FIT ESTIMATION IN STRUCTURAL EQUATION MODELING-A SYNTHESIS OF RELATED STATISTICS

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ABSTRACT

Structural Equation Modeling (SEM) as a multivariate data analysis technique is considered sophisticated one and becoming popular among researchers. Literature is not consistent on one of the important matter of SEM which is related with the determination of adequacy of model fit. In view of this shortcoming, the paper aims at accumulating opinions and notions of researchers which are evident from literature regarding fit of SEM model on the basis of indices of fit. Afterward, it constantly analyzes previous studies to give a new outlook to the topic. A criterion is proposed in the paper, based on which academicians and researchers can determine the level of fit for their estimated models. The estimated models may not always be perfect and even may not be acceptable as per the guidelines provided in literature. But the paper further proposes that any research model cannot be rejected just because the data which is analyzed does not fit it perfectly. Therefore, both researchers and practitioners are encouraged to contribute on the said aspect. To further develop the topic and enhancement in the research field of SEM, the studies with strong theoretical background even with poor fitting models should be published. Let the new studies do their job of examining, whether it is the research model that is not appropriate or the problem is associated only with the poor-quality and less reliable data.

Keywords: Structural Equation Modeling, Measurement Model, Structural Model, Fit Indices, Model Fit

Fit Estimation in Structural Equation Modeling- A Synthesis of Related Statistics

1. Introduction

One of the primary objectives of every researcher is to expand explanatory ability of the research and approach to a decent generalization about any particular phenomenon. For this purpose, a number of statistical methods commonly categorized as univariate, bivariate and multivariate are available through which researchers' can analyze the data and lead to their specified targets. In recent times, several statistical softwares aid in analyzing complex multivariate techniques, otherwise researcher restricts to employ only univariate and bivariate analysis. Structural Equation Modeling (SEM) is such a multivariate technique which has emerged as an integral tool to empirically test the causal models. SEM has its origin from the multi-equation modeling in econometrics; later principles of measurement from psychology and sociology also contributed in its development (Hair et al., 2006). Due to its advance nature, today the technique is much accepted and admired by researchers and academicians. It offers several benefits and solves many research problems together by the means of estimating a series of dependence relationships after incorporating the variables into an integrated model, the base of which is some theory (e.g. Theory of Planned Behaviour: TPB and Theory of Reasoned Action: TRA). SEM has potential both in terms of theory testing and theory development. These theories can be tested either in one stage (measurement and structural models combined) or in a two step procedure (firstly examination of measurement model and then assessment of structural models which are known as path models). The availability of various statistical packages such as LISREL, AMOS, SAS, MPLUS and STATISTICA etc. have also made the task simple and save the researcher to unnecessarily disperse efforts for cumbersome calculations.

In spite of everything, like many other statistical techniques, there are several limitations associated with its use. One of the problems related with it is the lack of consistency among researchers about the level of fit of data to any research model. A number of researchers (Joreskog and Sorbom, 1984; Bollen, 1986; Byrne, 1989; Mulaik et al., 1989; MacCallum, 1990; Steiger, 1990; Bollen and Long, 1993) started inscribing and developing the topic of model fit and its related statistics. Today, a number of new writings on SEM are also available and researchers (Schumacker and Lomax, 2004; Hancock and Mueller, 2006; Hooper et al., 2008; Byrne, 2010) recently offers different perspectives and commendations on the matter. Unfortunately, no one has still approach to a consensus on the two questions. The first one is: which of the indices of model fit are best to employ; and secondly, what is the criterion for deciding an adequate model fit on the basis of these indices. Although, the technique has been invented since long, authors are still writing and trying to settle on the above two questions. The paper is also a modest attempt in this direction to provide researchers a synthesis of selected model fit statistics and offer guidelines to the practitioners of SEM related to criteria of selection of model fit.

