EVALUATION OF MEASURMENT AND STRUCTURAL MODEL OF THE REFLECTIVE MODEL CONSTRUCTS IN PLS – SEM

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ABSTRACT: This paper reports the procedure ofthe assessment of measurement model and the structural model of the reflective constructs by using newly origin second generation multivariate statistical technique of PLS – SEM(Partial Least Squares - Structural Equation Model). As a conceptual paper, it highlighted the differences between the concepts of covariance based SEM and variance based SEM, measurement model and structural model focusing reflective models. The general objective of the study is to investigate the sequential steps and prerequisites of convergence of any PLS - SEM based model. As a newly origin statistical tool (by using PLS 3 version analysis) the procedure and required steps to follow is ratherscant hence,this paper may provide appropriate and accurate guidance for Sri Lankan potential researchers. Study was based on a conventional review and analysis based on the extant literature froma series of texts which are obtain reviewing different data bases. As per the discussion basically, two main criteria called reliability and validity have to be achieved in measurement model before evaluatingthe structural model. Internal reliability and composite reliability scales were commonly employed to asses construct reliability of the intended constructs. However, convergent validity achieved through Average Variance Extracted and factor loadings. Discriminant validity can be evaluated by assessing the cross loadings among constructs, Fornel-Larcker criterion, and Heterotrait- Monotrait Ratio of correlation (HTMT). After satisfying prerequisites of measurement model analysis have to proceed the evaluation of thestructural model. In order to evaluate the structural model basically have to follow five stepsas assessing astructural model for collinearity issue ,assess the path co efficient,assess the level of R^2 ,assess the effect size f^2 ,assess the predictive relevance Q^2. All the threshold values against to each and every criterion were clearly represented under the conclusion to have comprehensive understand about the evaluation of measurement and structural model.

Keywords: Structural Equation Model, Measurement Model, Structural Model, Reliability, Convergent Validity, Discriminant Validity

1. INTRODUCTION

Structural Equation Modeling (SEM) is “family of statistical models that seek to explain the relationship among multiple variables (Hair, Black,Babin & Anderson 2010) . SEM examines the structure of interrelationships expressed in a series of equations where these equations illustrate the relationships among constructs presented in a theoretical framework.SEM is capable of assessing and addressing the measurement error associated with the measurement. It incorporates measurement errors, correlated measurement errors, and feedbacks directly into the analysis (Baron & Kenny, 1986). Futher, SEM can incorporate both the observed and unobserved variables into analysis hence it allows a researcher to better represent a theoretical concept by using multiple measures of a concept(Hair et al.,2013). Finally,SEM capable of modeling multivariate relationships and of estimating direct and indirect effects specifically, a less biased assessment of moderating effects in case of compounding measurement error when computing interaction term (Holmbeck, 1997)**.**These features will provide the researcher with an opportunity for more comprehensive data analysis and to make more valid conclusions.

There are two types of SEM as covariance based SEM (CB – SEM) and partialleased squares SEM (PLS – SEM). CB –SEM is primarily used to confirm or reject theories. It does this by determining how well a proposed theoretical model can estimate the covariance matrix for a sample data set (Hair, Hult, Ringle, Sarstedt, 2017). In contrast, PLS-SEM is primarily used to develop theories in exploratory research maximizing the predictive ability. It focuses on explaining the variance in the dependent variables when examining the model. A crucialdifference between these two approaches is the way each method treats the latent variables included in the model. CB- SEM considers the constructs as common factors that explain the covariation between its associated indicators. PLS –SEM on the other hand uses proxies of interest which are weighted as composites of indicator variables for a particular construct. In this paper specifically focus on PLS- SEM as a novel second generation multivariate statistical technique.

PLS-SEM or partial least squares path modeling is a variance-based structural equation that has become very popular in recent years (Henseler, Hubona &Ray, 2016). It is a second generation multivariate analysis technique (Wold, 1982) that combines the features of the first generation (principal components and linear regression analysis). PLS- SEM is a regression based approach that explores the linear relationships between multiple independent variables and a single or multiple dependent variables. Among variance based SEM methods PLS path modeling is regarded as the fully developed general system and has been called a silver bullet (Hair, Hult, Ringle, Sarstedt, 2014).This technique appropriately functions with structural equation models that have latent variables and series of acause-and-effect relationship. PLS-SEM provides researchers an opportunity to explore relationships among variables and identify the existing pathways among the variables as such, it is regarded as an appropriate tool for building thestatistical model as well as prediction (Ringle, Wende & Will, 2012). Further, PLS - SEM will have greater statistical power and converges quickly handling much larger and complex models.

