Problems, Common Beliefs and Procedures on the Use of Partial Least Squares Structural Equation Modeling in Business Research

Abstract

Partial least squares structural equation modeling (commonly referred to as PLS-SEM) was not developed without reason. PLS-SEM was developed as an alternative to covariance-based SEM, allowing researchers to conduct exploratory research. In addition, PLS-SEM is considered capable of providing flexibility related to data characteristics, model complexity, and model specifications. Undoubtedly, PLS-SEM is the most frequently used method in many fields of business research. However, many researchers use PLS-SEM incorrectly and even expect more without understanding the basic structural equation modeling method. For this reason, this article will discuss various types of problems and general beliefs about the use of PLS-SEM in business research. In addition, this article can be used as a reference to make it easier for applied researchers to decide what methods, techniques, and tools will be used to complete their research. In addition, at the end of this article, we will discuss how PLS-SEM can be applied to develop theory in business research through a series of technical introductions taking into account user needs. For this reason, this article will be equipped with a systematic procedure that discusses the evaluation flow of each PLS-SEM test through illustrations with a notated model using SmartPLS.

Keywords : *Partial least squares, Structural equation modeling, Smart-PLS.*

1. Introduction

In behavioral research, especially in the business field, a large and normally distributed sample size is required to obtain an ideal data set. However, the reality on the ground does not support this. Many applied researchers have only limited respondents, which often happens because of the nature and characteristics of the research itself. For this reason, researchers are often faced with difficulties in carrying out statistical analysis of the data they have, especially on structural equation modeling (SEM) on latent variables where CB-SEM methods such as LISREL (linear structural relationship) and AMOS (*analysis of moment structures*) has strict data quality assumptions. For this reason, the PLS-SEM method is designed as an alternative to CB-SEM for researchers using the SEM approach, which makes it easier to direct model predictions and is considered capable of reducing the requirements to meet data quality and relationship specifications that CB-SEM has set (Dijkstra, 2010; Jo reskog & Wold, 1982; Rigdon, 2012; Sarstedt et al., 2014).

Herman Wold first proposed the PLS-SEM method in 1982, and the method was introduced as an alternative method to CB-SEM, not as a substitute method. Since the introduction of this method, many studies have emerged that view the incompatibility of the PLS-SEM method in empirical research (Antonakis et al., 2010; Vandenberg, 2006; Ronkko & Evermann, 2013; Aguirre-Urreta & Marakas, 2014; Mcintosh et al., 2014; Goodhue, Lewis & Thompson, 2012; Aguirre-Urreta & Ronkko, 2018; Afthanorhan, Awang & Aimran, 2020). The study discusses the alleged insurmountable weaknesses in PLS-SEM use and explicitly or implicitly calls for the prohibition and condemnation of the use of PLS-SEM.

On the other hand, studies conducted by Lohmoller (1989) and Henseler, Hubona, and Ray (2016) stated that PLS-SEM is still relevant if the research has exploratory objectives. Hair et al. (2017) specifically mention that a study is exploratory when the research is aimed at finding patterns in data with the assumption of lack/absence of theory or previous literacy on the variables being tested, while confirmatory nature is carried out when the research is aimed at testing hypotheses of theories and concepts. that existed before. In addition, another reason for the relevance of using the PLS-SEM method is the alleged error in the measurement model specification in previous studies. These errors can be identified if the researcher is unsure of the causal effect or the relationship between the exogenous and endogenous constructs they will test (Afthanorhan, Awang & Aimran, 2020). For this reason, PLS-SEM is more appropriate to predict than to estimate the relationship between latent variables or constructs in the hypothesized model.

Although, since the beginning, PLS-SEM has been known as a method for research that has exploratory purposes, several studies have explained that PLS-SEM can be used for both confirmatory and exploratory purposes (Ringle et al., 2018; Sarstedt et al., 2016; Schuberth, Henseler, & Dijkstra, 2018). Throughout their discussions, the PLS-SEM method seems to be accepted in many journals or publications for confirmatory purposes because it uses strong theoretical support for established theory testing (Afthanorhan, Awang & Aimran, 2020). Since then, the debate on the true nature of PLS-PM has been endless, specifically on statistical methodologies, and this condition makes applied researchers ignore articles on statistical flaws within PLS-SEM. They use the method in all situations and for various research purposes.

This article will discuss some of the problems that often arise from the inappropriate and excessive use of the PLS-SEM method and return the basic principles of PLS-SEM into structural equation modeling. Researchers need to understand that there are appropriate situations and conditions for PLS-SEM and CB-SEM when conducting data analysis. In other words, there are times when they have to understand why PLS-SEM can/cannot be applied in management research to avoid the decision that PLS-SEM can be used as the main choice in various domains. Applied indeed often finds itself in exhaustion when researchers are asked to decide to use the CB-SEM approach method. The fatigue is due to the necessity to understand CB-SEM use, which requires far more complex and complicated statistical assumptions. As a result, applied researchers always consider that PLS-SEM is a reliable method because it does not require any effort to understand the basics of statistics (Afthanorhan, Awang & Aimran, 2020). The findings from publications that are still the goal of using PLS-SEM for confirmation are questionable because they contradict the original purpose of PLS-SEM, which was developed naturally for exploratory purposes. Therefore, the decision to use PLS-SEM is inappropriate when the research has a confirmatory goal because most previous findings do not meet the current dynamics of progress (Afthanorhan, Awang & Aimran, 2020).

In addition to the problems mentioned above, many applied researchers still use inappropriate procedures when carrying out the PLS-SEM method. For this reason, this article will identify and conduct a study of common mistakes often made by comparing the opinions of various statistical methodologists from various literacy sources. Furthermore, this article will present a systematic flow for evaluating tests on the PLS-SEM method. The flow will be presented using a notated example with the SmartPLS application. The study in this article is expected to be a reference for applied researchers in adopting the PLS-SEM method and helping them decide which method is appropriate for them to use.

2. Literature Review

Applied researchers in the social sciences have been familiar with statistical analysis tools for decades. It starts with using univariate and bivariate analysis to understand the data and the relationship between variables. However, along with the transformation that occurred in social research, researchers began to face research models that were quite complex due to the progress of current business dynamics. Therefore, researchers need more sophisticated multivariate data analysis methods to understand the more complex relationships related to the current research direction. *Multivariate analysis* is a statistical method that can simultaneously analyze multiple variables, starting from using the first generation technique, namely cluster analysis, exploratory factor analysis, multidimensional scaling, and developing into the second generation, namely PLS-SEM. On the other hand, in this case, confirmatory research, the first generation technique starts from the analysis of variance, logistic regression, multiple regression, and confirmatory factor analysis, which develops into CB-SEM (Hair et al., 2017).

Structural equation modeling (SEM) allows researchers to examine complex sets of relationships, where these conditions cannot be done if using another analysis technique. SEM analysis is divided into two types: SEM based on covariance (CB-SEM) and SEM based on partial least squares (PLS-SEM). According to Hair et al. (2017), CB-SEM confirms (or rejects) pre-existing theories and hypothetical relationships. This can be done by determining how well the proposed theoretical model can estimate the covariance matrix for the sample data set. Instead, PLS-SEM is used to develop theories in exploratory research that may not have existed before. It can be done by focusing on explaining the variance in the dependent variable when examining the model.