The paper is divided into six sections. Section one is described above (introduction). Section two, defines the purpose and methodology. Section three, with two subsections, is prepared to define a theoretical background of the fit indices. Section four, talks about standpoint of various researchers on the employment and criteria of model fit on the basis of fit statistics. It analytically considers notions of various researchers and provides a foundation of SEM model fit that may range from very poor to ideal. Section five presents the conclusion and in lack of any empirical explanations, talks about the limitation of the paper. Finally, section six gives some recommendations and directions to the future researchers and practitioners of SEM.

2. Purpose and Research Methods

2.1 Purpose and Objectives

An investigation of literature on fit indices comes out to be very much comprehensive and there are various pieces of puzzles scattered over places. The paper endeavors to fit these pieces together to confirm their joint shape. This can benefit both academics and scholars working with SEM as they can get results of a wide literature under one roof. Intended towards this purpose, specifically following two objectives are worked upon.

1). To gather views of various researchers regarding acceptability of model fit according to some selected fit indices.

2). To contently analyze these views and decide a criteria of SEM model fit on their basis.

2.2 Methodology

The paper uses secondary data and reviews a collection of research papers, books, reports and internet websites based on structural equation modeling and confirmatory factor analysis. Content analysis is exercised by which selected portions of the text are systematically rearranged to abridge literature and draw synergy from the individual work of the authors.

3. Theoretical Background

3.1 Model Fit: Meaning and Types

Model fit means how closely the estimated covariance matrix matches the observed (sample) covariance matrix (Malhotra and Dash, 2012). In general, any statistical software package on SEM provides fit estimation for three models: estimated model, saturated model and the independence model.

- Estimated Model: Estimated model is one specified by the researcher in his/her study.
- Saturated Model: Saturated model is a model in which every variable is connected to every other variable through a single or double headed arrow. This implies that estimated co-variance matrix is equal to observed covariance matrix, consequently chi-square of the model becomes zero and the fit statistics for this model remain ideal.
- Independence Model: Independence model goes to the opposite extreme of saturated model. The null or independence model is the worst case scenario as it specifies that all measured variables of a model are uncorrelated (Hooper et al., 2008). Therefore, it is so severely constrained that provides a poor fit to any interesting set of data.

The saturated model and the independence model can be viewed as two extremes between which estimated model is proposed to lie. Any estimated model may be similar to saturated model and in expectation of an acceptable fit to the estimated model, a researcher always expect that this model remains far behind from independence model. To confirm, the level of acceptability of any model dozens of statistics have been developed and proposed by a number of researchers. Different statistical software packages such as LISREL, AMOS, SAS, MPLUS and STATISTICA (as mentioned above) calculate most of these statistics for providing a ground of appropriateness to any estimated model. Next section, in this direction explains the broad classification of these statistics as are generally exercised in literature.

3.2 Model Fit – Measures and Statistics

Model evaluation is one of the most unsettled and comprehensive issue connected with SEM and no single statistical test best describes the strength of the model's predictions. SEM is still evolving as a data analysis technique and researchers are in disagreement on various aspects of structural modeling such as acceptability of model fit by employing different indices as are developed over time. Firmly, three measures: 'measures of absolute fit', 'measures of incremental fit' and 'measures of parsimonious fit' are common to determine fit of any model. The paper considers the measures of absolute fit and measures of incremental fit. Parsimonious fit measures are not described as they are specifically invented only for inter-model comparisons and not appropriate for evaluating the fit of any single model (Hair et al. 2006; Malhotra and Dash, 2012). Owing to the reason, parsimonious fit measures are not frequently utilized whereas absolute and Incremental are the two statistics which are commonly reported in any SEM study; thus require much clarification than the measures of parsimony.

3.2.1 Measures of Absolute Fit

Absolute fit measures determine the degree to which the overall model predicts the observed covariance or correlation matrix (Hair et al., 2006). Consequently, these measures are derived from the fit of the obtained and implied covariance matrices and from the Maximum Likelihood function. Researchers have divided the measures of absolute fit into two categories: 'goodness of fit measures' and 'badness or lack of fit measures'.

