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Comparison Between CB-SEM and PLS-SEM: Testing and Confirming the Maqasid Syariah Quality of Life Measurement Model

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Abstract

Structural Equation Modelling (SEM) is a powerful multivariate statistical analysis technique which combines both factor analysis and multiple regression analysis. It is capable of analysing the inter-relationships among latent constructs simultaneously in a model. These latent constructs are measured using certain number of items in a questionnaire. Covariance-based SEM (CB-SEM) or full SEM have become the choice for many researchers in a variety of disciplines because of their ability to evaluate complex relationships using parametric statistical approach. Researchers could also opt for Variance-based SEM (VB-SEM) or Partial Least Square-SEM (PLS-SEM) when their data failed the parametric assumptions such as multivariate normality distribution and minimum sample size. However, the approach of VB-SEM or PLS-SEM is a non-parametric instead of a parametric approach in CB-SEM. This article compared the performance of both SEM approaches using the same dataset to validate the Measurement Model for Maqasid Syariah Quality of Life (MSQoL). The findings of both analyses suggested that CB-SEM or full SEM is more appropriate to validate and confirm the MSQoL measurement model.

Keywords: Partial least square SEM; Covariance-based SEM; Maqasid syariah quality of life; Measurement model.

1. Introduction

Structural Equation Modelling (SEM) has been considered one of the most important statistical developments in social sciences in recent years (Hair *et al.*, 2011) and has grown in a large number of academic disciplines including marketing, management, tourism (Afthanorhan *et al.*, 2017; Mohamad *et al.*, 2012; Yusof *et al.*, 2017), healthcare (Kashif *et al.*, 2016) and social sciences (Mohamad *et al.*, 2016; Mohamad *et al.*, 2017; Mohamad *et al.*, 2018). Its ability to simultaneously examine the multiple models while accounting for measurement errors has been acknowledged since 1970. Given the importance and uniqueness in evaluating the measurement models and structural model, SEM has become one of the key methods for theory testing and theory development. As Dijkstra and Henseler (2015). Point out, SEM has two families: Covariance-based SEM (CB-SEM) and Variance-based SEM (VB-SEM). Several methods of analysis using VB-SEM have been introduced such as Generalized Structure Component Analysis (GSCA-SEM), Partial Least Squares Path Modelling (PLS-PM), regression on sum scores, Partial Least Squares Regressions (PLSR), and path analysis. Among them, PLS-PM has been increasingly applied in various disciplines such as international marketing (Henseler *et al.*, 2009), psychology (MacCallum and Austin, 2000), accounting (Lee *et al.*, 2011), strategic management (Ringle *et al.*, 2012), marketing Hair *et al.* (2015), and operations management (Peng and Lai, 2012).

2. Structural Equation Modeling (SEM)

SEM is a powerful and robust multivariate statistical analysis technique that enable researchers to examine the inter-relationships among latent constructs based on theories and their respective observable indicator variables. In most cases, researchers embraced SEM to test complete theories and concepts (Hair *et al.*, 2015). There are two types of SEM approaches: Covariance-based technique (CB-SEM) and Partial Least Square (PLS-SEM). Both CB-SEM and PLS-SEM complement each other and the research objectives is the acid-test in regards to which approach to employ in a particular research. As a guideline, CB-SEM is more appropriate when the research is confirmatory in nature and its objective is theory testing and theory confirmation. On the other hand, PLS-SEM is appropriate

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when the research is exploratory in nature and its objective is prediction and theory development (Hair *et al.*, 2011). In the case of confirmatory testing, CB-SEM is recommended more than PLS-SEM because CB-SEM uses chi-square to determine the discrepancy between observed and implied covariance matrix. More importantly, CB-SEM has several Goodness-of-Fit (GoF) indexes to indicate the fitness of empirical data to the proposed measurement model. Among them are Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Root Mean Square of Error Approximation (RMSEA) and Normed Chi Square (Chisq/Df). However, there is no such GoF measure for assessment of model fit in PLS-SEM. Thus, this method is more suitable for exploratory study leading to theory development rather than confirmatory study leading to theory testing and confirmation.

