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A Critical Look at the Implication of PLS-SEM in Existing Literature

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Abstract

In behavioural research studies, Partial Least Square SEM plays a vital role and is gaining momentum continuously. The present study aims to understand the concept of PLS-SEM and its implications. For this purpose, a review of the available related literature has been done to understand areas of application of PLS-SEM. The findings revealed that PLS- SEM is primarily useful for behavioural studies with non-normal data, small sample size and reflective or formative in nature.

Keywords: *Structural Equation Modelling, PLS-SEM, Partial Least Square, Behavioural Studies*

Introduction

Applications of Structural Equation modelling (SEM) have been in existence for many years. SEM helps to understand relationship between constructs and their latent variables in a structural path model. It includes the analysis of measurement properties as well as structural model simultaneously (Muthusamy, 2011). To achieve this, it involves use of exploratory factor analysis as well as analysis of structural path model.

Earlier, Co-variance based Structural Equation Modelling (CB-SEM) was the main focus of researchers. However, CB-SEM losing its popularity due to some assumptions like normality of data and being unsuitable for small sample size. Partial Least Square is a substitute for the same. With minimum requirements regarding sample size and its ability to cope with non-normal data, the use of PLS SEM is gaining momentum day by day in various fields of study such as business, marketing, engineering, psychology etc. It is a multivariate data analysis technique that helps to identify cause and effect models or behavioural relationship in the observed and latent variables within the structural path model of the study.

The main aim of this paper is to understand the concept of PLS-SEM and its implications. First section deals with introduction. Section two provides detailed understanding by reviewing available literature which is, lastly, followed by the conclusion.

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Literature Review

PLS-SEM helps to analyse complex structural path models and understand the concepts of observed and latent variables. This section reviews the existing literature available in the field of structural equation modelling.

Selection of PLS-SEM as Data Analysis Technique

Lowry and Gaskin (2014) discussed two generations of data analysis techniques. The first generation (1G) techniques analyse the casual relationship using correlation, regression and hypothesis tests (such as z-test, f-test, t-test). They identify only the casual relationship among variables of the study. In other words, they study the change in dependent variable due to change in independent variable. Moreover, they fail in the field of behavioural research. Therefore, use of second generation (2G) techniques, namely, SEM has proved their superiority over the former (Chin, 1998). Here, various paths exist between exogenous and endogenous constructs and each path depicts a different proposed relationship to the latent variables based on theoretical assumptions. CB-SEM and PLS-SEM are two forms of SEM (Lowry and Gaskin, 2014). CB-SEM is based on some assumptions related to normal distribution of data, reflective constructs, and large sample size. Further, it is confirmatory in nature and requires a pre-theoretical background to support the model (Lowry & Gaskin, 2014). However, PLS-SEM acts as a substitute when any of the assumptions of CB-SEM are not fulfilled (Hair, Sarstedt, & Ringle, 2012). PLS-SEM was developed by Herman Wold in the 1996 (Chin, 1998). It is component-based structural equation modeling and preferred over CB-SEM due to minimum requirement regarding measurement scale and sample size (Monecke & Leisch, 2012; Kummer, 2013). It can be used with both formative as well as reflective indicators (Lowry & Gaskin, 2014). It aims at maximising the explained variance. There is no need of empirical support to test a theory, thus, is preferred to explore theoretical relationship among the constructs (Peng & Lai, 2012). On the same track, Wetzels, Odekerken-Schroder, and Oppen (2009) commented that it is more applicable for prediction-based study and new approach which lacks of strong theoretical framework. Moreover, it can be used for confirmatory studies also or to confirm a theory (Barroso, Carri´on, & Rold´an, 2010). Further, it has been successfully used in the study of behavioural intention by previous research namely, Jayasingh and Eze (2009); Muthusamy (2011).

Sample Size Requirement

PLS-SEM indeed does not require large sample size. However, researchers need to be cautious about analysing data with very small samples, as it can lead to overestimation of outer loadings and underestimation of structural paths. Therefore, sample size needs to be determined carefully. In this context, the 'ten times rule method' has been widely used by previous research studies, which suggests that the sample size should be at least ten times the maximum number of paths pointing at any latent construct in the inner or outer model (Kock & Hadaya, 2016). Additionally, Chin (1998) proposed that the sample size should be ten times the largest of the following:

a) The largest number of formative indicators (i.e., the largest measurement equation).

b) The largest number of independent latent variables predicting a particular dependent variable.

Muthusamy (2011) also employed the same rule to determine the sample size for PLS-SEM analysis. Moreover, Chin, Marcolin, & Newsted (1996) opined the requirement of sample size of approximately 100 in a study consisting of six to eight indicators.

Model fitness

PLS-SEM includes the analysis of two models, namely, the structural model (inner model) and the measurement model (outer model). There is no global index for evaluation of PLS model (Monecke & Leisch, 2012; Garson, 2016). Therefore, it is necessary to assess fitness of both the models separately. The correctness of both the measurement and structural models results in fitness of the final research model and provides a better estimation of model parameters (Chin, 1998). The assessment of measurement model ensures validity and reliability of the proposed research model, whereas structural model aims to assess significance of path coefficient and explanatory power of the exogenous constructs.