- Goodness of Fit: Goodness of fit indicates how well the specified model fits the observed or sample data. Therefore higher values of these measures are desirable (Malhotra and Dash, 2012). Two goodness of fit indices GFI (Goodness of Fit) and AGFI (Adjusted Goodness of Fit) are discussed in the paper.

- Badness of Fit: As the name indicates, badness of fit or lack of fit indices measure error or deviation in some form, so lower values on these indices are required (Malhotra and Dash, 2012). CMIN/DF (Chi-square statistic divided by degrees of freedom), RMR (Root Mean Residual) and RMSEA (Root Mean Square Error of Approximation) are explained and illustrated upon from this category.

3.2.2 Measures of Incremental Fit

Measures of Incremental fit evaluate how well the specified (observed) model fits the sample data relative to some alternative model that is treated as a baseline model (Hair et al., 2006; Hooper et al., 2008; Malhotra and Dash, 2012). The baseline model is also treated as null model which is defined as a model from which the estimated model should be expected to exceed (Hair et al., 2006). Due to this reason the incremental fit statistics in AMOS are also known as baseline comparisons. In this paper, NFI (Normed Fit Index), RFI (Relative Fit Index), IFI (Incremental Fit Index), TLI (Tucker-Lewis Index) and CFI (Comparative Fit Index) are exploited in the category of incremental fit. The procedure of calculation of all these statistics considers chi-square and degrees of freedom both for the estimated model and baseline model in one or the other form.

4. Explorations and Discussions

4.1 Statistics of Model Fit - Assimilation and Description

This section describes on various fit statistics and elucidates opinions of researchers on their predicting power regarding the fit of any SEM model. None of the measures (except chi-square) has an associated statistical test for the acceptance or rejection of any index. However, in many instances guidelines have been suggested, which are illustrated with the description of each index.

4.1.1 Chi-Square Statistic

The chi-square for the model is also called the discrepancy function, likelihood ratio or chi-square goodness of fit. In AMOS, it is also known as CMIN. Chi-Square is the mainframe model fit statistic which indicates the difference between observed and expected covariance matrices. Chi-square is criticized by many researchers because of shortcomings associated with its use. Being very sensitive to sample size, many researchers discard the index if sample size exceeds 200. Hooper et al. (2008) quoted the reason that when the size of sample is large, chi-square rejects nearly all the models. Arbuckle and Wothke (1999) too define that when the sample is large, chi-square test will show that the data are significantly different from those expected on a given theory even though the difference may be only slight and negligible. Along with large sample, problems too relate with the use of small sample sizes. Arbuckle and Wothke (1999) again quote that if the sample is small the chi-square will show that the data are not significantly different from quite a wide range of very different theories. Same reflections also glimpse from Gatignton (2010) as he considers that one difficulty with small sample sizes is that researchers may fail to reject the hypothesis (or "accept" the model) due to a lack of statistical power (Type I error). Likewise, in large samples, one may fail to find a model that fits even better (Type II error). As a result, other measures of fit have been developed. Albright and Park (2009) have reported that each developed index that work in lieu of chi-square also have its own advantages and disadvantages. But it is recommended that although chi-square suffers from serious limitations, it must be reported in SEM studies as most of the fit indices are derived and based upon its value.

Acceptability: Chi-square must be not significant for regarding the model as acceptably fit which means that the observed covariance matrix is similar to the predicted covariance matrix. So, smaller difference between the two matrices is preferred. A value of zero is the exact fit and values closer to zero indicate a better fit.

4.1.2 Goodness of Fit (GFI)

The GFI was devised by Joreskog and Sorbom (1984) for ML and ULS estimation but work of Tanaka and Huba (1985) also generalized it to the other estimation criteria (cited in Arbuckle and Wothke, 1999). Hair et al. (2006); and Hooper et al. (2008) reported that the range of GFI is always between 0 and 1.