PLS-SEM applies the similar models as CB-SEM which could examine the structural equations with both observed variables as well as latent constructs taking into consideration the measurement errors but both have different complementary research and objectives (Aimran *et al.*, 2017). More precisely, PLS-SEM addresses on the explanation of total variances of endogenous construct which is useful for predicting the path in a model (Shmueli *et al.*, 2016). In contrast, CB-SEM focuses on estimating the path in a model by considering constructs as common factors. The common factors employed variance and covariance between variables in a model to produce parameter estimates. Therefore, the unique variance and the error of variance are dropped from the analysis before the research model is examined. On the other hand, PLS-SEM employed linear combination of indicator variables as proxies to explain the total variance of the construct in the structural model (Rigdon *et al.*, 2017). Thus, the PLS-SEM is compromised as a composite method because it accounts for all the unique variances including error of variances. The use of PLS-SEM method is only appropriate as an alternative to CB-SEM when the assumptions for parametric analysis are violated and this is one of the reasons many scholars view it as less suitable (Hair *et al.*, 2011). PLS-SEM can be used for hypothesis testing when the research is exploratory in nature, the data distribution is non-normal, sample size is small, and when the model is very complex which include both reflective and formative constructs and also when the model comprises higher-order constructs (Hair *et al.*, 2017a; Henseler, 2017).

The CB-SEM and PLS-SEM methods have two elements when evaluating and testing the measurement models and structural models. The first element is called an inner model which represents the structural path between the main constructs in a model, and the second element is called an outer model which represents the relationships between measurement model and associated indicator variables. Moreover, there are two types of construct when using SEM method: exogenous and endogenous constructs. Exogenous construct, which is also known as an independent latent variable, is used to explain other constructs in a model. On the other hand, the endogenous construct is the dependent latent variable in a model. The outer model is constructed differently depending on the type of measurement theory. If the constructs are measured with reflective or effect indicator, the model is represented by arrows pointing from construct to the indicator variables. In contrast, when the constructs are measured with formative or causal indicator, the model is represented by arrows pointing from indicator variables to the constructs. The difference between two different measurement models (reflective and formative) influence the computation and convergence estimates. Thus, if the model is specified incorrectly, the result will be biased and eventually tend to provide an improper solution and non-convergences estimates.

When the researcher draws on SEM method, the validity measures are considered critically to allow for more precise assessment (Hair *et al.*, 2017b). As such, the other qualitative measures such as content validity, face validity and criterion validity are not sufficient evidence of validities where these measures are not assessed in the case of statistical inferences. The assessments for reflective and formative construct differ substantially. The reflective constructs are assessed for internal reliability as well as discriminant and convergent validity prior to further analysis. The internal reliability can be assessed using Cronbach Alpha, Omega rho, Dijkstra & Henseler rho, McDonald rho and Composite Reliability or Joreskog rho. However, CR is much more useful than other reliability measures as it considers the indicator variables with different weights (Dijkstra and Henseler, 2015). Specifically, the indicator weight is assessed through the value of factor loadings, whereas other traditional measures uses the indicator weight equally (tau equivalence) which tends to underestimate the true reliability.

Convergent validity is assessed through computing the Average Variance Extracted (AVE) using a factor loading from each construct. For PLS-SEM, the minimum requirement for indicator loading in the model is 0.70 because the square of that value is equivalent to 0.5 or 50% of the variable variance (Hair *et al.*, 2017a). Indicators with 0.40 to 0.70 of factor loading were suggested to be deleted, however, they may be considered for the analysis as long as the convergent validity is satisfied (Hair *et al.*, 2017a). The rule of thumb for minimum AVE is 0.5, indicating that more than half of indicator variance is explained in the construct score. The minimum factor loading for CB-SEM is 0.50, and the item deletion should not exceed 20% of the total indicators in the model(Hair *et al.*, 2017a). In addition to convergent validity assessment, the formative constructs are assessed based on collinearity among indicator variables as well as the significance of indicator weight. The collinearity assessment is evaluated by examining the Variance Inflation Factor (VIF) and Tolerance (Tol). The present study employed reflective constructs for measurement model as depicted in Figure 1 and VIF and Tol analysis is not reported.

