. Comparison of the Evaluation Results of the CB-SEM and PLS-SEM Models

Category	CB-SEM	PLS-SEM
Evaluation of Measurement Models	The built indicators have been able to measure variables well (Valid and Reliable)	The built indicators have been able to measure variables well (Valid and Reliable)
Structural Model Evaluation	a. The model is not yet fit because the results of the GoF test show that there are differences in the predicted and actual input matrices. b. Coefficient direction rγ_i, β_i accordingly c. There are 2 insignificant relationship variables, namely CEM to MP and DBI to MP	a. The model is quite fit because the exogenous construct in predicting the endogenous construct is classified as weak and moderate. b. Coefficient direction rγ_i, β_i accordingly c. There are 2 insignificant relationship variables, namely CEM to MP and DBI to MP

Based on the evaluation of the measurement model and the structural model in Table 7, it can be concluded that the best model to determine the factors that influence MP is PLS-SEM. Based on the results of the evaluation of the measurement model, both CB-SEM and PLS-SEM gave the result that the built indicators were able to measure variables properly. Based on the evaluation results of the structural model, it was found that the PLS-SEM model was better than CB-SEM. This result is also supported by the results of data exploration that the distribution of data on variables does not meet the normality assumption, so PLS-SEM is the right method to use in this study because it does not require data normality assumptions.

3.5. Hypothesis Test

The test is based on the PLS-SEM model. Hypothesis testing is done by examining path coefficients and t-statistics values. The significant test used is the error rate $\alpha = 5\%$ with significant criteria when the t-statistic value is > 1.96. The results of testing the hypothesis are presented in Table 8.

Table 8. Path Coefficient and T-Statistics Values

Latent Variable	Path Coefficient	T-Statistics	Conclusion
CEM → DBI	0.77	19.63	Significant
CEM → DOE	0.65	12.86	Significant
CEM → MP	0.13	1.78	Not Significant
DBI → MP	0.08	0.75	Not Significant
DOE → MP	0.50	5.09	Significant
CEM → DBI → MP	0.06	0.75	Not Significant
CEM → DOE → MP	0.33	4.55	Significant

Based on Table 8, it can be seen that the indirect effect of the CEM latent variable on the MP latent variable through the DOE latent variable is full mediation. That is, to increase MP, it must go through the DOE latent variable.

3.6. Research Implications

The results of this study imply that DOE is a mediator that can increase the influence of CEM on MP. Meanwhile, DBI has no significant effect in increasing the influence of CEM on MP. These findings serve as a reference for company management and practitioners in the ICT industry in Indonesia regarding the importance of developing DOE and CEM in an effort to improve company MP. Companies can also prioritize programs based on the results of hypothesis testing that has been done.

Based on the research results, it is known that the latent variable CEM has no significant effect on MP either directly or through the mediation of DBI. This is because the research was conducted during the Covid-19 pandemic, where this situation had an impact on economic stability in general, as well as affecting the stability of conditions and company performance in the ICT industry in Indonesia. The pandemic conditions forced customers to interact with digital products, but on the other hand there was also a decrease in people's purchasing power due to unstable economic conditions. During this pandemic, companies, especially in the ICT industry in Indonesia, were forced to transform towards digital in order to survive amidst the intense competition with emerging startups. This is a considerable challenge for companies in the ICT industry in Indonesia because not all companies have dynamic and agile organizations to meet changing needs during the Covid-19 pandemic, and not all companies have institutions with the customer experience and innovation management. For good digital business, this condition can indirectly affect the mindset and point of view of company management so that it does not reflect CEM and DBI data for companies in the ICT industry in Indonesia under normal circumstances.

In addition, the lack of effect of CEM on a company's financial performance, marketing performance, business performance, and other performance can be caused by various factors that also influence the scope of a company or Industry. The real conditions in the field show that the core business, characteristics, and corporate culture, which are differentiators in the type of company, can cause different results in implementing CEM in improving MP.

Based on research findings that Customer Experience can improve MP through DOE because companies engaged in the industry begin to optimize their ability to identify opportunities for continuous improvement to increase the effectiveness of work processes, optimize business processes quickly, have qualified resources in product-based development digital, and to build a roadmap for developing digital talent to support operations.

4. CONCLUSIONS

The best model to find out the factors that influence MP in the ICT Industry in Indonesia is PLS-SEM, with the level of accuracy of the latent variable CEM in predicting the latent variable DBI classified as moderate, while the level of prediction of the latent variable CEM in predicting Digital Operational Excellence variables is relatively weak and the level of accuracy of the variables Customer Experience Management, Digital Business Innovation, and DOE together in predicting MP variables is classified as weak.

Based on the results of hypothesis testing, it is known that DOE is a mediator that can increase the influence of CEM on MP. Based on the findings of the mediation analysis, DBI as a partial mediation can be removed from the initial model because the existence of DBI does not change the effect of CEM on MP. However, keep in mind that CEM also plays a role in increasing DBI. Therefore, it is important for companies in the Information and Communication Technology industry in Indonesia to prioritize the implementation of programs that are considered to improve MP, adjusted to the company's conditions. The company's readiness to adapt to digital business and carry out digital transformation is an important factor in encouraging the development of CEM, Digital Business Innovation, and DOE. The diversity of companies in the Information and Communication Technology industry in Indonesia is also one of the factors that can affect the company's condition in implementing these three main aspects in increasing MP because of course, every company has a business focus and culture that is different from one another.

Suggestions that can be given for further research are to evaluate the goodness of the CB-SEM and PLS-SEM models by adding the Digital Value Co-Creation moderating variable and observing changes in each measurement and structural model evaluation of the two models. In addition, the researcher suggests future researchers test this research model in normal situations to test the consistency of the research model.

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