3. Critical Review

1st Problem : Incompatibility of using pls-sem

A scientist named Herman Wold first introduced the PLS-SEM method in 1982. This method is the answer to problems that arise from the use of the CB-SEM method, problems that arise include the lack of flexibility related to data characteristics, the development of research models that have high complexity, etc. Initially, PLS-SEM was introduced as an alternative to CB-SEM, which adopted the composite factor method to generate parameter estimates from a latent construct's linear combinations of observed variables. In contrast to CB-SEM, where the method used is a common factor. For this reason, many differences were found between both methods (see Table 1).

Table 1. Composite Factor (PLS-SEM) Versus Common Factor (CB-SEM)

Composite Factor Method	**Common Factor**
Partial Least Squares Path Modeling (PLS-PM)	Maximum Likelihood-based CBSEM (ML-CBSEM)
Generalized Structure Component Analysis (GSCA)	Diagonal Weighted Least Squares (DWLS-CBSEM)
Consistent PLS (PLSc)	Weighted Least Squares Maximum Variance (WLSMV-CBSEM)
Weighted PLS	Asymptotic Distribution Free (ADF-CBSEM)
PLS Predict	Generalized Least Squares (GLS-CBSEM)
Statistical Software	
SmartPLS	AMOS
Warp PLS	LISREL
PLS Graph	MPLUS

Source : Afthanorhan, Awang and Aimran (2020)

Composite-based structural equation modeling is known to have three approaches, namely (1) regression on sum scales, (2) generalized structured component analysis, and (3) PLS analysis. The three approaches use ordinary least squares estimation, which aims to obtain path coefficients and loading indicators with the help of an iterative algorithm to minimize the criterion function. However, only “PLS analysis” uses two steps called measurement model estimation and structural modeling (Hwang, Takane & Tenenhaus, 2015; Ronkko, McIntosh & Antonakis, 2015; Ronkko et al., 2016). Some researchers believe that composite-based is the only reason for exploratory purposes because PLS-SEM (composite factor) predicts a more general model than CBSEM and does not consider model specification errors. The estimates obtained are meaningless if the common factor model is not accepted, and thus the common factor is always seen as a confirmatory tool (Antonakis et al., 2010; Afthanorhan, Awang & Aimran, 2020).

Many researchers revealed that their decision to choose PLS-SEM was based on the belief that PLS-SEM can be used for both confirmatory and exploratory purposes. Hair et al. (2017) explain the difference between the two, which explains that a study is exploratory when the research aims to find patterns in a data with the assumption of lack/absence of theory or previous literacy on the variables tested, while the confirmatory nature is carried out when the research is aimed at test hypotheses of pre-existing theories and concepts. In short, if the research is aimed at developing a theory, then the research is exploratory. On the other hand, when the research aims to re-examine existing concepts, the research is confirmatory. However, the difference between exploratory and confirmatory research is not as clear-cut as defined; there are many accompanying objective criteria (see Table 2).

Table 2. Confirmatory Versus Exploratory

CONFIRMATORY	**EXPLORATORY**
Replicating an established theory into a new domain Confirming a pre-specified relationship	Develop a new model based on lack of evidence or fact Connecting ideas to understand cause-effect
For estimating purpose Statistically significant results Definitive answers to hypotheses	For prediction purpose Potential relationships Novel relevant questions
For theory-driven Hypotheses testing methods Highest accuracy numerical models	For data-driven
For theory testing Testing a priori hypotheses Maximizing the confidence in conclusions	For theory development (exploration purpose) Developing promising a posteriori hypothesis Designing efficient experiments Reinforcing confirmed conclusion
For the common factor model	For the composite factor model
Modified the existing theory by included a new path or construct	Entirely changing the measurement item in existing theory
Integrating theory	Change the relationships between construct from prior theories (reciprocal relationships)
Example: Customer Satisfaction, Customer Loyalty, Trust, Distrust, Attitudinal, Communication, Affective, Emotion, Leadership, Performance	Example: Brand equity, Type of system, Information source, Decision-making perspective, Network structure, Network capability, Technology, Device, Location
Recommendation Method: CB-SEM	Recommendation Method: PLS-SEM

Source : Afthanorhan, Awang & Aimran (2020)

For this reason, applied researchers need to understand that the two research objectives, both confirmatory and exploratory, have different goals and techniques; not only that, the different criteria that must be met are one of the reasons for researchers to understand the conditions and situations that will lead them to make decisions. When researchers make decisions, not in line with their research objectives and methods, the consequences are irresponsible research results (Ioannidis, 2005), where inappropriate results can lead to conclusions that will impact managerial decisions, it can happen because various perspectives arise when researchers want to carry out their research projects. Situations and conditions like this can be bad in many ways, such as wrong logic, inappropriate design, and incorrect statistical methods (Wagenmakers et al., 2012). Henseler (2017) argues that the characteristics of latent constructs can determine the character of research designs. Therefore, every factor that describes the behavioral construct should be checked with CBSEM (confirmatory method), while the design-construct should be tested with PLS-SEM (exploratory method).

2nd Problem : Inaccuracy in using the Goodness of Fit (GoF) test

As previously stated, PLS-SEM was developed to be a predictive method. However, methodologists are still trying to develop the PLS-SEM method so that it can be used to test confirmatory research. These efforts can be seen in the development of model fit criteria from time to time. The model fit index allows assessing how well the hypothesized model structure fits the empirical data and helps identify model specification errors (Hair et al., 2017). The initial submission of model criteria in PLS-SEM was proposed by Tenenhaus et al. (2004) and Tenenhaus et al. (2005). They proposed the GOF criterion, a single measure used to validate the combined performance of the measurement model (outer model) and structural model (inner model). The GoF index value is obtained from the average communalities index and R^2 statistical formula model as follows $GoF = \sqrt{Com\ x\ R^2}$. Tenenhaus et al. (2004) proposed the goodness-of-fit (GoF) index as a solution to validate the PLS model globally (Tenenhaus et al., 2004). However, Henseler and Sarstedt (2013) conducted a trial on the index proposed by Tenenhaus et al. (2004) on two models, including the conceptual and empirical models. The results of the trials concluded that GOF could not represent the goodness-of-fit criteria in PLS-SEM (Henseler & Sarstedt, 2013; Hair et al., 2017). In addition, GoF, unlike the fit measure in CB-SEM, the criterion cannot separate valid models from invalid ones. Since GoF also does not apply to formatively measured models and cannot meet over-parametric attempts, applied researchers are advised not to use the GoF criteria proposed by Tenenhaus et al. (2004).