Discriminant validity is the last step for establishing the validity of measurement model. The constructs in a model must be discriminant to each other in order to avoid the issue of multicollinearity problems. Discriminant validity is established when each construct captures a unique phenomenon not represented by any construct in a model (Franke and Sarstedt, 2018). A conventional approach for establishing the discriminant validity is the Fornell and Larcker (1981), which compare the square root value of AVE of the construct with the correlations between constructs. It was widely applied with CB-SEM and PLS-SEM. However, this approach is not meaningful for the composite method because PLS-SEM does not take into account the shared variance within (Henseler *et al.*, 2015;

Voorhees *et al.*, 2016). As a consequence, the Heterotrait-Monotrait ratio (HTMT) is proposed to cater for limitation lies in the composite method.

CB-SEM employed the parametric statistical method, whereas PLS-PM employed the non-parametric statistical method; and statistically, the parametric approach is much more powerful than the non-parametric approach. More importantly, the algorithm employed in CB-SEM is Maximum Likelihood Estimator (MLE) which is much more superior and efficient compared to the Ordinary Least Squares (OLS) estimator in PLS-SEM. In additions, PLS-SEM cannot produce immediate results for Null Hypothesis Statistical Significance Testing (NHSST) because it relies on bootstrapping results (typically using 10,000 bootstrap samples) to derive standard error of parameter estimates, whereas the statistical significance is produced simultaneously in CB-SEM.

3. Model Assessment Using the Two Approaches of SEM

Figure 1 displays the theoretical model of Maqasid Syariah Quality of Life (MSQoL) in this study to compare the two approaches of SEM method: CB-SEM and PLS-SEM. The model is based on the MSQoL model developed by Mohamad *et al.* (2017) based on a sound Maqasid Syariah theory. Generally, *Maqasid* refers to objective, principle, intent, goal or purposes behind Islamic laws. The theory suggests that there are five dimensions of MSQoL: Protecting the Religion, Life, Mind, Lineage and Property.

Figure-1. The Measurement Model of Maqasid Syariah Quality of Life (MSQoL)

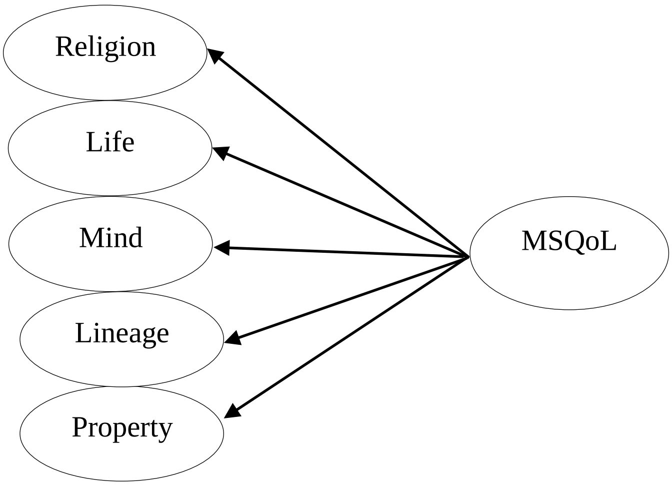

Table 1 provides the definition of each dimension and their respective indicators. The real data used to obtain the solutions for the examples in this research paper is from the Mohamad *et al.* (2017), study. This study was conducted among 465 drug-abuse inmates. All items were measured on a ten-point Likert-type interval scale coded as 1 = strongly disagree, to 10 = strongly agree with the given statement.