Acceptability: According to Hair et al. (2006), no absolute threshold levels for acceptability of this index has been established but higher values of GFI indicate better fit. Malhotra and Dash (2012) have point out these higher values that should be in the range of 0.90 and above. But Hooper et al. (2008) define that the values of 0.95 and above should be termed as more appropriate. Despite all, Hair ét al. (2006) report GFI of 0.865 as marginal in their worked example. GFI of 0.850 is also considered for a claim of mediocre or moderate fit by Dunn (2008) and Zakuan et al. (2010).

4.1.3 Adjusted Goodness of Fit Index (AGFI)

AGFI takes into consideration the degrees of freedom available for a model; when GFI is adjusted for these degrees of freedom, the index is termed as AGFI. Hair ét al. (2006) take AGFI as an incremental fit index but Hooper et al. (2008) and Malhotra and Dash (2012) write it as an index of absolute fit. Going with Hooper et al. (2008) and Malhotra and Dash (2012), the present study procures AGFI as an absolute fit measure. Hooper et al. (2008) mention that values of AGFI can fall outside the range of 0 to 1.

Acceptability: The AGFI of one indicates an ideal fit. Regarding acceptability, Hair et al. (2006) and Malhotra and Dash (2012) recommend a value either greater than or equal to 0.90 but for AGFI, a criteria of greater than 0.8 is also provided (Njite and Parsa, 2007). Hair et al. (2006) also consider value of 0.810 as marginally accepted and Zakuan et al. (2010) too regard AGFI of 0.826 calling the model fit as moderate.

4.1.4 Relative Chi-Square (CMIN/DF)

This index is also known as Normed Chi-Square. CMIN/DF is the chi-square value divided by its degrees of freedom. Chi-square being very sensitive to sample size, its applicability in this form has increased considerably in recent times.

Acceptability: The ratio should be small and close to one for perfect model fit. As per Byrne (1989) and Dion (2008), a ratio greater than 2 represents an inadequate fit. Even though, there is no consensus among researchers regarding an acceptable ratio for this statistic. According to Carmines and McIver (1981), a ratio of 3 to 1 is indicative of an acceptable fit. Suggestions for the use of this index also range from as high as 5 and as low as 2 (Arbuckle and Worthke, 1999; Hooper et al, 2008).

4.1.5 Root Mean Residual (RMR)

RMR is the square root of the average squared amount by which the sample variances and covariances differ from the obtained estimates, thus it is the mean of squared residuals. Hooper et al. (2008) report that RMR becomes difficult to interpret if the scale of measurement changes (for example: some items measured on five point and other measured on seven point scale). Due to this, its standardized version SRMR (Standardized Root Mean Square Residual) is popular. Also, maximum range of RMR is unlimited (Moss, 2009).

Acceptability: As RMR is a fit of badness, in the words of Arbuckle and Wothke (1999), smaller values are better and a RMR of zero indicates an ideal fit. In line with Hooper et al. (2008), well fitting models should obtain RMR values less than 0.05. Authors (Arbuckle and Wothke 1999; Hooper et al., 2008; Malhotra and Dash, 2012) too have described that values of 0.08 or less are also deem acceptable for adequacy of this index.

4.1.6 The Root Mean Square Error of Approximation (RMSEA)

RMSEA was first developed by Steiger and Lind (1980: cited in Hooper et al., 2008). This index is the square root of the mean of the squared residuals (Malhotra and Dash, 2012). It is defined as sensitive to the number of parameters estimated but relatively insensitive to size of sample (Albright and Park, 2009). About its range, it is recognized that the upper range is unbounded but it is only rarely experienced in different studies that RMSEA exceed 1 (Brown, 2006).

