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STRUCTURAL EQUATION MODELLING ANALYTICAL APPROACH: MODEL FIT, RELIABILITY AND VALIDITY

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ABSTRACT

There are widespread empirical studies that employ structural equation modelling statistical technique for simultaneously testing and estimating causal relationships among multiple independent and dependent factors in social science research. While this methodological technique offers tremendous advantages over the traditional methodologies (multiple regression, factor analysis, ANOVA and MANOVA), it is often seen as complicated and difficult to understand. Thus, this paper intends to resolve some potential uncertainties that researchers seeking to use SEM might face. Consequently, the authors provide the general principles and criteria for determining model fit and assessment of reliability and validity of constructs. This paper serves as a useful guide for inexperienced researchers employing SEM for the first time and also as a reference material for researchers with a better understanding of the methodology.

INTRODUCTION

Structural equation modelling has become one of the most preferred statistical techniques of choice for researchers across various disciplines within the social science since analysing research data and results interpretation can be complex and confusing. However, with the recent proliferation of fit indices at the disposal of the researcher coupled with the wide disparity in agreement of the actual and acceptable cut-off values of those indices, a researcher may be confused with the conflicting information during model evaluation and subsequent acceptance. Furthermore, the fact that SEM utilizes several statistical tests to determine the adequacy of model fit to the data has added more possibilities of errors in result reporting among researchers. To elucidate this issue to SEM users, the common and most widely indices used along with their interpretive values in determining model fit are reported.

Determining Model Fit

Whereas traditional methods of statistics mostly employ a single statistical test to establish the significance of the analysis, structural equation modelling relies on numerous statistical indices to assess the appropriateness of model fit to the data. A model test statistics is a test or indices of whether the covariance matrix inferred by the researcher's hypothesized model closely reflect the sample covariance matrix that the differences might reasonably be considered as being due to sampling error Kline, (2011). Currently, there is no agreement among researchers on which model fit indices should be reported by researchers. On the other hand, (Hair et al. 1995; 2012; Holmes-Smith, 2006) recommend the use of at least three model fit indices by reporting at least one test statistics from each three category of model fit indexes (absolute fit index, incremental fit index and parsimonious fit index). Accordingly, since several indices are available to assess model fit, models approximating the observed data are acceptable Weston & Gore, (2006). In this regard, therefore, the most universally respected and reported model fit indices along with their interpretive values in assessment of model fit should be considered and appropriately reported. Furthermore, the recommendation of Hair and Holmes-Smith should be adhered to by reporting at least one index from each of the three model fitting category. Thus a diverse criteria and best overall picture of the fitness of the model will be reflected. The various fit indices categories and their respective test statistics in addition to their level of acceptance are briefly discussed below and subsequently tabulated.

Absolute Fit Indices

Absolute fit indices determine how well the hypothesized model fits the sample data (Hooper et al. 2008) by interpreting the indices as a proportion of the covariances in the sample data matrix explained by the model Kline, (2011). Among the absolute fit indices, chi-square (x^2) is considered the best measure of model fit. A significant value of (x^2) relative to degrees of freedom indicates that the observed and implied variance-covariance matrices differ (Schumacker & Lomax, 2010). An insignificant value of (x^2), on the other hand, signifies the probability that the two matrices are alike (the implied theoretical model significantly reproduces the sample variance-covariance relationships in the matrix). Researchers argue that there are a number of limitations associated with (x^2). For instance, the (x^2) test statistics assumes multivariate normality and a significant deviation from normality causes model rejections even in a case of a correctly specified model (Weston & Gore, 2006). Additionally, (x^2) test statistics is sensitive to sample size and normally rejects model when a large sample size is used (Hooper et al. 2008). Consequently, due to this restrictiveness of the (x^2), it is not solely relied upon in deciding the rejection or acceptance of models. Rather, it is used in conjunction with other fit indices.

The second fit indices under the absolute fit category is the Goodness-of-Fit index (GFI) proposed by Jöreskog and Sörbom (1981). It is created as an alternative to the chi-square test statistics and calculates the proportion of variance that is accounted for by estimated population covariance Tabacknick & Fidell, (2006). This index ranges between 0 and 1 with larger sample sizes increasing its value (Hooper et al. 2008). It has also been found that an increased in the number of parameters also increases its value in addition to upward bias when large sample sizes are used. A minimum cut-off value of 0.9 is recommended among researchers.