Table-1. Items Measuring the Dimensions of MSQoL - Protecting Religion, Life, Mind, Lineage and Property

Constructs	Definition	Items
Protecting Religion	Refers to the belief in and worship of Allah in fulfilling human natural needs which require a life guidance to save them from destruction.	I read the Holy Quran everyday (A1)
		I perform the five daily obligatory prayers (A2)
		I always perform the optional voluntary prayers (A3)
		I fast for a full month during Ramadhan (A4)
		I perform the optional fasting regularly (A5)
		I give zakat (A6)
Protecting Life	Life is the existence of human beings and protecting life refers to individuals' efforts to protect their life and others by performing activities that can increase the safety of life such as keeping healthy by eating nutritious food and exercising.	I practice the *sunnah* dietary habits as a form of medical treatment (N1)
		I practice the readings of the verses from the Holy Quran for health (N2)
		I practice the readings of the verses from the Holy Quran for safety (N3)
		I am actively participating in recreation programmes (N4)
		I exercise to keep fit (N5)
		I fill my free time with exercising (N6)
		Exercising can calm my mind (N7)
Protecting Mind	Mind refers to individual's ability to think and reasons. Protecting mind means using it appropriately to develop and guard the mind	I practice time management so that I will not be stressed (AK1)
		I give admonition to those committing bad deeds (AK2)
		I share my views regarding everyday life with others (AK3)

	from negative influence, such as drugs and alcohol.	I respect the views of others (AK4)
		I am careful in making decisions so as to not break the commandments of Allah SWT (AK5)
		I contribute my view in discussion regarding matters of everyday life (AK6)
		I strive to complete my tasks within the allocated time (AK7)
Protecting Lineage	Related to the relationship between family members, friends and neighbours, as well as law enforcements to ensure the prosperity and happiness in life.	I choose my life partner with good lineage (K1)
		I choose my life partner because of his/her religion (K2)
		Marriage can strengthen the relationship between families (K3)
		I fulfil my responsibilities as a husband/wife (K4)
Protecting Property	Obtaining wealth through legally activities and utilising properties in a way that can benefit individuals and society.	I set aside a portion of my money for charitable causes (H1)
		I make a personal budget (H2)
		I have personal financial planning (H3)
		I gain money legally (H4)
		I make a living through working (H5)

Source: Mohamad and Ali (2016) and Mohamad *et al.* (2017).

4. Results

The theoretical model consisted of five reflective constructs, as illustrated in Figure 1. The result for measurement model assessment between the two SEM methods is reported in Tables 2, 3, 4 and 5. Both CB-SEM and PLS-SEM met their respective indicator loading minimum requirements as illustrated in Table 2. In the case of PLS-SEM, the minimum acceptable requirement for indicator loading in the model is 0.70 and above. In contrast, CB-SEM minimum acceptable indicator loading is 0.50 and above.

Table-2. Indicator Loadings

	CB-SEM					PLS-PM				
	Religion	**Life**	**Mind**	**Lineage**	**Property**	**Religion**	**Life**	**Mind**	**Lineage**	**Property**
A1	0.62					0.71				
A2	0.68					0.73				
A3	0.85					0.85				
A4	0.65					0.75				
A5	0.71					0.78				
A6	X					X				
N1		X					0.72			
N2		0.57					0.76			
N3		0.57					0.75			
N4		0.81					0.80			
N5		0.89					0.83			
N6		0.85					0.81			
N7		X					X			
AK1			0.75					0.77		
AK2			0.82					0.83		
AK3			0.72					0.76		
AK4			X					X		
AK5			0.66					0.71		
AK6			0.75					0.81		
AK7			X					X		
K1				0.79					0.84	
K2				0.68					0.77	
K3				0.70					0.80	
K4				0.70					0.77	
H1					0.68					0.73
H2					0.85					0.81
H3					0.86					0.82
H4					0.50					0.75
H5					X					0.71