The stage of developing the model fit criteria was continued by Henseler et al. (2014), who assessed the suitability of the standard criteria for the root mean square residual (SRMR), which is a fit index adopted from the CB-SEM method. SRMR was defined as the mean square root difference between the observed and implied-model correlations. The SRMR index is a measure of absolute fit, where a value of zero indicates a perfect match. In the CB-SEM method, values less than 0.08 are generally considered suitable (Hu & Bentler, 1998). However, this threshold is likely too low for PLS-SEM (Hair et al., 2017). The statement is not without reason; the differences between the observed correlation and the implied-model correlation play different roles in CB-SEM and PLS-SEM. The CB-SEM algorithm aims to minimize the differences; whether PLS-SEM, the differences result from the model estimates, aiming to maximize the explained variance of the endogenous constructs.

In addition to the SRMR criteria, as a measure of alternative model fit, researchers can use the root mean square residual covariance (RMS_{theta}), which uses the same logic as SRMR but depends on the covariance. These criteria were introduced by Lohmöller (1989) but have not been widely explored by PLS-SEM researchers. Initial experimental results show a (conservative) threshold for RMS_{theta} of 0.12. An RMS_{theta} value below 0.12 indicates a suitable model, while a higher value indicates a less suitable model (Henseler et al., 2014). Finally, Dijkstra and Henseler (2015b) introduced the exact fit test. The chi-square-based test applies a bootstrapping procedure to obtain the p-value of the difference between the observed correlation and the correlation implied by the model.

Unlike SRMR, the discrepancy is not expressed in residuals but in terms of distances, which are calculated in two forms (Euclidean and geodesic distance). Initial experimental results showed that SRMR, RMS_{theta}, and Exact Fit Test were able to identify various model specification errors (Dijkstra & Henseler, 2015a; Henseler et al., 2014). It is still too early, and little known literacy about how these measurement criteria can be accepted for various data and model constellations, so more research is needed to explore other criteria. Moreover, these criteria cannot be easily implemented in standard PLS-SEM software. However, SmartPLS provides SRMR, RMS_{theta}, and exact fit test (Hair et al., 2017).

Then, is PLS-SEM unable to carry out confirmatory research? Several researchers (Ringle et al., 2018; Sarstedt et al., 2016; Schuberth, Henseler, & Dijkstra, 2018) agree that PLS-SEM can be used for confirmatory research along with the start of exploring the development of model fit criteria. However, those three eligibility criteria must be met using the PLS-SEM method for confirmatory purposes.

3rd Problem: Poor loadings

Many applied researchers switched from CB-SEM to PLS-SEM only because they found the loading values were greater than CB-SEM (Afthanorhan, Awang & Aimran, 2020). On the other hand, there are still differences of opinion on the threshold of the loadings indicator value. According to Hair et al. (2017), the significant value of outer loadings is still very weak, so the general rule determined for the outer loadings value threshold is above 0.708. However, applied researchers in the social sciences often find loadings values below 0.70, especially when they carry out exploratory research. For this reason, researchers are advised to store items with loading values between 0.4 to 0.7 as long as the internal consistency reliability values (In this case, Average Variance Extracted, Composite Reliability, etc.) have met the test requirements. For this reason, the decision to take the threshold of loadings must consider many factors and conditions, both from the research objective (exploratory or confirmatory) and the condition of the internal consistency reliability value itself. As a side note, research conducted by Afthanorhan, Awang & Aimran (2020) shows a condition where the validity and reliability of a construct are very sensitive and depends on the number of items per construct and the value of the loadings itself; the higher the value of loadings, increasing the AVE and CR values.

4th Problem: Lack of discriminant validity

Discriminant validity is used to see how a construct differs from other constructs by using empirical standards. Thus, testing discriminant validity can help researchers to be able to see whether a construct is different from other constructs, as well as capture phenomena that other constructs in the model may not represent. Traditionally, researchers have relied on two measures of discriminant validity. Cross-loading is usually the first approach to assessing the discriminant validity of an indicator. The next criterion is Fornell-Larcker, where the approach aims to assess discriminant validity by comparing the square root of the AVE value with the correlation of the latent variables. (Hair et al., 2017). However, Henseler et al. (2015) suggested using HTMT instead of Fornell's larcker criterion. This is based on the failure of the Fornell-Larcker Criterion test to identify discriminant validity in large cases. The Fornell larcker criterion test is carried out by comparing the square root of the AVE for each construct with the correlation value between constructs in the model (Hair et al., 2017). A construct is declared valid if it has the highest AVE square root correlation with the target construct compared to the AVE square root with other constructs. One alternative to the Fornell-Larcker criterion is the heterotrait monotrait ratio of correlations (HTMT).

However, the threshold value of HTMT is still debated (Hair et al., 2017). Henseler et al. (2015) research suggests a threshold value of 0.90 if the path models have very similar conceptual constructs. However, when the constructs in the path model are conceptually much different, a lower threshold value of 0.85 is strongly recommended (Henseler et al., 2015; Hair et al., 2017). For this reason, researchers are advised to look at $HMT_{inference}$ through a bootstrapping procedure with a confidence interval value. As an initial step to running the HMTInference test, a bootstrapping procedure with a subsample of 5000 is executed to obtain the confidence interval value. Subsamples are drawn randomly (with replacement) from the original data set (Hair et al., 2017). Then the sub-samples are used to estimate the model, where the process is repeated until the specified number is determined; the recommended sub-samples are 5,000. The parameters estimated from the subsample (in this case, the HTMT statistic) are used to obtain the standard error for the estimate.

Research conducted by Henseler et al. (2015) critically tested the cross-loading criteria and the Fornell-Larcker criteria for discriminant validity assessment. The research has found that neither approach can detect discriminant validity issues accurately. They reveal that cross-loading fails to show a lack of discriminant validity when the two constructs are perfectly correlated, making this criterion ineffective for empirical research. Similarly, the Fornell-Larcker criterion performs very poorly, especially when the indicator loadings of the considered constructs differ only slightly. When the variable loading indicator is stronger, the performance of the Fornell-Larcker criterion in detecting discriminant validity problems increases but overall still tends to be poor. In conclusion from the above debate, applied researchers are advised to be able to make decisions by considering the existing situations and conditions, which have been described previously.

1st Common Belief : PLS-SEM selection based on small sample size

PLS-SEM has been recognized as a method that offers special sampling capabilities that other multivariate analysis tools do not have. However, this is disputed by Sarstedt, Ringle, and Hair (2017), who state that, indeed, PLS-SEM can be applied with smaller samples in many cases. However, the legitimacy of the analysis depends on the size and nature of the population (for example, in terms of heterogeneity). No statistical method (including PLS-SEM) can compensate for a poorly designed sample (Sarstedt et al., 2017).

The decision to use PLS-SEM based on the availability of a small sample is not allowed; this is because the estimation method developed by PLS-SEM does not solve the sample problem. If we return to the basic methodology, population sampling is selecting a portion of a group of subjects or respondents who represent the entire population (Polkinghorne, 2005). The size of the estimated sample obtained based on the sampling of the population must be reflected with the actual population to ensure that the actual estimate can answer the research question. To ensure the feasibility of such estimates, sufficient sample sizes are required for statistical methodologies involving a structural equation model approach (Afthanorhan, Awang & Aimran, 2020). Hair et al. (2017) suggest using some sample calculations, such as multiplying the sample by five to ten times the number of indicators observed. However, when researchers are faced with a limited/small number of samples, they must look at the criteria for limiting the significance of loadings according to the number of samples they have (see Table 3).