The third measure of model fit commonly used under this category is the Root Mean Square Error of Approximation (RAMSEA). This is the square root of the difference between the residuals of the sample covariance and the hypothesized covariance model Hooper et al. (2008). The value of the RAMSEA decreases with more degrees of freedom or a large sample size (Kline, 2011). Many researchers have recommended different acceptable values for RAMSEA. For instance, Holmes-Smith et al. (2006) suggested a value of RAMSEA less than 0.05 while MacCallum& Browne, (1993) recommended a cut off value of up to 0.10 as acceptable. Nevertheless, it has been found that a RAMSEA values ranging from 0.05-0.08 is generally acceptable. Going by Chen et al. (2008) suggestion that the choice of cut-off value for RMSEA depends on model specification, degrees of freedom and sample size, it seems appropriate to adopt a threshold of ≤ .10 as an acceptable cut-off mark for RMSEA especially where complex hypothesized model and large sample size is proposed.

Incremental Fit Indices

Incremental fit indices otherwise known as comparative (Miles and Shevlin, 2007; Kline, 2011) or relative (McDonald and Ho, 2002) fit indices are a category of indices which do not utilize the chi-square to a baseline model such that the models' null hypothesis is that all variables are not correlated. In other words, incremental fit indices shows the relative improvement in fit of the researcher's model compared with a statistical baseline model (Kline, 2011). Among the test statistics in this category, Adjusted-Goodness-of-Fit-Index was found to be one of the most important indices and therefore most commonly adopted among researchers. This index is adjusted for degrees of freedom of a model relative to the number of variables Schumacker & Lomax, (2010). AGFI exhibits tendency to increase with sample size and like GFI, its values ranges between 0 and 1 with a value of 0.9 or greater indicating well-fitting models Hooper et al. (2008).

In addition to AGFI under incremental fit indices, Normed Fit Index (NFI) is also one of the most popular incremental measures (Hair et al. 2010) and the first to appear in LISREL computer package output Hooper et al. (2008). This statistics assesses the model by comparing chi-square value of the model to that of the null model. For instance, NFI = .60 means that the researcher's model has increased fit by 60%. This index, however, does not control for degrees of freedom and, as such, Bentler, (1990) has used the index alongside Comparative Fit Index (CFI). Comparative Fit Index (CFI) is therefore a revised form of NFI which considers sample size and performs well even when a small sample is employed (Tabacknick & Fidell, 2007; Hooper et al. 2008). Like the NFI, this index assumes that all unobserved variables are uncorrelated and compares the sample covariance matrix with the null model. As with CFI, values for this statistic range between 0 and 1 with values approaching 1 signifying a well fitted model.

The last test statistics under the incremental fit indices is Tuker-Lewis Index (TLI). Developed by Tucker & Lewis in (1973), this index was originally intended for factor analysis. It was later extended to structural equation modelling Schumacker & Lomax, (2010). TLI basically combines a measure of parsimonious fit indices into a comparative fit index between the proposed and null models thereby testing whether measures of unobserved variables are consistent with a researcher's understanding of the nature of that variable. It also has values ranging from 0 to 1 where a value of close to 0 indicates a poorly fitted model.

Parsimonious Fit Index

Parsimony refers to the number of estimated parameters needed to realize a certain level of model fit (Schumacker & Lomax, 2010). Consequently, this model fit index has, in its formula, a built-in correction for model complexity. Since parsimonious models generally have higher degrees of freedom, a parsimony-adjusted index would normally favour simpler models

(Schumacker & Lomax, 2010). The normed chi-square (x^2/df) is the most common parsimonious fit index used to assess the suitability of models under this category (Hair et al. 1995). A range of cut-off values for (x^2/df) have been recommended by SEM experts. For instance, (Bollen, 1989; Hair et al., 1995; Tabachnick and Fidell, 2001) suggested a value ≤ 2.0 whereas (Carmines &Mclver, 1981) puts a cut-off value of ≤ 3.0. Accordingly, (Wheaton et al. 1977) was more liberal by suggesting a value of ≤ 5.0. It should be noted that (x^2/df) is sensible to sample size since (x^2) is the major component of the index. Consequently, this study used this measure not as a basis for accepting or rejecting models but as an indicator of overall fit in combination with other indices. The table below summarises the goodness-of-fit indices including their cut-off points.