Note: (X) Represents deleted indicators

Results in Table 2 suggest that, overall the indicator loadings for PLS-SEM are higher than CB-SEM as PLS-SEM does not calculate factor loadings, but composite loadings. Consequently, the CR and AVE statistics for PLS-SEM are also overestimated as illustrated in Table 3. Indicator reliability was assessed using composite reliability (CR). The findings in Table 3 suggests that all constructs achieved factor loading of more than 0.80 exceeding the recommended level of acceptable factor loading (0.70 both CB-SEM and PLS-SEM). The internal reliability assessment is composite reliability (CR). The results from Table 4 show that both PLS-SEM and CB-SEM achieved the value of composite reliability threshold. The convergent validity is assessed using AVE criterion. As illustrated in Table 3, both PLS-SEM and CB-SEM results satisfied the convergent validity requirement when all values for each construct is greater than 0.50, indicating that the construct explains more than half of the variance of its indicator variables. The AVE values of PLS-SEM are higher than the CB-SEM values. It means that the indicator loadings from PLS-SEM estimates are much higher than the estimates in CB-SEM. According to Rönkkö and Evermann (2013), the factor loading produced by PLS-SEM is always biased upwards or overestimated due to the presence of measurement error which could affect the parameter estimates and eventually lead to the committing of type I error. Type I error is also known as false positive which means the effects are detected as significant but in actual fact it does not occur in the real situation.

Table-3. Construct Reliability and Validity

	CB-SEM		PLS-PM	
	Composite Reliability	**AVE**	**Composite Reliability**	**AVE**
Religion	0.83	0.50	0.88	0.60
Life	0.90	0.75	0.91	0.62
Mind	0.86	0.55	0.88	0.59
Lineage	0.81	0.52	0.87	0.64
Property	0.84	0.64	0.88	0.59

Discriminant validity criterion was evaluated by establishing the Fornell & Larcker criterion for both CB-SEM and PLS-SEM for the comparison purpose even though the HTMT criterion was recently proposed for PLS-SEM. The results, as illustrated in Table 4, indicate that both methods satisfied discriminant validity requirements. The square root of each construct's AVE is higher than its correlations with any other constructs. Moreover, it also revealed that the values of construct correlations for PLS-SEM is lower than the CB-SEM. This study supported the work of who suggested that the construct correlations from PLS-SEM are always biased downwards or underestimated due to the capitalization on chance correlation existing.

Table-4. Discriminant Validity for CB-SEM and PLS-PM (Fornell & Larcker approach)

	CB-SEM					PLS-PM				
	Religion	**Life**	**Mind**	**Lineage**	**Property**	**Religion**	**Life**	**Mind**	**Lineage**	**Property**
Religion	0.707					0.597				
Life	0.348	0.865				0.228	0.618			
Mind	0.436	0.611	0.742			0.130	0.405	0.594		
Lineage	0.209	0.315	0.529	0.718		0.033	0.119	0.222	0.635	
Property	0.340	0.543	0.668	0.431	0.803	0.107	0.326	0.394	0.212	0.587

5. Conclusion

Debates and discussions regarding the two SEM approaches increased rapidly in tourism, advertising, marketing, and business research with the aim being to advance the recent method. Our findings summarises the difference and similarities between PLS-SEM and CB-SEM which could give some clear guidelines for applied researches. Researchers opposing the use of PLS-SEM (Aguirre-Urreta *et al.*, 2013; Antonakis *et al.*, 2010; Evermann and Tate, 2016; Rönkkö and Evermann, 2013) . Argue that it has no common factor, no goodness of fit indices, no measurement error, capitalises on chance correlations, and produces biased and inconsistent parameter estimates. However, the structural models with good measurement properties generally achieved the comparable results with either approach (Reinartz *et al.*, 2009). In this paper, the results of the two prominent SEM approaches have been compared and contrasted and the following conclusion has been made for MSQoL measurement model.