Table 3. Significance Loadings based on Sample Size

Sample Size	***Loadings***
50	0.75
60	0.70
70	0.65
85	0.60
100	0.55
120	0.50
150	0.45
200	0.40
250	0.35
300	0.30

Source : Hair et al. (2017)

2nd Common Belief : PLS-SEM algorithm does simultaneously calculate all the relationships (simultaneously)

As explained in the previous chapter, PLS-SEM is an alternative to CB-SEM, with a different parameter estimation technique. However, several things need to be clarified concerning the objectives of the current research. Some applied researchers still have expectations that PLS-SEM can carry out simultaneous relationships. Different from CB-SEM, which is based on common factors, the PLS-SEM algorithm does not simultaneously calculate all model relationships (simultaneously) but uses ordinary least squares regressions to estimate the model regression relationships partially – this can be expressed from the name, partial least square (Sarstedt, Ringle & Hair, 2017). PLS-SEM applies ordinary least squares regressions (OLS) to minimize residual variance from endogenous constructs. For this reason, PLS-SEM can estimate the coefficients of the path model relationship that maximizes the R^2 value of the endogenous construct. Therefore PLS-SEM is the recommended method for exploratory research purposes, so PLS-SEM is considered a variance-based approach to SEM.

4. Procedures of PLS-SEM Model Specification

First Step : Designing the measurement model (outer model)

The latent variable must be measured in SEM by the observed variable (indicator, item, or manifest variable). The outer model (the measurement model) determines the relationship between latent variables and their indicators. More precisely, each construct has a measurement model (outer model) that determines the relationship between each construct (circle) and its indicator variable (rectangle). In determining the measurement model for each construct, there are two choices of measurement models, namely reflective and formative. There are two different ways of measuring latent variables (Sarstedt et al., 2014). The first step is to connect the latent construct to the indicator or commonly referred to as reflective measurement. In Figure 1, the latent variables are denoted by ξ2, η1 and η2 using a reflective measurement model. The second way is to link indicators to latent constructs or commonly referred to as formative measurements. In Figure 1, the latent variable is denoted by ξ1 using a formative measurement model.

In the reflective measurement model, the latent variable is the cause of the reflective measurement indicator. The reflective measurement indicator reflects the results or observable consequences of the latent variable. In contrast, in the formative measurement model, the latent variable is understood as a consequence of the formative measurement indicator where the latent variable represents an exact linear combination or is free from measurement error (Fornell & Bookstein, 1982; Edwards & Bagozzi, 2000; Diamantopoulos, 2011). The reflective indicator equation model can be written as follows:

$$x = \lambda x \xi + \delta$$

$$y = \lambda y \eta + \varepsilon$$

Where x and y are indicators for exogenous (ξ) and endogenous (η) latent variables, meanwhile, x and y are outer loadings matrices that describe simple regression coefficients that relate latent variables to their indicators. Residuals are measured by and can be interpreted as measurement error or noise. While the formative indicator equation model is written as follows:

$$x = \pi x \xi$$

$$y = \pi y \eta$$

Where x and y are indicators for exogenous (ξ) and endogenous (η) latent variables. While x and y are outer weights matrices that describe the relationship between indicator variables and latent variables.

Step Two: Designing a structural model (inner model)

After the measurement model is formed, the next step is to design a structural model (inner model). According to Hair et al. (2017), the evaluation of the structural model (inner model) aims to predict the relationship between latent variables. The endogenous latent variables are identified in the structural model with the notation (η) and the exogenous latent variables with the notation (ξ). Figure 1 shows how exogenous and endogenous variables are related and can be identified with the existing notations.

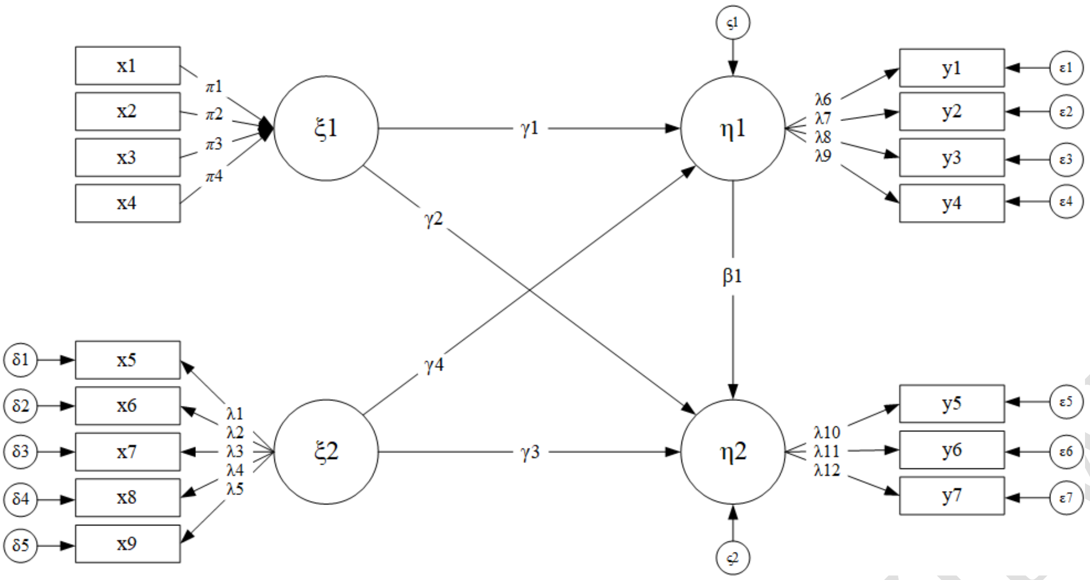

Fig. 1. *Notated Structural Model Illustration*

Where the notations used are:

ξ = Ksi, Latent exogenous variable
η = Eta, Latent endogenous variable
x = Manifest measurement variable of a latent exogenous variable
y = Manifest measurement variable of a latent endogenous variable
λx = Lamnda, loading factor of exogenous latent variable
λy = Lamnda, loading factor of endogenous latent variable
β = Beta, path coefficient of endogenous variables to endogenous variables
γ = Gamma, path coefficient of exogenous variables to endogenous variables
ς = Zeta, Residual of latent endogenous variable
δ = Delta, measurement error on manifest variable for exogenous latent variable
ε = Epsilon, Residual of a reflective measurement variable endogenous

The structural equation above can be written as follows:

$\eta 1 = \gamma 1\xi 1 + \gamma 4\xi 2 + \varsigma 1$

$\eta 2 = \beta 1\eta 1 + \gamma 2\xi 1 + \gamma 3\xi 2 + \varsigma 2$

5. Procedures of PLS-SEM Model Evaluation

In evaluating the PLS-SEM model, there are two stages of testing, which have been illustrated in Figure 2. Stage 1 tests the measurement model (outer model evaluation); the test is carried out by seeing whether the model includes a reflective measurement model (Stage 1.1), a formative measurement model (Stage 1.2), or even both. If the evaluation of the measurement model gives satisfactory results and is declared to have passed the test, the researcher can proceed to Stage 2, which involves evaluating the structural model. Stage 1 examines measurement theory, while Stage 2 includes the structural theory used to determine whether the structural relationship is significant and test hypotheses.