Fit Index Category	**Index Name**	**Level of Acceptance**	**Comments**
Absolute Fit Indices	Chi-square (x^2)	P > 0.05	Sensitive to large sample size > 200
	Goodness-of-fit Index (GFI)	≥ 0.90	Values close to 0 indicates a poor fit while values close to 1 indicates a perfect fit
	Root Mean Square Error of Approximation	RMSEA < 0.08	Values up to 0.10 are acceptable
Incremental Fit Indices	Adjusted Goodness of Fit Index (AGFI) Comparative Fit Index (CFI) Normed Fit Index (NFI) Tuker-Lewis Index (TLI)	≥ 0.90	Values close to 0 indicates a poor fit while values close to 1 indicates a perfect fit
Parsimonious Fit Index	Normed Chi-square (x^2/df)	≤ 5.0	Value should be < 5.0

Table 1 : Summary of Goodness-of-Fit Indices

Reliability and Validity

In order for research data to be of value and of use, they must both be reliable and valid. In academic research involving SEM, the assessment of reliability and validity comes immediately after unidimensionality of constructs were established (Anderson and Gerbing, 1982; Anderson and Gerbing, 1988; Hair et al, 2012; Kline, 2011; Awang, 2012). The concepts of reliability and validity are significant characteristics of any measurement procedure (Gaur & Gaur, 2009) and are some of the most prominent criteria for the evaluation of social science research (Bryman, 2008). As Gaur & Gaur, (2009) noted, reliability of a measuring instrument does not guarantee its validity. Thus, in order to secure the quality of all the findings and subsequent conclusions in research using SEM, both reliability and validity of all constructs and the entire structural model should be assessed. Cronbach's (1951) coefficient alpha and Construct reliability (CR) are mostly employed to assess reliability, whereas content, construct, criterion and external validities should be observed for validity.

Reliability

Reliability is basically concerned with the question of whether the results of a particular study are repeatable (Bryman, 2008) in terms of consistency of measures devised to address a certain construct. Reliability, therefore, refers to the confidence we can place on the measuring instrument of a particular construct to give the same numeric value when the measurement is repeated on the same construct (Gaur & Gaur, 2009). In essence, reliability of a measure shows the extent to which it is without bias (error free) and consequently ensures consistent measurement across time and across the several indicators in the instrument (Sekaran&Bougie, 2009). Reliability and error are related such that the larger the reliability, the smaller the error. The goal of reliability is to reduce the errors and biases in a research (Krefting, 1991; Yin, 1994; 2014). Some degree of inconsistency is present in all measurement procedure.

Each observation of a measurement (X), for instance, is equal to true score (t) plus measurement error (e).

According to Sekaran&Bougie, (2009), there are two tests of assessing stability of measures (reliability) (1) test-retest and (2) parallel-form. The first test of reliability i.e., test-retest reliability is the reliability coefficient obtained by repetition of the same measure on a second occasion. The correlation between the scores obtained at two different times from one and the same set of respondents should be higher to indicate better test-retest reliability and, accordingly, the stability of the measures across time. The second form of stability measure (parallel-form reliability) emphasizes high correlation between two comparable sets of measures designed to tap the same construct. In confirmatory factor analysis, as is the case in covariance-based SEM, the above measures have some limitations. In the test-retest method for instance, participants may have gained and learned from the first test to change their mind in the second test. In the second form of reliability measure (parallel-form reliability), it is difficult in all cases to construct two or more versions of the same instrument.