Acceptability: Smaller values of RMSEA indicate better model fit; the exact fit of RMSEA is 0.000. As per Hooper et al. (2008), cut-off points for RMSEA have been reduced noticeably in recent times. According to Hu and Bentler (1999), a value of 0.06 or less is an indication of acceptable model fit. Arbuckle and Wothke (1999); Dion (2008) and Albright and Park (2009) all point out a value of about 0.05 or less as a sign of a close fit. But in line with Albright and Park (2009), the figure 0.05 is based only on subjective judgment of researchers, thus cannot be regarded as infallible. In view of this, investigators (Arbuckle and Wothke, 1999; Hair et al., 2006) also agree on the point that values less than or equal to 0.08 can also indicate mediocre fit. Also, Hair et al. (2006) and Arbuckle and Wothke (1999) suggest upper threshold of 0.10, above which the models will not be employed.

4.1.7 Normed Fit Index (NFI)

The Bentler and Bonett (1980) Normed Fit Index is the ratio of difference in the chi-square value for the proposed model and the null model divided by the chi-square of null model. NFI cannot go above 1 (range ≐ 0 to 1) which is the ideal fit for it (Hancock and Mueller, 2006).

Acceptability: The values of greater than or equal to 0.90 are considered acceptable for the index (Malhotra and Dash, 2012; Hair et al., 2006; Hooper et al., 2008). Along with more recent recommendations on NFI; it should be greater than 0.95 for a perfect fit. Even with these cut-offs, authors also take values such as 0.828 as marginally accepted (Hair et al., 2006).

4.1.8 Relative Fit Index (RFI)

Relative fit index is known as Bollen's RFI and according to Byrne (2010), it represents a derivative of the value of NFI. For the calculation of RFI, relative chi square (CMIN/DF) of estimated model is divided by relative chi-square of baseline model, then this ratio is subtracted from one. The range of RFI is always between zero and one.

Acceptability: Relative fit index (RFI) close to one indicates a superior fit. Consistent with Byrne (2010), values greater than 0.95 indicate perfect fit and as with other indices values greater than 0.90 and above are also adequately acceptable.

4.1.9 Incremental Fit Index (IFI)

The Incremental Index of Fit (IFI) was developed by Bollen (1989) to address the issues of parsimony and sample size which were known to be associated with the NFI, so IFI is relatively insensitive to sample size (Byrne, 2010). To compute it, first the difference between the chi square of the baseline model (in which variables are uncorrelated) and the chi-square of the estimated model is calculated. Next, the difference between the chi-square of the estimated model and the degrees of freedom for the estimated model is calculated. The ratio of these calculated values represents IFI.

Acceptability: This index can exceed 1.0 and values close to 1.0 indicates perfect fit (Arbuckle and Wothke, 1999). IFI of 0.962 is stated as reflecting a well fitting model by Byrne (2010). However, similar to other statistical coefficients those exceeding 0.90 are acceptable too.

4.1.10 Tucker-Lewis Index (TLI)/Non-Normed Fit Index (NNFI)

The Tucker-Lewis coefficient was discussed by Bentler and Bonett (1980) and is also known as the Bentler-Bonett non-normed fit index (NNFI). The coefficient of TLI is estimated by dividing the difference of relative chi-square of baseline model and relative chi-square of estimated model by the difference of relative chi-square of baseline model and one. According to Hooper et al. (2008), the main problem associated with its use is its non-normed nature, meaning values can go beyond 1.0 and thus can be difficult to interpret. Arbuckle and Wothke (1999); Hooper et al. (2008) and Malhotra and Dash (2012) also prescribe that although the typical range for TLI is between zero and one, but it is not limited to that range and values too can fall outside it.

Acceptability: TLI values close to 1 indicate a very good fit. For the index, values as big as 0.95 is favoured but as low as 0.80 is also preferred (Hu and Bentler, 1999: cited in Hooper et al., 2008).

4.1.11 Comparative Fit Index (CFI)

CFI is a revised form of NFI and was first given by Bentler (1990) so it is also known as Benter's comparative fit index. For the calculation of CFI, along with chi-square and degrees of freedom, non centrality parameter (NCP) is also considered both for estimated and baseline models. CFI values again range from 0 to 1, with larger values (values close to 1) indicating better fit (Arbuckle and Wothke, 1999; Hooper et al., 2008; Malhotra and Dash, 2012).