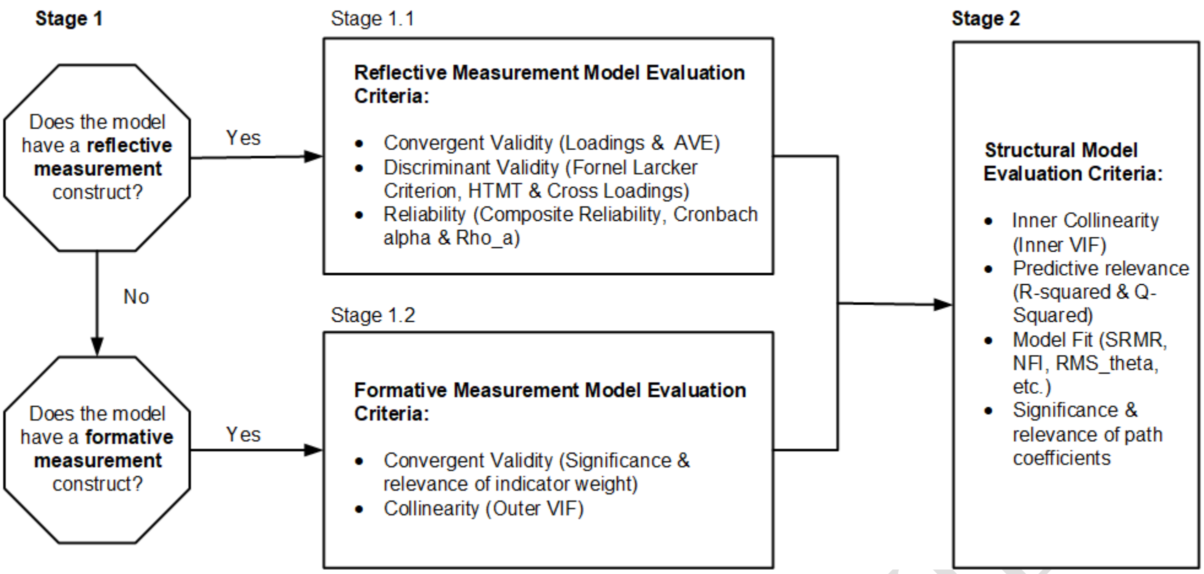

Fig. 2. *PLS-SEM Evaluation Stage*

Stage 1.1 : Evaluating the Reflective Measurement Model

When the research has a reflective measurement model, the researcher can examine the loadings indicator value. When the loading value is above 0.50, it indicates that the construct can be explained by the associated indicator variance of 50%. The loadings value is obtained through the PLS Algorithm procedure in the SmartPLS application. Figure 3 and Table 4 show the results where the loading value for each indicator has explained the latent construct above 50%. However, the minimum loadings limit will vary depending on the methodology and research objectives (see the third problem study).

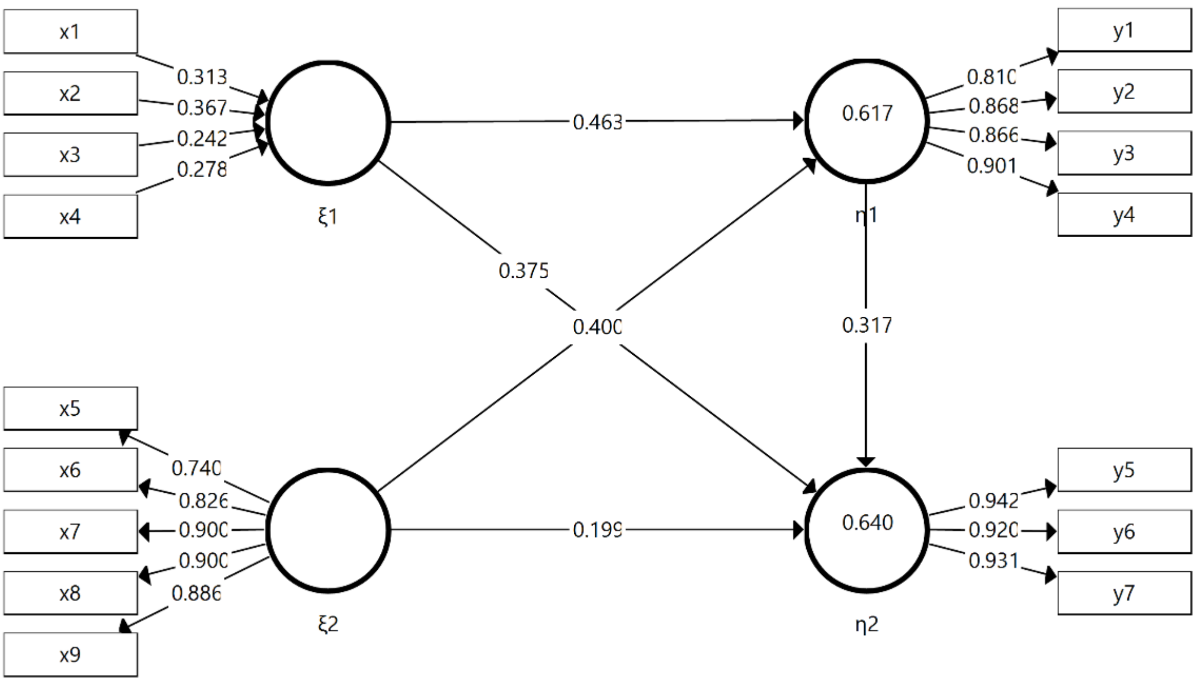

Fig. 3. *Test Results Using the PLS-Algorithm Procedure*

The evaluation criteria for the next reflective measurement model is average variance extracted (AVE). This value is included in the convergent validity test, and the test measures the extent to which the constructs converge in the indicators by explaining the item variance. Convergent validity was assessed by average variance extracted (AVE) for all items associated with each construct. The AVE value is calculated as the average load squared for all indicators related to a construct. The acceptable AVE is 0.50 or higher, indicating that, on average, the construct explains more than 50% of the variance of the items (see Table 4).