Because of the above mentioned issues, the researcher using SEM should decide to employ the most common method of assessing internal consistency reliability estimates by use of Cronbach's coefficient alpha (Cronbach, &Shavelson, 2004; Shrout, 1998; Peterson, 1994; Sekaran, 2013; Sekaran&Bougie, 2009). Cronbach's alpha is a reliability coefficient that assesses inter-item reliability i.e. the degree of internal consistency or homogeneity between variables measuring a certain construct/concept i.e. the degree to which different indicators measuring the same variable attain consistent results. The Cronbach's coefficient alpha value varies from 0 to 1 and a value of 0.6 or less usually indicates unsatisfactory internal consistency reliability. In assessment of reliability using Cronbach's coefficient alpha, various authors suggest different level of acceptance. For instance, Chakrabarty et al. (2007) in addition to Tabachnik&Fidell, (2007) recommended a cut-off point of0.70 whereas George &Mallery, (2003) recommended the following rule of thumb: >0.9 – Excellent, >0.8 – Good, >0.7 – Acceptable, >0.6 – Questionnable, >0.5 – Poor, <0.4 – Unacceptable. Similarly, Nunnally and Bernstein (1994) suggest a Cronbach's coefficient level of higher than 0.70, with level as low as 0.60 being acceptable for newly developed scales. While diverse views have been suggested about levels of acceptance, it is generally agreed that an alpha of 0.70 and above is acceptable. Therefore, this cut-off point of (0.70) has been adopted as the minimum for assessing internal consistency of scales in majority of SEM research.

Consequently, since researchers usually report at least one of three model-based estimates of reliability (Malhotra et al. 2006), internal consistency in research using SEM should be assessed using confirmatory factor analysis (CFA). To assess reliability using CFA, the approach recommended by Fornell and Larcker (1981), and supported by (Farrell, 2010; Shiu et al. 2011) should be adopted. Fornell and Larcker warned on relying solely on the fit indices obtained during factor analysis and advised heavily on critically examining the factor loadings, correlations and variances. They further advised on the importance of examining Construct Reliability (CR) and significance level of standardised loadings. CR measures the internal consistency of a set of indicators rather than the reliability of a single variable to capture the degree to which a set of indicators depicts the common latent construct (Holmes-Smith et al., 2006; Phillips, 2014). Here, the main advantage is that CR is based on estimates of model parameters and has wide applications. Therefore, CR should be calculated distinctly for each multiple indicator construct using a mathematical formula since Amos does not compute for this statistic directly (Farrell, 2010; Hair, et al. 2011). Farrell & Rudd, (2009) in addition to Phillips, (2014) and Ugulu, (2013) recommended that CR should be equal to or greater than 0.60 and since this cut off mark is widely accepted in organizational and other social science research, it should be embraced by researchers.

Validity

Reliability alone is insufficient to fully assume that an instrument is adequate (Anderson &Gerbing, 1988; Hair, Hair, et al. 2010; Gaur & Gaur, 2009; Bryman, 2008) since it only considers consistency/repeatability of measurement. Therefore, validity also needs to be determined to validate the constructs and to base the research upon sound methodological practice (Farrell & Rudd, 2009). Glossary of terms from Saunders et al. (2009) defines validity as the extent to which research findings are actually about what they profess to be. Creswell, (2012) offers an extended definition. Creswell suggested that "validity is basically the development of a sound evidence to demonstrate that the intended test interpretation (of the construct that the test is assumed to measure) matches the proposed purpose of the test. This evidence is based on test content, responses processes, internal structure, relations to other variables and the consequences of testing". In a simpler term, validity means that our measuring instrument actually measures the construct it is assumed to measure Gaur & Gaur, (2009). The better the fit between the conceptual and operational definitions, the greater the validity of the measurement (Neuman, 2006).

According to Nunnally& Bernstein, (1994), there are primarily three significant facets of a valid construct: (1) The construct should be seen as a good representation of the domain of observables associated with the construct (2) The construct under study should adequately represent the alternative indicators and (3) The construct should be sufficiently related to other constructs of interest. Considering the above three aspects of a construct, three types of validity i.e. content, construct (both convergent and discriminant validity) and criterion should be examined during research involving SEM which are related to the internal validity of the scales and their corresponding indicators. For the purpose of generalization of the research findings, external validity should also be assessed.