The research objective. Although both approaches produced similar results for MSQoL measurement model, the CB-SEM is more appropriate for validating and confirming the MSQoL measurement model. Hair *et al.* (2011). stressed that neither of the two SEM approaches is generally superior to the other. However, this study found that CB-SEM to be more appropriate than PLS-SEM since the objective is to validate and confirm the MSQoL measurement model. On the other hand, PLS-SEM is more appropriate for prediction and theory development. In other words, the PLS-SEM is appropriate when the phenomenon being investigated is relatively new and the measurement models are at the exploratory stage (Wold, 1985). Nevertheless, Rönkkö and Evermann (2013), stressed strongly that PLS-SEM is not an appropriate choice for early-stage theory development because of its inability to identify model misspecifications and construct scores and path estimates calculated from an incorrect model are likely to be severely biased (Evermann and Tate, 2010).

Sample size. PLS-SEM allows the use of small sample size. Researchers should use small sample size with caution because a sample size which is too small could reduce the power of the test and increase the margin of error, which render the study to be meaningless. The power of the test is used to detect the probability of Type II errors. The Type II error occurs when the results support the null hypothesis of the study when, in fact, an alternative hypothesis is true. Even though PLS-SEM can work with small sample size, researchers should exercise extra caution since inadequate sample size could lead to increased sampling error (do Valle and Assaker, 2016) since inadequate sample would not be representative of the entire population. The best solution is to collect sufficient data proportionate to the target population. The generally accepted rule-of-thumb for determining sample size is the sample size should be 5 to10 times the number of measuring items in the questionnaire (Hair *et al.*, 2014a). The measurement model of the present study consists of five constructs with a total of 25 measuring items. Thus, the appropriate numbers of cases should be between 125 (5 x 25) and 250 (10 x 250). The sample size obtained for this study was 465; this number satisfied the assumptions for employing parametric statistical analysis of which CB-SEM is part.

Normal distribution of data. PLS-SEM performs well with non-normal data and employed the non-parametric statistical approach. Nonetheless, if the non-normal data resulted from biased response where the subjects are responding under fear or pressure, then the data was invalid in the first place. The other possibilities for non-normal data distribution are the use of wrong target population, wrong method of sampling, wrong method of data collection, ambiguous items, biased items, and non-cooperating respondents. Thus, analysing these data is like a "rubbish-in rubbish-out" kind of process since the method of data analysis is not capable of correcting the wrong committed by the researcher. In other words, the rubbish data due to wrong methodology cannot be cured by using PLS-SEM. Thus, researchers should observe the methodological discipline properly at every stage of the research process. The normality assessment for the current study was made by assessing the measure of skewness and kurtosis for every item. Findings of the study illustrated that the value of skewness was within the range between -1.415 and 1.693 and kurtosis was within the range between -1.431 and 1.774. This showed that the requirement level of -2.58 and 2.58 as suggested by Hair *et al.* (2014b). Was achieved. It showed that the data used in this study are normally distributed. In the case where parametric statistical assumptions are satisfied, the researchers should employ CB-SEM instead of PLS-SEM since the parametric approach is much superior to the non-parametric approach.

Model-fit-indices. The model fit indices reflect the extent of fitness of data to its measurement model. The absence of omnibus model fit assessment in PLS-SEM is another downgrading factor. This study employed CB-SEM because of its ability to assess model fit and provide critical examination to obtain meaningful solution, particularly for decision making. The GFI, CFI, RMSEA and Chisq/Df are among the important indicators of model fit. As a final remark, it is stressed again that the method of analysis cannot remedy the poor data quality resulting from the violation of methodological disciplines by the researcher. Thus, researchers should take note seriously that the emergence of PLS-SEM is not meant to correct the wrong, especially in the methodological part. Researchers should follow the research methodology discipline thoroughly and rigorously to produce quality data and thus, obtain meaningful research findings.

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