Table 4. Reflective Measurement Model Test Results

Latent	Observed	Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE
ξ2	**x5**	**0.740**	**0.905**	**0.911**	**0.930**	**0.727**
	x6	**0.826**				
	x7	**0.900**				
	x8	**0.900**				
	x9	**0.886**				
η1	**y1**	**0.810**	**0.884**	**0.890**	**0.920**	**0.743**
	y2	**0.868**				
	y3	**0.866**				
	y4	**0.901**				
η2	**y5**	**0.942**	**0.923**	**0.923**	**0.951**	**0.867**
	y6	**0.920**				
	y7	**0.931**				

After exceeding the testing criteria for convergent validity, the next criteria that need to be tested are problems related to discriminant validity in each construct with the correlation value between constructs in the model (Wong, 2019). Wong (2019) stated several testing steps to measure discriminant validity: the Fornell larcker criterion, heterotrait monotrait ratio of correlations (HTMT), and cross-loadings. Table 5 illustrates how the Fornell Larcker criterion test has met the test requirements, where the correlation of the square root of AVE with the target construct is higher than the square root of AVE with other constructs. As a side note, when the researcher assesses the Fornell-Larcker criterion on a model that includes a construct with a formative measurement model, the researcher only needs to compare the square root value of the AVE on the reflective construct with all the correlations of the latent variables. However, according to Hair et al. (2017), the square root of the AVE of formatively measured constructs should not be compared with correlations. As shown in Table 5, the square root of AVE is not even reported for formative constructs in SmartPLS.

Table 5. Fornell Larcker Criterion Test Results

	η1	**η2**	**ξ1**	**ξ2**
η1	0.862			
η2	0.729	0.931		
ξ1	0.725	0.735	Formative	
ξ2	0.703	0.667	0.654	0.853

If referring to the opinion of Henseler et al. (2015), which has been described in the previous chapter, states that the Fornell-Larcker criterion approach fails to identify discriminant validity in the majority of cases. Researchers are advised to assess discriminant validity using the heterotrait monotrait ratio of correlations (HTMT). Ramayah et al. (2017) explained that if the researcher found the HTMT value to be smaller than $HTMT_{0.85}$ (Kline, 2011) or the $HTMT_{0.90}$ value (Gold et al., 2001), as shown in Table 6, the HTMT value was found to be smaller than $HTMT_{0.85}$. It can be concluded that there is no problem with discriminant validity.

Table 6. HTMT Criterion Test Results

	η1	**η2**	**ξ2**

η1			
η2	**0.804**		
ξ2	**0.769**	**0.712**	

Furthermore, another alternative in testing the problem of discriminant validity is to test the $\text{HMT}_{\text{inference}}$ through a bootstrapping procedure by looking at the confidence interval value. Table 7 shows the confidence interval (CI) value, where if the value is found to be less than 1.00 at the CI (2.5%) and the CI (97.5%), it can be identified that there is no problem with discriminant validity (Henseler et al., 2015).

Table 7. $\text{HMT}_{\text{inference}}$ Test Results

	Original Sample (O)	**Sample Mean (M)**	**2.5%**	**97.5%**
η1 -> η2	0.317	0.316	0.133	0.497
ξ1 -> η1	0.463	0.474	0.344	0.633
ξ1 -> η2	0.375	0.379	0.196	0.551
ξ2 -> η1	0.400	0.391	0.219	0.523
ξ2 -> η2	0.199	0.199	0.033	0.355
ξ1 -> η1 -> η2	0.147	0.149	0.062	0.249
ξ2 -> η1 -> η2	0.127	0.124	0.043	0.219

The next stage in testing discriminant validity is to look at the value of the cross-loadings test. An indicator is declared valid if it has a higher loadings correlation between the intended constructs than the loadings correlation with other constructs (see Table 8). Thus, latent constructs predict indicators in their block better than indicators in other blocks (Hair et al., 2017).

Table 8. Cross-Loadings Test Results

	η1	**η2**	**ξ1**	**ξ2**
x1	0.563	0.609	**0.803**	0.530
x2	0.626	0.629	**0.859**	0.561
x3	0.638	0.620	**0.862**	0.579
x4	0.593	0.590	**0.810**	0.513
x5	0.699	0.682	0.678	**0.740**
x6	0.503	0.449	0.431	**0.826**
x7	0.549	0.549	0.500	**0.900**
x8	0.629	0.602	0.595	**0.900**
x9	0.547	0.488	0.509	**0.886**
y1	**0.810**	0.542	0.511	0.577
y2	**0.868**	0.657	0.613	0.608
y3	**0.866**	0.673	0.711	0.596
y4	**0.901**	0.630	0.646	0.642
y5	0.692	**0.942**	0.684	0.610
y6	0.668	**0.920**	0.694	0.599
y7	0.676	**0.931**	0.675	0.655

When the researcher has confirmed the validity of the construct, the reliability test is carried out using the composite reliability test and Cronbach's alpha by looking at all values of the latent variable having a composite reliability value > 0.7 and Cronbach's alpha and rho_a 0.6, where it can be concluded that the construct has good reliability or the questionnaire used as a tool in research have been reliable or consistent. Table 4 shows that all the internal reliability consistency values have met the requirements. As an additional note, Cronbach's alpha is the lower limit, and composite reliability is the upper limit of internal consistency reliability (Hair et al., 2017).

Stage 1.2 : Evaluating Formative Measurement Models

To evaluate the formative measurement model, there is a significant difference in evaluating the model on reflective measurement. Convergent validity in the formative measurement model is determined based on the extent to which the formatively measured construct correlates with the reflectively measured construct, which has the same meaning as the formatively measured construct (Sarstedt et al., 2014). Research conducted by Hair et al. (2017) suggested that the formatively measured construct should explain at least 65% of the variance of the reflective measured item, which is indicated by a path coefficient of around 0.80. However, a path coefficient of 0.70 is also acceptable in most cases. To evaluate more specifically, researchers are advised to look at the significance of the values of the weights through the bootstrapping procedure with a suggested subsample of 5000. Using a subsample of 5000, researchers can calculate the standard bootstrapping error, which calculates the t-value (and p-value) for each indicator weight of reflective measurements. Based on the t-value, the significance of the weight can be determined to make the following decisions (1) If the weight value is found to be statistically significant, the indicator can be maintained, (2) If the weight value is found to be insignificant, but the value of the loading is 0.50 or higher, the indicator is still allowed to be maintained, but this must be supported by theory and expert judgment, (3) If the weight value is not significant and the load is low (i.e., below 0.50), the indicator should be removed from the measurement model.

However, omitting formative indicators from the model is recommended to be avoided. This is because each indicator of the formative model represents the meaning dimension of the latent variable. For this reason, eliminating indicators in the formative model is the same as eliminating the meaning dimension, causing the meaning of the latent variable to change (Garson, 2016). It is unlike reflective measurement models; formative indicators are not interchangeable. Therefore, removing formative indicators has detrimental consequences on the content validity of the measurement model (Hair et al., 2014).

Table 9. Formative Measurement Model Test Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Outer VIF
x1 -> ξ1	0.313	0.313	0.084	3.740	**0.000**	**1.686**
x2 -> ξ1	0.367	0.364	0.098	3.741	**0.000**	**2.011**
x3 -> ξ1	0.242	0.244	0.098	2.464	**0.014**	**2.585**
x4 -> ξ1	0.278	0.274	0.094	2.962	**0.003**	**1.991**

In addition to looking at the criteria above, the evaluation of the formative measurement model is done by looking at the value of the outer VIF. To assess the level of collinearity between the formative indicators, researchers must calculate the variance inflation factor (VIF). In determining the value limit, a higher VIF implies a greater degree of collinearity between indicators. As a limit, a VIF value above five indicates collinearity between indicators (see Table 9).