2. OBJECTIVE AND METHODOLOGY

Being a conceptual paper literature materials for this study were obtained from different research methodology books and databases including EBSCOhost, Taylor & Francis, JStor, Sage, ScienceDirect, and Emerald. Measurement and Structural model evaluation were used as specific key words on the library databases to find the relevant scholarly articles. Then, thoroughly evaluate all materials to summarize the key outcomes of the respective statistical analysis. The relevant downloaded scholarly articles were reported and critically analyzed to show the developments, extensions and the differentiations of the particular analytical method against to other analytical methods. As newly origin, apopular second generation data analysis method in social sciences, PLS - SEM interpretation and the way of doing the analysis is somewhat different against to covariance analytical methods. Even though, conventional CB- SEM method much focus on theory confirmation with the reflective measurement models PLS-SEM more focuses the predictive relevance of the constructs specifically with reflective and formative measurement models.The general objective of the study is to investigate the sequential steps and prerequisites of convergence of any PLS - SEM based modelspecifically when the model is in reflective nature (not for formative models).Being newly practicing and very popular and flexible analytical tool in thesocial sciences,literature on PLS- SEM specifically,conceptual papers and empirical studies rather scant in Sri Lankan context.However, still more practise theory confirm CB- SEM methods by using AMOS statistical tool. Therefore, this article may greatly benefitfor the potential researchers those who wish to employ the advanced statistical technique like variance based PLS- SEM. Consequently, this paper may shed light for new methodological approach contributing to research methodology literature.

3. Discussion

3.1. Measurement Model

In PLS analysis, the first step is to assess the measurement model or the outer model. The measurement model specifies the rules of correspondence between measured and latent variables (Hair et al., 2010). Further, it enables the researcher to use any number of variables for a single independent or dependent construct. The two main criteria used in PLS analysis to assess the measurement model or what is alternatively called the outer model include validity and reliability (Ramayah, Lee, & In, 2011). Reliability test tries to find stability and the consistency of the measuring instrument whereas validity tests try to find out how accurate an instrument measures a particular concept it is designed to measure **(**Sekaran & Bougie, 2010). The individual item reliability, construct internal consistency and construct validity are considered in assessing the outer model in PLS .The reliability, convergent and discriminant validity of the instruments used in this study are evaluated using the approaches developed for a PLS context.

3.2. Assessment of Reflective Measurement Model

It should be noted that there is a controversy in the literature with regard to the proper statistical modeling procedure for reflective and formative models (Garson, 2016). Adherents to the PLS approach it can be applicable to both reflective and formative models. In reflective models, indicators are a representative set of items which all reflect the latent variable they are measuring. Reflective models assume that indicators can use interchangeably and dropping one indicator may not matter much since the other indicators are representative also. In formativemodels, each indicator represents a dimension of meaning of the latent variable. The indicators cannot employ interchangeably and dropping of one indicator in a formative model is causing to change the meaning of the construct.

The first step of PLS – SEM analysis involves developing a measurement model and conducting of assessment of the measurement model constructs. The measurement model analysis was conducted to assess the relationship between constructs and items similarly to assess the correlations between the constructs.

3.2.1. Assessment of Construct Reliability

Reliability is a quality criterion of a construct; it requires a high level of correlation among the indicators of a particular construct (Kline, 2011). According to Hair et al., (2010) reliability extends to which a variable or set of variables is consistent in what it is intended to measure. There are two common measures of construct's reliability: Cronbach alpha and composite reliability. Coefficient alpha used as a more conservative measure of items and it estimates the multiple item scale's reliability. The internal reliability of a construct is said to be achieved when the Cronbach's Alpha value is 0.7 or higher (Nunnally & Beinstein, 1994**,** Pallant, 2001)

Unlike Cronbach alpha, which is usually used by thenon-PLS model, composite reliability does not assume an equivalency among the measure with the assumption that indicators are equally weighted (Chin et al.,1992). Composite reliability more concern on individual reliabilityreferring to different outerloadings of the indicator variables (Hair et al., 2017). The cut off for composite reliability is the same as any measure of reliability and score between 0 .6 and 0.7 is a good indicator of construct reliability (Hensele&,Sarstedt, 2013).