Assessment of Measurement Model

The measurement model measures whether variables are representative of related constructs or not. It is the outer model and shows relationship between observed item(s) and respective latent variable(s) (Chin, 1998). Each observed item should be related to a single latent variable only otherwise, the assessment of structural relationship will be of no use. The study of the measurement model depends on the nature of the model, either reflective or formative. In a reflective construct model, observed indicators are the effects of the latent variable (Lowry & Gaskin, 2014), and the arrow goes from the latent to the manifest variable. On the other hand, in a formative construct model, the relationship is reversed, i.e., the latent variable is considered as the effect of the manifest variable, resulting in the arrow going from the manifest variable to the latent variable.

Convergent Validity

It is stated that items related to a construct should have high loadings on the related construct and not on others. To check convergent validity, item reliability, internal consistency, and average variance

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extracted (AVE) are used (Muthusamy, 2011). Among these techniques, item reliability involves investigating individual item loadings (Kummer, 2013). Item loading represents the amount of variance in indicators explained by the latent construct (Chin, 1998), and poor loading depicts the unreliable nature of the item or excessive influence of different factors on the item. Most researchers, such as Peng and Lai (2012) and Barroso et al. (2010), have described a minimum item loading value of 0.7. However, Neil (2008), Matsunaga (2010), and Hamid, Sami, and Sidek (2017) stated a minimum threshold value of 0.4 for item loading to retain an item. Additionally, Hair et al. (1998) suggested that a loading value of 0.3 is also acceptable. Further, internal consistency measures the consistency of the construct in producing the same results every time. Poor consistency represents the multidimensionality of the factor. Composite reliability or Cronbach's Alpha may be used to evaluate internal consistency. Composite reliability is based on the actual factor loadings, whereas Cronbach's alpha adopts an equal weighing approach (Chin, 1998). Composite reliability overcomes deficiencies of Cronbach's alpha and is an improved form of it (Hair et al., 2012; Muthusamy, 2011). Previous research studies have suggested that a composite reliability value of more than 0.7 indicates a good level of internal consistency (Hair, Sarstedt, Hopkins, & Kuppelwieser, 2014). AVE, the third indicator to ensure convergent validity, shows the amount of variance in the item that is explained by the related construct. The thumb rule specified for AVE is 0.5 by previous research studies, namely Fornell and Larcker (1981), Hair et al. (2014), Chin (1998), and Gye-Soo (2016). If any construct has a lower AVE value, the related item should be removed according to item loading, with the lowest loading item removed first.

Discriminant Validity

After confirming convergent validity, one must ensure the presence of discriminant validity, which measures the extent to which one construct differs from another. In other words, each item should be highly related to its own construct compared to others. This ensures that the results of hypothesized relationships in the research model are accurate. To check for discriminant validity, two criteria need to be evaluated: The Fornell-Larcker criterion and cross-loading.

The Fornell-Larcker criterion states that a construct should share more variance with its related construct than with any other latent variable (Urbach & Ahlemann, 2010). In the analysis table of Fornell-Larcker, diagonal elements show the square root of AVE (Average Variance Extracted), and the lower diagonal elements represent correlations among different latent variables. To ensure discriminant validity, the square root of AVE should be greater than the correlations with other latent variables (i.e., the correlation with other latent variables should not be high).

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The second criterion to ensure discriminant validity is the assessment of cross-loading, also known as item-level discriminant validity (Henseler, Ringle, & Sarstedt, 2015). It indicates that an item should have a high loading value with the construct it is intended to measure and lower cross-loadings with other constructs. Additionally, there should be a minimum difference of 0.2 in the loading of an item with its related construct compared to other constructs. This ensures that the item is more strongly associated with its intended construct than with other constructs.

Structural Model Evaluation

After validation of measurement model, there is need to assess structural model in order to assess hypothesized relationship. The structure model, also known as inner model, depicts the paths among latent variables. It measures predictive ability and relationship among constructs (Duarte & Raposo, 2010). The validity of structural model can be assessed using several indicators, including coefficient of determination (r^2), effect size (f^2), Stone Geisser's Q^2, path coefficients and their related levels of significance. The coefficient of determination shows the explanatory power of exogenous constructs i.e. proportion of variance of endogenous construct that is accounted by exogenous construct. R^2 ranges from 0 to 1. The more it is closer to 1 the more it depicts predictive power of independent variable. However, higher value does not ensure presence of real causal impact (Moksony, 1990). Further, effect size (f^2) measures changes in r^2 in order to understand practical impact of independent variables over dependent variable. In interpretation of f^2 for structural model, it has been suggested that when f^2 value is 0.35 then effect size is large, effect size is medium with f^2 value =0.15 and small if $f^2 = 0.02$ (Chin, 1998). Further, Stone and Geisser's Q^2 measures predictive relevance of endogenous construct by exogenous construct. It can be computed in two ways either construct cross validated and construct cross validated redundancy. Hair et al. (2011) suggests use of construct cross validated redundancy.

Conclusion

In the present, a detailed analysis of PLS-SEM has been done. The discussion covers sampling requirement, model fitness and the process of doing structural analysis using partial least square approach. Undoubtedly, the application of PLS-SEM is continuously increasing, and this study would guide future researchers in understanding the concept of PLS based SEM. Furthermore, it would contribute significantly to existing literature in the area of structural equation modelling. It would provide reference to new researchers in the area of structural equation analysis regarding development and application of theory. Additionally, the study reviews available literature from different nations, providing a multinational context and making it universally relevant."

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