Stage 2 : Evaluating the Structural Model

As long as the measurement model assessment shows that the quality of the measurement model is satisfactory, the researcher can proceed to the second stage of the PLS-SEM evaluation process (Figure 2), which is evaluating the structural model. In contrast to CB-SEM, which has several goodness-of-fit (GOF) criteria, PLS-SEM has another standard: the assessment of model quality based on its ability to predict endogenous constructions. Researchers can refer to the criteria for the coefficient of determination (R^2), cross-validated redundancy (Q^2) and model fit. However, before carrying out some of these test criteria, researchers must examine the potential for collinearity in the structural model between exogenous constructs (inner VIF). Assessing the model with PLS-SEM begins by looking at each endogenous latent variable's R-Square (R^2). R-Square (R^2) or the value of the coefficient of determination shows how much the exogenous variable explains the endogenous variable. The R-square (R2) value is zero to one; if the value of R-Square (R^2) is getting closer to one, then the exogenous variables provide all the information needed to predict the variation of endogenous variables. The R-square (R^2) value has a weakness; namely, the value of R-Square (R^2) will increase every time there is an addition of one exogenous variable even though the exogenous variable has no significant effect on the endogenous variable.

Table 10. Predictive Relevance Test Results

	SSO	SSE	Q² (=1-SSE/SSO)	R Square	R Square Adjusted
η1	680.000	379.311	0.442	0.617	0.612
η2	510.000	235.985	0.537	0.640	0.633
ξ1	680.000	680.000			
ξ2	850.000	850.000			

According to Hair et al. (2011, 2017), as a guideline, R-Squared values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial levels. However, if an R-Squared adjusted is used (Hair et al., 2017), this coefficient can be biased upward in complex models where more paths lead to endogenous constructs. Based on the illustration shown in Table 9, it was found that the endogenous variable η1 could be explained by 61.7% by the exogenous variable; this was due to the finding of an R-Square (R^2) value of 0.617. Meanwhile, endogenous variable η2 can be explained by 64% by the exogenous variable; this is due to finding an R-Square (R^2) value of 0.640.

The next criterion is to evaluate the cross-validated redundancy (Q^2) to measure how well the observed values are generated from the structural model. According to Hair et al. (2017), if the Q² value is greater than zero for certain endogenous latent variables, the PLS-SEM path model has predictive relevance. A sample reuse technique called “Blindfolding" obtained these statistical values”. The removal distance is set between 5 and 12, where the number of observations divided by the distance of removal is not an integer (Hair et al., 2012). For example, if you select an omission distance of 7, every seventh data point is omitted, and the parameter is estimated with the remaining data points. According to Hair et al. (2017), the omitted data points are considered missing values replaced with average values. The estimated parameters help predict the omitted data points and the difference between the actual data points and the predicted data points becomes the input for the Q^2 calculation. Blindfolding is only applied to endogenous constructions with reflective indicators. If Q^2 is greater than zero, it shows the value of predictive relevance to the path model in endogenous construction and the corresponding reflective indicators.

Applied researchers must be careful in reporting and using model fit criteria in PLS-SEM (Hair et al., 2017). This is not without reason; the criteria are still in the early stages of research and have not been fully approved by statistical methodologists (e.g., threshold values). However, some researchers have started to report the fit model in the PLS-SEM method. SmartPLS has provided several model fit criteria, but these values still need to be reviewed repeatedly to be applied properly. In several previous studies, these criteria were not reported or used to assess PLS-SEM results (Hair et al., 2017). Hair et al. (2017) suggest that researchers use SRMR, RMS_{theta}, or Exact Fit values. However, due to the absence of in-depth research on these three criteria, researchers are advised to follow a conservative approach. If the SRMR value is less than 0.08 and the RMS_{theta} value is less than 0.12, the fit model can be accepted. Of note, Hair et al. (2017) forbid using the GOF criteria (proposed by Tenenhaus et al., 2004) to evaluate this test (see the previous section on the study of problem findings).

Hypotheses Testing

This stage examines how the exogenous latent variable is connected with the endogenous latent variable. To test the hypothesis that has been proposed, researchers can see the path coefficient value, T-Statistic value and p-value through the bootstrapping procedure. In carrying out the bootstrapping procedure, Hair et al. (2017) confirmed that researchers should use the Bias-Corrected and Accelerated (BCa) Bootstrap method to assess the significance of the path coefficients in the structural model. Alternatively, the researcher can return to the p-value (<0.05).

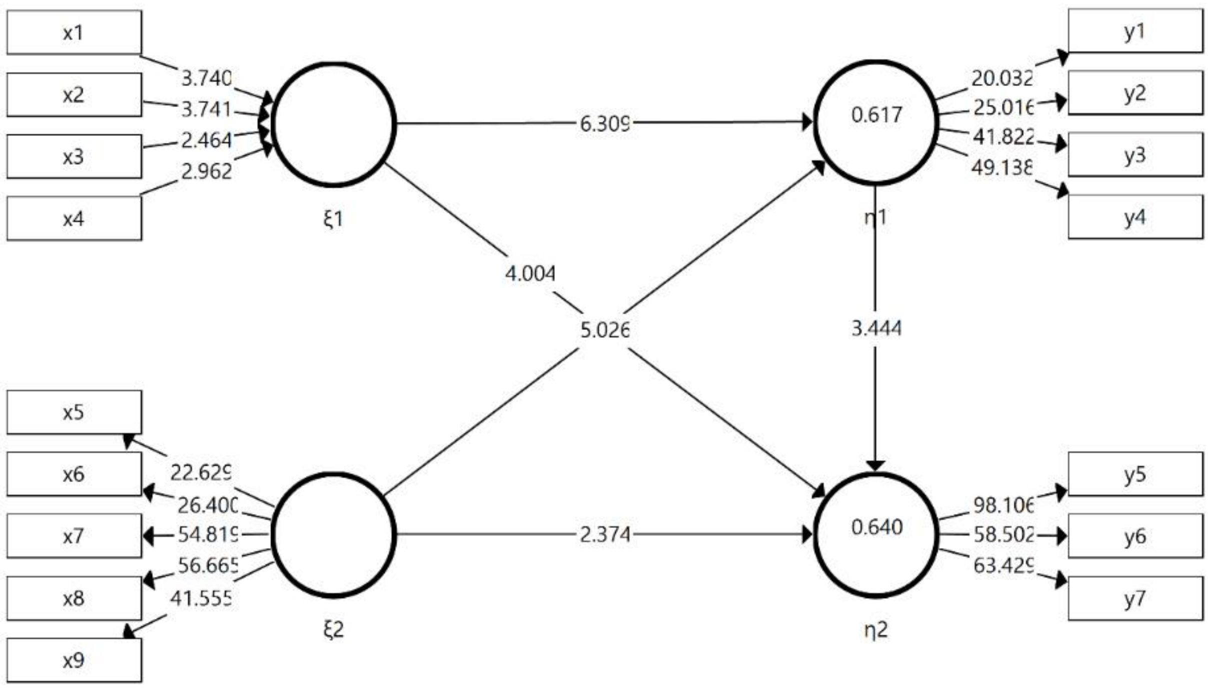

Fig. 4. *Bootstrapping Procedure Test Results*

Hair et al. (2014) explain that the path coefficient value is always -1 to +1. The path coefficient value approaching +1 represents a strong positive relationship, and the path coefficient value of -1 indicates a strong negative relationship. Based on the path coefficient test in Figure 4 and Table 11, it can be seen that all relationships have a positive relationship direction because the value is close to +1. Furthermore, the researcher can see the T-Statistic value to see the significant value between constructs. The limit for rejecting and accepting the proposed hypothesis is ±1.96, which if the t-statistic value is below 1.96, then the hypothesis will be rejected or, in other words, accept the null hypothesis (H0).