3.2.2. Assessment of Validity

Validity concerns the soundness of the accuracy of a measure or the extent to which a score truthfully represents a concept (Zikmand,Babin, Carr&Griffin, 2013). According to Cronbach and Meehl(1955),construct validity is more relevant appropriate in social sciences.Construct validity examines how well the results obtained from the use of a measure fit the theories upon which the test is designed (Sekaran & Bougie, 2010. As such, it provides answers whether the instrument used in the test tap the actual concept theorized in the study. In order to achieve validity analysis, two kinds of validity tests were performed on the measurement scales namely: convergent validity and discriminant validity (Sekaran & Bougie, 2010; Tore, 2005).

i) Convergent Validity

Convergent validity is the extent to which a measure correlates positively with an alternative measure of the same construct. In examining the convergent validity of a measure in PLS, the average variance extracted (AVE) and item loadings are assessed (Hair et al., 2013). AVE is the average variance shared between a construct and its measures. It is defined as the grand mean value of the squared loadings of the indicators associated with a particular construct (the sum of the squared loadings divided by the numbers of indicators) (Hair et al., 2013) The average variance shared between a construct and its measures should be greater than that shared with the other constructs in the same model (Couchman & Fulop, 2006).In PLS, the calculation of AVE is inbuilt into the analysis software. AVE value equal or higher than 0.50 indicates that on the average, the construct explained more than half of the variance of its indicators. Conversely, an AVE of lesser value than 0.50 indicates that more error remains in the items than the average variance explained by the constructs. As such, the rule of thumb is that an AVE value greater or equal to 0.50 is acceptable (Hair et al., 2013; Barclays et al., 1995).

ii)Discriminant Validity

Discriminant validity is concerned about the uniqueness of a construct, whether the phenomenon captured by a construct is unique and not represented by the other constructs in the model (Hair et al., 2013). Discriminant validity can be evaluated by assessing the cross loadings among constructs, by using Fornel-Larcker criterion and Heterotrait- Monotrait Ratio of correlation (HTMT).At first, in order to achieve discriminant validity, the loadings of the construct must be high on itself and low on other constructs (Vinzi, Henseler,Chin & Wang,2010).The second discriminant validity of a construct can be assessed by comparing the square root of the AVE values with latent variable correlations (Fornell & Larcker, 1981). The square roots of AVE coefficients are presented in the correlation matrix along the diagonal. The squared root of each constructs' AVE should be greater than its highest correlation with any other construct to evidence discriminant validity (Hair et al., 2013). Finally, a new criterion HTMT was introduced by the recent research done by the Henseler,Ringle and Sarstedt (2015) based on their Monte Carlo Simulation. According to Henseler et al., (2016) in order to achieve discriminant validity the HTMT score should be between confidence interval value -1 and 1.

3.3. Assessment the Structural Model

The structural model and its latent variables represent the stable, theoretically and conceptually established acontextual link between observed data on the input and output sides. Based on the structural model the goal of the analysis is to predict the output layer data by means of the input layer data. In other words, thestructural model is used to illustrate one or more dependence relationships liking the hypothesized model's construct. In order to assess the structural model Hair et al., (2014) proposed five stepstructural model assessment procedure. 1) Assess structural model for collinearity issue2) Assess the path co efficient3) Assess the level of R^2 4) Assess the effect size f^2 5) Assess the predictive relevance Q^2

In either a reflective or a formative model, there is potentially in multicollinearity issue at the structural level. Multicollinearity exists when two or more independent variables are highly inter correlated. Multicollinearity in Ordinary Least Squire (OLS) regression inflates standard errors, makes significant tests of independentvariable unreliable and prevents the researcher from assessing the relative importance of one independent variable compared to another (Garson, 2016). A common value of problematic multicollinearity may exist when the Variance Inflation Factor (VIF) coefficient is higher than 4.0. VIF is the inverse of the tolerance coefficient, for which multicollinearity is flagged when tolerance is less than 0.25 (Hair et al., 2014)

In assessing the PLS path modelling have to employ the bootstrapping technique for testing the significance of all the path coefficients because in PLS analysis, bootstrapping is the only mechanism for examining the significance of path coefficients (Chin, 2010).Bootstrapping is a non-parametricre-sampling procedure that involves repeated random sampling with replacement from the original sample (Efron & Tibshirani, 1993). It is a superior re-sampling method which attempts to approximate the sampling distribution of an estimator by re-sampling with replacement from the original sample (Good, 2000). Despite, the role of bootstrapping in PLS, the procedure is still not a standardized one as the user decides the number of bootstrap retrials to undertake based on peculiarity of the situation. By using the same method stated above, the path coefficients estimate using t-statistics. The significance level of the t-value was assessed by a one-tailed or two tailed distribution(Chin & Newsted 1999**;** Cho & Abe, 2013).

