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Statistical Role of CB-SEM Vs PLS-SEM in the Field of Social Science

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ABSTRACT

There are various statistical method which are available for social science researchers but which technique will be appropriate for their research is the big challenge. When research is based on covariance, CB-SEM approach is used and when it is based on total variance, then PLS-SEM is an appropriate approach. This paper tries to capture the attention of the researchers who face problems when to use CB-SEM and when to use PLS-SEM. With the help of this paper, the effort is made to clearly define that CB-SEM is a parametric approach and PLS-SEM is non parametric approach. In case of PLS-SEM, two measurement models are considered namely measurement model(outer model) and structural model(Inner Model). In case of PLS-SEM, internal consistency reliability is checked with the help of two namely Cronbach's alpha and Composite reliability and there are other ways of checking reliability and validity such as Composite reliability, Discriminant validity, HTMT and overall model fit with the help of inner relationship between the constructs. In case of CB-SEM, Fornell Larcker method is an appropriate method and finally, overall model fit is checked. With the help of this paper, I try to elaborate the conceptual knowledge of CB-SEM and PLS based SEM.

Keywords: structural equation modelling; SEM; PLS-SEM; CB-SEM

INTRODUCTION

The use of structural equation modelling (SEM) has grown significantly in recent years (Matthews et al., 2016b; Rutherford et al., 2011, 2012). This is due to the advanced methods to assess the reliability and validity of multi-item constructs measures as well as structural model relationship(Bollen (1989) and Hair et al. (2012b).

SEM uses exploratory factor analysis and structural path analysis for evaluating both measurement and structural models simultaneously (Lee et al., 2011). SEM is a very powerful tool that explains the total variance and also includes total effect i.e. Direct and Indirect effect (Lee et al., 2011).

There are two methods that are available for the researchers namely CB-SEM(Joreskog, 1978, 1993) and PLS-SEM(Lohmoller, 1989; Wold, 1982).

CB-SEM is a covariance based SEM whereas PLS SEM is partial least squares. It is crucial for the researchers to understand the difference between CB-SEM and PLS-SEM while deciding which approach researchers want to apply for their research.

If there is an already established theory or explanation which means it is already confirmed that research is based on some prior established theory, it means confirmatory research or CB-SEM(Sarstedt et al., 2014a).

If research is not based on any prior theory or explanation, it means it is based on exploratory research and therefore prediction is made in respect of the effect of exogeneous variables on the endogenous variables and the relationship among the constructs and relationship among the inner model is created with the help of PLS-SEM.

The purpose of this paper is to demonstrate the difference between two approaches which are used by the researchers for their research. For this, we will understand the differences between these two approaches by testing them into the same theoretical model and data and to check how the results differ empirically and accordingly to choose the best approach.

Difference between CB-SEM Approach and PLS-SEM Approach

The statistical objectives of both the methods are different. CB-SEM estimates model parameters that minimizes the difference between observed sample covariance and the covariance estimated the theoretical model is confirmed(Hair et al., 2012b) whereas the statistical objective of PLS-SEM is to maximize the variance explained in the dependent variables(Hair et al., 2012a).

There is a fundamental difference between the CB-SEM and PLS-SEM. CB-SEM approach is based on common factor model whereas PLS-SEM is based on composite model(Hair et al.,2017c).

The common factor model assumes that analysis should be based on the common variance in the data and this is done by calculating the variance between the variables and only common variance is used for the analysis. Therefore, in CB-SEM approach, the specific variance and the error variance is completely removed before the theoretical model is examined. There is a limitation of CB-SEM approach and that is the removal of specific covariance that could be used to predict the dependent variable. On the other side, in case of composite model, all types of variance whether common, specific and even error variance from the exogeneous variables are calculated that helps to predict the variance in the dependent variable.

Due to the random error included in the composite model and indeterminacy in case of common factor model [i.e., an infinite number of different sets of construct scores that

will fit the model equally well; Grice (2001) and Steiger (1979)]. Both the approaches only produce the approximations of the conceptual variables that conceptual variables or constructs seek to represent (Rigdon et al., 2017). Both the approaches play a vital role in the field of research and no one can say that common factor is better than composite factor model or vice versa.

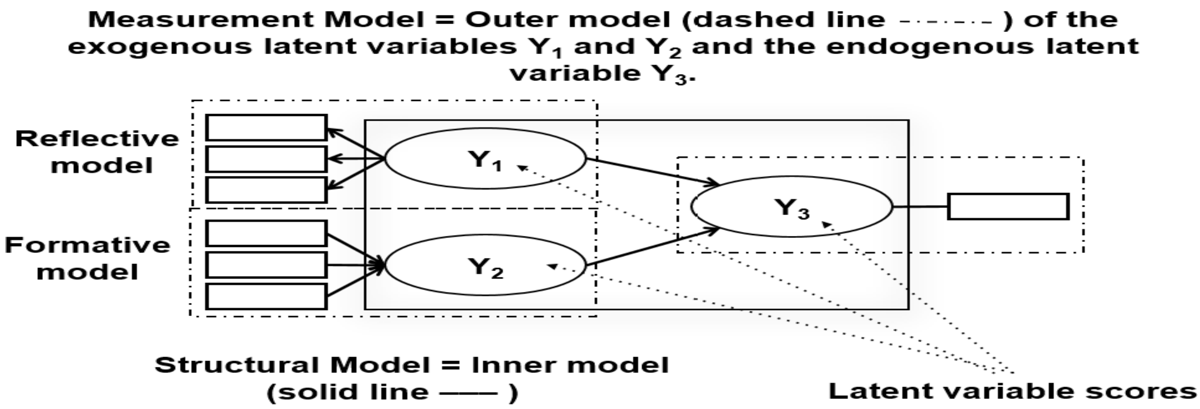

Figure 1 : Theoretical SEM and Constructs

Under the SEM statistical model, two types of elements are included namely Measurement Model(Outer Model) which create the relationship between the construct or conceptual variable or latent variable and its indicators and other element is known as structural model which shows the relationship from construct to construct by displaying the structure path in the model. Besides the above two elements, Under SEM, there are two types of variables namely exogeneous construct that explain the other construct in the model and a conceptual variable or construct being explained by the exogeneous variable is called endogeneous variable(Hair et al., 2017c).

