Article Review

Tomarken, Andrew J. and Waller, Niels G. (2005). Structural Equation Modeling: Strengths, Limitations, and Misconceptions. **Annu. Rev. Clin. Psychol.**1: 31-36.

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I

Structural Equation Modeling (SEM) is a second-generation multivariate statistical data analytic technique that is often used in current research in both natural and social sciences. This is mainly due to the believe that it can test theoretically supported linear and additive causal models. In the field of marketing, for example, with SEM marketers can virtually examine the relationships that exist among variables of interest in order to prioritize resources to better serve their customers. Additionally, the fact that unobservable, hard-to-measure latent variables can be used in SEM makes it ideal for tackling business research problems (Wong, 2013).

In principle, SEM involves observable or manifest variables or indicators and unobservable or latent variables, causal modeling, confirmatory factor analysis, multiple regression, and path analysis. SEM technique is used mainly to see if empirical data fit the proposed causal model by the examination of x^2 and indexes of goodness of fit.

II

Tomarken and Waller ,in their article titled "Structural Equation Modeling : Strengths, Limitations, and Misconceptions", point out the increasing popularity of SEM over the past 20 years since the availability and accessibility of new software programs such as LISREL, SPSS AMOS, and EQS-to mention only a few. Although the traditional use of SEM has been research on self – report or behavioral measures, a broader set of applications has appeared in recent years, e.g., in psychophysiological studies to model properties of autonomic nervous system. Moreover, there has been a growing

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recognition that SEM can be applied to an even wider array of data analytic problem, e.g., latent growth modeling (LGM) and multilevel covariance structure modeling.

The popularity of SEM is a positive development, yet it is associated with potential downsides: misconceptions and ignorance about its limitations and constraints. The authors outline the problem of omitted variables, the importance of lower-order model components, potential limitations of models judged to be well fitting, the inaccuracy of some commonly used rules of thumb, and the importance of study design.

By omitting important variables that are implicated in the causal processes or other features of SEM, models present a misleading picture of the measurement and/or causal structure and commonly result in biased parameter estimates and inaccurate estimate of standard error. Additionally, users of SEM technique are sometime unaware that a model can fit perfectly, yet accounts for well below 1% of the variance of the primary endogenous variables. SEM analyses encourage researchers to focus on global fit at the expense of an assessment of various lower-order features of the data in that the SEM analyst may predict that construct x causes construct y, but is unaware that it is associated with problematic lower-order components, e.g., parameter estimates that are biased, small in magnitude or opposite to theoretical expectations.

There are problems with estimations and test of parameters and the formation of confidence interval. For example, different ways of identifying a model may produce different ratios of a give parameter to its standard error. In addition, although the Wald z test assumes that the sampling distribution of a parameter is normal, it is likely that such distributions often are not symmetrical given the sample sizes used in practice.

It is impossible to prove that a model is correct using statistical analyses or other means as alternative models may be available that could fit the data equally well or better. Unfortunately, SEM researchers are often ignore it and tend to overstate the strength and certainty of the conclusions reached by a SEM.

Researchers of SEM often use rules of thumb to guide decision making and justify the decisions made. Such rules of thumb, in many cases, are oversimplified or not universally true. For example, the commonly practice that alternative ways to identify a model, e.g.

fixing a factor loading at one versus fixing a factor variance at one, always produce identical results.

SEM cannot compensate for limitations in design and method. Meditational models are very popular among SEM research that are cross-sectional designs. Cross – sectional meditational designs will yield unbiased estimates of divert and indirect causal effects only under highly restricted conditions unlikely to be met in practice in that the specific estimates obtained are highly dependent on the relation between the temporal lag of the actual causal effects and the time lags between measurement occations.

III

As concluding remarks, the authors argue that SEM is not a statistical magic bullet that can be used to prove that a model is correct and it cannot compensate for a poorly designed study. Strengths and limitations should be carefully considered before employment of SEM.

Compared with hierarchical linear model (HLM) or hierarchical regression analysis, the authors also assert that SEM approach has some advantages, e.g., measures of overall model fit, more flexible modeling of residual structures and capacity to model latent variables and their multivariate associations. On the other hand, HLM models are generally easier to specify, are less likely to be associated with estimation problems, and are able to perform certain types of analyses that the SEM approach cannot easily handle, e.g., inclusion of individual groups of variables step-by-step.

IV

The strengths, limitations and misconceptions concerning with SEM that are outlined by Tomarken and Waller are worth careful condiseration before planning for, and implementation of, data analyses for research in the social sciences. In addition to the authors, there are also other people who have provided useful comments on SEM. For example, Kerlinger and Lee (2000) have made their reservations regarding the use of SEM as follows:

“When should this procedure be used?... it should not be used routinely or for ordinary statistical analysis and calculations.... If it is possible to use a simpler procedure- like multiple regression, multiway contingency tables, or analysis of variance and obtain answers to research questions, the using structural equation modeling is pointless".

Kerlinger and Lee (2008) asserted further that the most difficult problems is that of identification and that SEM is most suited to the study and analysis of complex structural theoretical models in which complex chains of reasoning are used to tie theory to empirical research. It is definitely not a panacea for badly designed studies.

Moreover, Nebojsa (2014) has reviewed and criticised the use and misuse of SEM in management research. Furthermore, according to Bugozzi (2016), SEM is a modeling tool with many ambiguities and there is need for caution and humility in its use.

Statistics is what statisticians do. Traditionally, they do it on a basis of assumptions. The SEM by LISREL model is based on the following assumptions (Fox, 2006: 116-117) :

1. The measurement errors:
   - Have expectations of o;
   - Are each mutivariately-normally distibuted;
   - Are independent of each other;
   - Are independent of the latent exogenous variables, latent ecdogenous variables, and structural disturbances.
2. The N observations are independently sampled.
3. The latent exogenous variables are multivariate normal.
   - This assumption is unnecessary for exogenous variables that are measured without error.
4. The structural disturbances
   - Have expectations of o;
   - Are multivariate-normally distributed;
   - Are independent of latent exogenous variables.

It is also advisable that researchers in the social sciences consider these assumptions seriously if their research design and empirical data meet with the assumptions before an application of SEM for analytical purposes in their research.

References

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