Acceptability: Like other fit indices, a CFI value of 0.90 (Hancock and Mueller, 2006) is advanced as acceptable and values greater than 0.95 is recognized as indicative of a perfect fit (Dion, 2008; Hooper et al., 2008). Going with Dunn (2008), comparative fit Index (CFI) of 0.87 can also be relevant for a claim of mediocre fit.

4.2 Statistics of Model Fit : Clarifications

In line with the above explanations of model fit indices, it can be said that the answer to the question is still inadequate and literature suffers from large inconsistency and ambiguity to settle on the aspect of model fit. Albright and Park (2009) too have declared that no single evaluation rule exists regarding model fit by means of fit indices on which majority of researchers agree. Actually, fit of the model can be viewed somewhere between the extremes of very poor to ideal. The model fit statistics which can be called very poor are statistics of independence or null model and the ideal fit indices are the indices of saturated model. The researchers wish for their models to be near to saturated one but factually, models may not always be ideal and perfect. Consequently, every study must articulate some criteria on the basis of which acceptability of model fit is decided. The scale of fit indices is not very easy to interpret and it is much difficult to say about how much deviation of fit indices from the ideal representation is bearable. Since, there are no golden and rigid standards established till date for the use of fit indices and regarding the employment of sample sizes; in line with accepted threshold levels and description of fit indices by various authors, table 1 presents some guidelines on the aspect.

Table 1. Acceptability Criteria for Absolute and Incremental Fit Indices

Fit Indices	Range	FIT CRITERION						
	Lower	Upper	Poor Fit	IdealFit	PerfectFit	GoodFit	Marginal Fit	Not/Less Acceptable
Absolute Fit Indices								
Goodness of Fit								
GFI	0	1	0	1	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Less than 0.80
AGFI	Outside the range of 0 to 1		0	1	0.90 and Above	—	Between 0.80 and 0.90	Less than 0.80
Badness of Fit								
CMIN/DF	—	Upper bound is unlimited	—	0	Between 0 and 1	Between 1 and 3	Between 3 and 5	Above 5
RMR	Lower bound is restricted to zero	Upper bound is unlimited	—	0	0.05 and Below	—	Between 0.05 and 0.08	Above 0.08
RMSEA	Lower bound is restricted to zero	Generally do not exceed 1	—	0	0.05 and Below	Between 0.05 and 0.08	Between 0.08 and 0.10	Above 0.1
Incremental Fit Indices								
NFI	0	1	0	1	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Below 0.80
RFI	0	Can go beyond 1	0	—	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Below 0.80
IFI	0	1	0	1	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Below 0.80
TLI	0	Can go beyond 1	0	—	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Below 0.80
CFI	0	1	0	1	0.95 and Above	Between 0.90 and 0.95	Between 0.80 and 0.90	Below 0.80

Source: Compiled by Authors

The table 1 is compiled on the ground of explanation and description of these fit indices in literature. First column of table 1 states about the fit statistics as are described in the paper and second column presents the range between which these indices are expected to lie. Under heading fit criterion, the criterion of model fit is divided into some sections. Primarily, these are the criteria of ideal fit, perfect fit, good fit and marginal or mediocre fit. The two indices of goodness of fit (GFI and AGFI) and all the indices of incremental fit (NFI, RFI, IFI, TLI, CFI) have ideal values as equal to one and the poor fitting models will have these values as zero or very near to it. Independence model is such an example of poor fitting model. However, if the particular index lie in between any given range, the model may be classified as a good fitting or mediocre fitting model. Opposite to the goodness of fit, the fit of badness in ideal model is equal to zero and worst models will have these values equal to 1.0. Indeed, between these extremes a well fitting range is decided upon which can be employed by any researcher basing on the value of the index. Last column also details a range of values beyond which a model can not be said as acceptable due to very less power of fit indices. Based on the table, researchers can very well decide whether their models are perfect fitting models, have marginal fit or are not acceptable at all. Although, data may not support some of the tested models, the conceptual background and theoretical foundation of any study must be considered. The substandard and low-quality data may not support even the unanimous theories. In this regard, after concluding the main theme of the paper, the last section will provide some recommendations to the practitioners of SEM.