In PLS analysis, thepredictive power of a particular model or construct and the determination of the standard path coefficient of each relationship between exogenous and endogenous variable is assessed using the R-squared (R^2) values of the endogenous variables. The interpretation of the values of R^2 in PLS is similar to those obtained from multiple regression analysis. The R2 values indicate the amount of variance in the construct that is explained by the model R-square indicates the amount of variance explained by the exogenous variable in its endogenous counterpart (Chin, 1998). It represents the quality of the model variables (Hair et al., 2010).

The assessment of the effect size f^2 seeks to evaluate whether exogenous constructs have a substantive impact on endogenous constructs. It is important to determine the relevance and the extent to which the examined path changes the explaining power of the endogenous construct (Cohen, 1988). As the path coefficient cannot provide any information about the effect size of the exogenous latent variables on the endogenous construct. In determining the effect size, Cohen F^2 value was used and calculated with the formula provided below by Cohen (1988):

$$\mathbf{F}2 = \frac{R^2 \text{ included} - R^2\text{excluded}}{1- R^2\text{included}}$$

Upon the determination of the effect size (f^2), nexthave to assess the predictive relevance (Q^2) of the model which was conducted to assess the predictive capacity of the model. The predictive relevance of the study model can be assessed through the Stone Geisser non-parametric test (Chin, 1998**;** Fornell & Cha, 1994**;** Geisser, 1975; Stone, 1974). The calculation of Q^2 conduct by using the blindfolding procedures of PLS through which the estimated results were obtained from the variable score from which the cross validated redundancy score was obtained. The extracted cross validated result determines the predictability of the endogenous constructs and thus, reveals the model quality.According to Hair et al.,(2012), Q^2 assesses not only the built around of values of the model but also the parameter estimates of the model.

4. Conclusion

With reference to the two criteria of evaluating reliability in PLS-SEM model to achieve internal consistent reliability of the construct, the Cronbach's Alpha value should be 0.7 or higher.Likewise, reliably scores between 0.6 and 0.7 is a good indicator of composite reliability provided that other indicators of a model's construct validity are also good.To achieve convergent validity AVE value should be equal or higher than 0.50 and on the average that it means construct explained more than half of the variance of its indicators. Conversely, an AVE of lesser value than 0.50 indicates that more error remains in the items than the average variance explained by the constructs. As such, the rule of thumb is that an AVE value greater or equal to 0.50 is acceptable .Similarly, high loadings on factor indicated that items within a construct are highly converged, Hair et al., (2010) claimed that standardized loading estimates should be 0.5 or higher and ideally 0.7 or higher.Discriminant validity can be obtained by assessing the cross loadings among constructs. According to therule of thumb taken tomean that intended loadings should be greater than 0.7 or 0.6 and cross loadings should be under 0.3 or 0.4. Otherwise,lack of simple factor structure diminishes the meaningfulness of factorlabels.Then by comparing the square root of the AVE values with latent variable correlations can assess the discriminant validity of the construct. To meet Fornell and Larcker criteria, square root of each constructs' AVE should be greater than its highest correlation with any other construct.

In assessing structural model at the first have to ensure whether there are any collinearity issues among constructs. A common cut-off value of problematic multicollinearity when the Variance Inflation Factor (VIF) coefficient is higher than 4.0. and when tolerance is less than 0.25. To be statistically significant path coefficient values should be more than 1.96 at 0.05 level. There are various criteria that can be utilized as R-square level guidelines. For example, R-square values of 0.26 or higher is substantial, those of 0.13 are considered moderate and those of 0.02 are considered weak. In another take, R-square values falling on or greater than 0.75 are considered as substantial, those that fall on 0.50 are considered moderate and those that are 0.25 are considered as weak (Hair et al., 2014).Based on the guidelines provided by Cohen (1988), f2 values of 0.02, 0.15 and 0.35 respectively represent thesmall, medium and large effect of the exogenous constructs on the endogenous constructs. However, the $Q2 > 0$ in a reflective endogenous variable indicates the model predictive relevance while a value of $Q2 < 0$ indicates the lack of predictive capability of the model.

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