Table 11. Research Hypothesis Testing Results

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Direct Effects					
η1 -> η2	0.317	0.316	0.092	3.444	**0.001**
ξ1 -> η1	0.463	0.474	0.073	6.309	**0.000**
ξ1 -> η2	0.375	0.379	0.094	4.004	**0.000**
ξ2 -> η1	0.400	0.391	0.080	5.026	**0.000**
ξ2 -> η2	0.199	0.199	0.084	2.374	**0.018**
Indirect Effects					
ξ1 -> η1 -> η2	0.147	0.149	0.049	3.009	**0.003**
ξ2 -> η1 -> η2	0.127	0.124	0.046	2.769	**0.006**

Assessing the Mediating Effect

The mediating effect is used to see the relationship between exogenous and endogenous variables through connecting variables. The effect of exogenous variables on endogenous variables does not occur directly but through a transformation process represented by mediating variables (Baron & Kenney, 1986). Testing the mediation effect can be done using regression techniques, but the regression technique is no longer efficient in complex models or with many paths leading to endogenous constructs. The Variance Accounted For (VAF) method developed by (Preacher & Hayes, 2008) and bootstrapping in the distribution of indirect effects is considered more suitable because it does not require any assumptions about the distribution of variables applied to small sample sizes.

However, the VAF method can only be carried out by considering several conditions such as (1) the direct effect of exogenous variables on endogenous variables must be significant, (2) each path, namely exogenous variables on mediating variables and mediating variables on endogenous variables must be significant to fulfil this condition. Suppose the two conditions above have been obtained. In that case, the researcher can use the VAF formula, namely the effect of the independent variable on the mediating variable multiplied by the effect of the mediating variable on the dependent variable (Hair et al., 2014). If the indirect effect is significant, then this indicates that the mediating variable can absorb or reduce the direct effect in the first test. Here is the VAF formula:

$$\text{VAF} = \frac{\text{indirect effect}}{\text{total effect}} \text{ .... Sarstedt et al. (2014)}$$

When the researcher found the VAF value above 80%, then the value indicated the full mediation role. Categorized as partial mediation if the VAF value ranges from 20% to 80%, but if the VAF value is less than 20%, it can be concluded that there is almost no mediating effect.

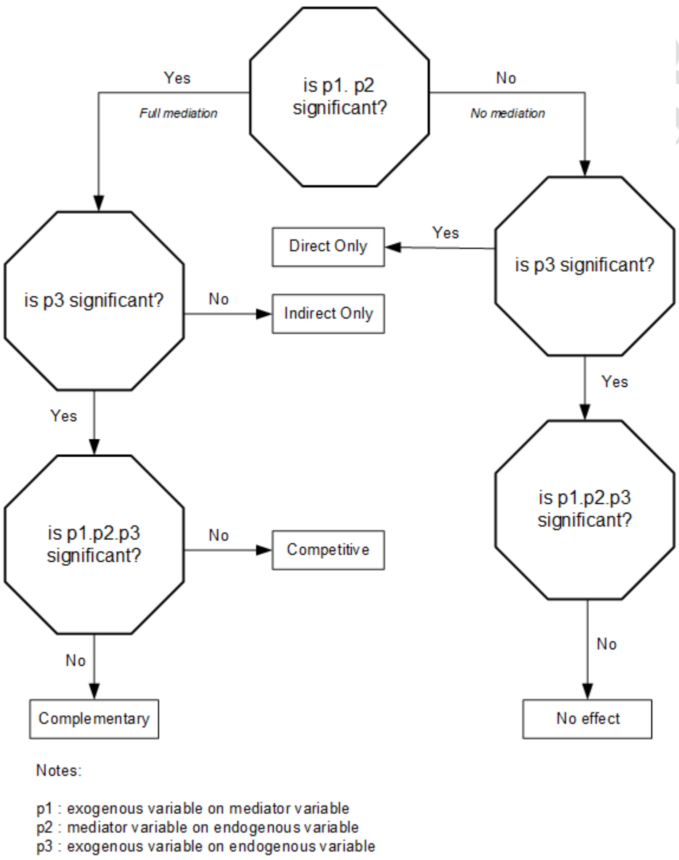

Figure 5. *Mediation Role Decision Tree*

However, in a later study, Hair et al. (2017) revised the method above by suggesting not to look at the VAF value anymore but suggesting to look at the changes in the existing effects (see Figure 5) from a direct to an indirect relationship with the following conditions (1) Direct-only nonmediation, the condition is found if the effect is a significant direct effect, but not with indirect effect; (2) No-effect non-mediation, a condition where the direct or indirect effects are found to be insignificant; (3) Complementary mediation, this condition is found when the indirect effect and direct effect are found to be significant and point in the same direction; (4) Competitive mediation, a condition where indirect and direct effects are found to be significant but have opposite directions; (5) Indirect-only mediation, is a condition where the indirect effect is significant but not with a direct effect. Table 8 illustrates how the mediating variable was found to have a complimentary mediation mediating role because the direct and indirect relationship effects were found to have a significant effect and lead in the same direction.

6. Concluding Remarks

The decision to use the CB-SEM or PLS-SEM methods is not based on which method is better. If researchers want to go back to the basics of developing statistical methodologies, they will understand the “how” and “what” each method was developed for. In addition, the decision to use it is also not based on one assumption and does not seem to see other assumptions; for example, applied researchers often decide to use PLS-SEM because of the small sample size, but rarely from researchers who consider the minimum value limit (such as loadings) required to cover the sample shortage. When a researcher decides to use SEM-PLS with an example of these reasons, the researcher will also be faced with fulfilling other assumption criteria that can cover the existing deficiencies. Another common reason for choosing is that PLS-SEM is perceived as the method of choice when researchers are faced with data that are not normally distributed. However, researchers still insist on testing the empirical model using excessive goodness-of-fit criteria. On the other hand, statistical methodologists are still trying to establish model fit criteria for PLS-SEM.

If you are a good researcher, you will make wise decisions by considering all the situations and conditions. Both CB-SEM and PLS-SEM have different parameter estimates and usage rules. Therefore, you must consider many assumptions when applying PLS-SEM in your research; for example, if your research is confirmatory, you should use the CB-SEM method. The author hopes that this article can help you decide which method you will apply for the quantitative research you are carrying out and provide a clear overview of the procedures and stages of using the PLS-SEM method.

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