5. CONCLUSION AND LIMITATIONS

In summary, it can be said that SEM literature is deficient regarding any established standard for the criteria of model fit on the basis of fit indices. Literature has only contributed certain guidelines on the subject and by synthesizing various guiding principles among these, the present paper endeavors to further develop this topic. Factually, it is emphasized that SEM is not only important for the testing of conventional theories but also significant for the development of new ones. Sometimes, the data may fit the model only marginally but the theoretical base of any research may be unique and absolutely robust. Consequently the future prospects even for the moderate fitting model can be strong. The theory or the model should not be rejected only on the ground that the fit is not very encouraging. Moss (2009) also holds the same opinion. He quotes the reference of Bollen (1989) who illustrates that some previous models in which CFI of 0.70 and 0.85 were discovered by the researchers actually represented progress in literature and thus recommend that these types of models should be acceptable. So, the paper proposes that model fit can be categorized according to a continuum ranging from very poor to ideal and define the most desirable indices of absolute and incremental model fit to settle somewhere between this continuum.

Although, the recommendation for the classification and criteria of model fit as given in the paper is highly suggestive of the unclear trend which is evident from the literature but in lack of any definite scientific enquiries, cannot be stated as rigid and cast-iron rules. Due to this shortcoming, the proposed commendation as given in the paper does not confirm itself as a set of laws on the employment of the fit statistics and approval as a universal and uniform criterion for all fields of study. Shadows of SEM work are visible in pure sciences (such as medical science) as well as in social sciences (like sociology, psychology, marketing etc). A model fit that is only marginal may be acknowledged in behavioural researches (a field of social science research) as the subject of investigation here is general human being who is much comprehensive to study and his/her behaviour gets influenced by a variety of factors. But in pure sciences, majority of studies must articulate the models only with perfect or atleast a good fit (as classified in table 1) due to the exactness and purity which is much needed in such fields. Hence, the paper is not saying that mediocre fitting models must also be equally accepted as perfect fitting models but only stresses that these must be considered for a new resumption. Accordingly, the paper offers some suggestions and directions to future researchers in the subsequent section.

6. Recommendations and Further Research

Firstly, it is inscribed at many places in literature that some fit indices are very sensitive to sample size whether small or large. Albeit, it is not much clear in literature about how much big or small a sample is talked about, and how fit of any model can vary while experimenting with different sample sizes. Perhaps, the employment of sample size in any SEM study may also depend upon the number of parameters that is to be estimated through a model. With some new work, future studies can prescribe a range of reasonable sizes of samples along with the predictable number of parameters for giving alleviation to future practitioners of the subject.

Secondly, the language of research must not be one which gives different impressions to the reader. Therefore, there must be uniformity among researchers in using the terminology for describing the fit of any model. Variety of expressions like reasonable fit, acceptable fit, satisfactory fit, good fit are exercised in various research articles and papers even to indicate the similar range of values. Accordingly, in order to characterize the framework of terminology and range of results, one criterion is proposed in this paper (Table 1) but only suggestive. The experts can further test its validity and provide some new standards and benchmarks according to which the future work on SEM can proceed.

Lastly, there is wide literature available on SEM but majority of studies confer only about the perfect fitting models. There is very less discussion about cases in which data may not perfectly support the model. The reason is that the studies with perfect model fits are usually published but the studies in which the model gets less support from the data are discarded for publication. Researchers themselves get less enthusiasm regarding the publication of their studies thinking about the probable criticisms. But due to this deprived thinking, a considerable point becomes out of their mind that the subject of SEM can be handled and understood only with the synergy of different individual studies. Other researchers can contribute in this course of action only if the research is published and they get an opportunity to revive it. More to the point, it must always be remembered that a good research is only one which always stands for the test of criticism.

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