Content Validity

Content (face) validity is the extent to which the measurement device, i.e. the measurement questions designed in the questionnaire, provides adequate representation of the intended domain of content (Saunders, et al. 2009; Gaur & Gaur, 2009). Content validity is subjective and requires experts' opinion on the adequacy of content representation (Malhotra, 2010). When it seems evident to the experts that the indicators adequately represent the construct, the measure has face validity (Fagerlin et al. 2007; Thanasegaran, 2009). To achieve content validity in research using SEM, a careful definition of the research through literature review should be carried out and discussion with experts from both academics and industry practitioners should also be conducted. This procedure is suggested by many authors (Saunders et al. 2009; Creswell, 2012; Bryman, 2008;Sarstedt et al. 2014). Therefore, numerous experts should express their opinion on the format and structure of the statements designed on the measuring instrument. Due to the subjective nature of content validity, it seems insufficient to provide a more rigorous account of research validity alone. Consequently, this validity measure is mostly considered as *a priori* to carrying out the final analysis.

Construct Validity

The second type of validity to be examined in SEM analysis is construct validity. It is one of the most commonly used techniques in organizational research (Gaur & Gaur, 2009) and basically refers to the extent to which researcher's measurement questions actually measure the presence of that construct he intended to measure (Saunders et al. 2009). Alternatively, construct validity deals with what the instrument is actually measuring. In this context, it is necessary to reflect on the theoretical questions about why the scales work and what inferences can be made based on the theory. For instance, without adequately assessing construct validity, a researcher cannot estimate and correct for the confusing effects of random error and method variance, thus the result of theory testing may be vague.

An assessment of construct validity should be done by analysing both convergent and discriminant validities. Whereas convergent validity assesses the extent to which indicators of the same construct are highly correlated, discriminant validity determines that the measures of a construct have not correlated too high with other construct (Phillips, 2014).

Some approaches have been suggested for the assessment of convergent and discriminant validities. Regression and correlation analysis and factor analysis are frequently used in addition to more advanced techniques such as confirmatory factor analysis in structural equation modelling (Malhotra, 2010; Hair et al, 2011). Since this paper is more inclined to covariance-based SEM analysis (which is a confirmatory factor analytical technique), convergent and discriminant validities should be assessed using confirmatory factor analysis. As suggested by Holmes-Smith et al. (2006), to establish evidence of convergent validity, the magnitude of the direct relationship between the indicators and latent variable (construct) should be statistically different from zero. Thus, evidence of convergent validity is present when a significant t-value is observed for each indicator (Bollen, 1989; Joreskog and Sorbom, 1989). All paths should test highly significant (t-value > 2.00), and, all factor loadings of the final CFA analysis for a particular factor should have high loading of atleast .50 or greater (Hair, 2006).

In case of discriminant validity, two approaches have been mostly employed by researchers. The first approach examines the computed correlations among the constructs which should not be greater than .85 as suggested by Kline, (2011). Thus, where two factors exhibit high correlation greater than .85, redundant items should be deleted or constrained (Awang, 2012). The second approach to assessment of discriminant validity is the examination of pattern structure coefficient to determine whether constructs in the measurement models are empirically distinguishable Schumacker& Lomax, (2010). Pattern coefficient is the standardized factor loadings obtained from Amos output in the course of analysis. Further still, aside these restrictive assessments of convergent and discriminant validity, construct validity should also be improved by assuring that the goodness-of-fit indices obtained from confirmatory factor analysis fits to the data adequately (Hsieh &Hiang, 2004). Results of construct validity should therefore be adequately reportedby researchers.

CONCLUSION

The present study was designed to summarize arguments/inconsistencies in determining model fit and assessment of reliability and validity in social science research involving structural equation modelling methodological approach. Since SEM has many model fit indices to decide the acceptance/rejection of the proposed model, inconsistencies in acceptable cut-off values of such indices may bring about confusion among researchers such that the entire integrity of the methodology may be questioned by others.In the light of this, the various categories of model fit indices (i.e absolute, incremental and parsimonious) were discussed along with their individual indices and an acceptable cut-off value for each. Additionally, reliability and validity was also discussed to remind researchers of their importance and recommended means of achieving them. SEM is a potential methodology for research in social science and as a final point, it must be noted that structural models are based on substantive theory.

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