The structure of the outer model is completely different depends on the type of measurement. If the constructs are measured with formative indicators then arrow will go from indicators to construct(Sarstedt et al., 2016) and if the measurement is reflective then arrow will head from construct to indicators.(Sarstedt et al., 2016). If the construct and its indicators are measured wrongly then the overall results will be bias and output will be incorrect.

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So, it plays a vital role that which measurement type researchers using in their research area whether it is formative measurement or reflective measurement.

As you may see in the above model, Y1 represents reflective measurement and Y2 represents formative model whereas Y3 is an endogenous variable. In case of Y1, arrow goes from Y1 to three indicators which indicates that construct reflects the indicators and in case of Y2 aas arrows goes from three indicator to Y2, it becomes formative model.

Since Y1 and Y2 are the exogenous variables and Y3 is an endogenous one. When we try to establish the relationship between construct and its indicators, then it is called the measurement model or outer model and when try to know the effect of one construct over another construct, then it is called the inner model or structural model.

When using SEM qualitative measures such as face validity, it is not considered sufficient evidence of validity and this is the reason that besides the face validity we always consider quantitative measurement approaches such as internal consistency reliability, convergent validity and discriminant validity. If the measurement is reflective in nature, then arrow will head from construct to its indicators and in such as case when establishing reliability and validity, researchers should not depend on the face validity, they must check reliability and validity measures and for internal reliability measurement, traditionally, Cronbach's alpha is used but Cronbach suggested that researcher should not only relay upon him for measuring internal consistence reliability but they also use different approach of internal consistency reliability and for this Cronbach suggested Composite Reliability. Composite reliability is recommended as more appropriate as it considers the indicators' differential weights (Chin, 1998; Dijkstra and Henseler, 2015), whereas Cronbach's alpha weights the indicators equally (tau equivalence).

In measurement model, outer loading of the indicators are calculated so that AVE(average variance extracted) can be easily calculated from each construct. The outer loadings of each indicator must exceed 0.708 because the square of the loading of each indicator indicates that atleast 50% variance in the indicator is included in the respective construct of that indicator and similarly, the loading of each and every indicator is computer and square of all these indicators which are represent by their construct is known as AVE(Henseler et al., 2015). Therefore, AVE is a summary indicator of convergence computer from the variance extracted for all indicators loading on an individual construct(Hair et al., 2010). If the value of AVE is greater than 0.50, then it indicates that more than half of the indicator variance is included in the construct score (Hair et al., 2017c).

In case of formative measurement, internal consistency reliability are not appropriate and that is the reason we take additional steps where constructs are assessed based on their statistical significance and size of the indicator weights and by evaluating the collinearity among the indicators (Hair et al., 2017c).

Discriminant validity indicates that a construct is empirically unique and different from the other construct in the SEM(Hair et al., 2010).

Discriminant validity means that each construct captures the unique phenomenon which is not represented by the other constructs in the model(Hair et al., 2017c).

For assessing the discriminant validity, the common approach is the Fornell-Larcker criterion(1981) that compares the AVE(shared variance within) of the constructs to the squared correlation between the constructs(shared variance between). For PLS-SEM(Variance based SEM, a more precise measure of discriminant validity is Heterotrait-Monotrait ratio of correlations(HTMT) which was recently proposed(Henseler et al., 2015). In case of CB-SEM, the Fornell-Larcker criterion still is the most widely used measure of discriminant validity. Both measures can be used for discriminant validity but as per Voorhees et al. (2016) , HTMT is more appropriate for measuring discriminant validity than Fornell-Larcker Criterion.

PLS-SEM is a non parametric method whereas CB-SEM is a parametric statistical method. PLS -SEM hinders the immediate determination of inference statistics and this is the reason researchers relay on the bootstrapping(5000 samples) for deriving the standard error estimates of the model parameters.

Whatever SEM method researcher uses, structural relationships in both the methods are evaluated by the size and the significance of the beta coefficients. In case of PLS-SEM, the structural model also considers the model's predictive capabilities which are known as the coefficient of determination (R2 value) which measures the model's in-sample predictive power(Hair et al., 2017c, 2017d) whereas in case of CB based SEM, goodness of fit(GOF) is the optimum measure for evaluating the measurement and structural models.

GOF(goodness of fit) is measured by the Chi-Square test that further indicates the difference between observed covariance and the estimated covariance. Besides using Chi-Square statistics for GOF, there are other means also for assessing GOF under CB-SEM approach. Researchers can calculate CFI, GFI and RMSEA also. But in case of PL-SEM, there is no established GOF measure.

When the sample size is small means less than 100, the PLS-SEM is an appropriate method and when the same size is large means more than 100, then CB-SEM is suitable but it is notion that PLS-SEM will be applicable for less than 100 sample size. If your sample size is greater than 100, you may still use PLS-SEM.

CONCLUSION

Both the methods play a vital role in the field of research while doing path analysis. It is upto the research objectives of the researchers which method he wants to adopt. When he tries to adopt CB-SEM technique, then confirmatory factor analysis will be used as it is considered when the prior theory is already established. When there is no prior theory, then PLS-SEM is the best approach.

In case of CB-SEM, problem comes when the data does not fulfil the criteria of normality because such condition of normality is not found in case of PLS-SEM.

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