An Introduction To SEM Techniques: For Beginners

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INTRODUCTION

Use of SEM (Structural Equation Modeling) is becoming more common as researchers are keen to produce scholarly work. 50 years ago, the top marketing journals contained articles that were virtually free of mathematical or statistical inference with significance tests or any form of multivariate data analysis (Barry J. B. et al., 2008). These articles lacked in statistical sophistication. Today, researchers are interested in writing papers rich in quantitative methodologies. Moreover, ideas backed by numerical justification enjoy credibility and accuracy. Papers using SEM rate more highly on conceptual/theoretical development, research methodology, and even in writing quality (Idem, 2008). The purpose of this paper is to demonstrate the SEM technique through three distinct stages of SEM, developing measurement model, developing structural model and interpreting results. It aims to present distinct characteristics of SEM and is a basic introduction to SEM (Structural Equation Modeling).

HISTORY OF SEM

Origin of SEM dates back to the second half of the twentieth century. SEM was first developed by researchers on genetics and economists, who were interested in causal relationship between variables (Habelmo T., 1943). However, due to its complexity, it could not gain much popularity until 1994. Thanks to computer advancements, more than 300 articles based on SEM were published in social science by the year 2000 (Hair J. F., et al, 2008). Today, SEM has become the dominant technique (Hershberger, S. L., 2003). SEM first appeared in the Journal of Marketing Research and was initially propagated and promoted by marketing researchers Anderson, Bagozzi and Fornell (Wynne W. C., et al, 2008).

WHAT IS SEM?

SEM is an acronym of Structural Equation Modeling. SEM examines the relationship between variables. In recent years, SEM has become a useful method in social and behavioral sciences for specifying, estimating, and testing hypothesized interrelationships among a set of substantively meaningful variables (Crowley and Xitao, 1997). It combines factor analysis and regression analysis and moves forward. It is rightly said to be an extension of both these. SEM is far sophisticated. It is a powerful tool that enables a researcher to test relationship between multiple independent variables and multiple dependent variables. Factor analysis, regression analysis and multiple regression analysis all have a limitation; all can examine only a single relationship (Hair J. F., et al., 2008). SEM can examine series of dependent relationships and can also test interdependent relationships. SEM is a collection of statistical techniques that allow a set of relations between one or more independent variables and one or more dependent variables (Jodie B. U., 2006). Due to such versatility, SEM is called by different names - causal modeling, causal analysis, simultaneous equation modeling, analysis of covariance structures, path analysis or CFA (Idem, 2006). SEM is also known by a variety of other names, including covariance structure analysis, latent variable modeling or causal modeling (Crowley and Xitao, 1997).

ADVANTAGES OF SEM

Following are the key advantages of SEM. **(1)** SEM estimates all coefficients in the model simultaneously (Paul A. D., 2008) i.e. it can examine series of dependence relationships simultaneously (Hair J. F., et al., 2008); **(2)** This is the only technique where a dependent variable becomes an independent variable in subsequent dependence relationship; **(3)** Assesses measurement and tests relationship in one technique; **(4)** Can test non-recursive relationship where a construct effects another construct, and is effected by this single construct (Idem, 2008); **(5)** Performs path analysis modeling with latent variables (Fornell C, 1987); **(6)** SEM accounts for measurement error in latent variables when estimating path relationships between latent variable (G. J. Medskar et al., 1989, Bagozzi R. P., 1982, Bagozzi R. P.,

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1977); **(7)** SEM is ideal for testing and comparing rival theoretical models (G. J. Medskar et al., 1989).

☸ **Constructs and Variables :** SEM is a test of relationship between variables. Thus, it becomes imperative to elaborate these variables used in the test. There are two kinds of variables found in a structural model: observed variables and unobserved variables. Unobserved variables are also called as latent variables or factors or constructs. They are represented by a circle or oval in the model. Latent variables cannot be measured directly; they require three or more measured variables (Indicators). Measured variables are observed variable. They can be measured directly. They are represented by a square in the model. Observed variables are also called as indicators or manifest variables. These measured variables are items on the scale. The scale items are indicators of the latent variable that is why they are named as indicators. Measurement theory suggests that minimum three indicators should be used to measure latent variables (Steenkamp J. B. and H. Van Trijp, 1991). However, it is possible to test a model with two indictors.

☸**Exogenous and Endogenous Constructs :** Constructs can be endogenous and exogenous. If you remember, a regression analysis is a mathematical relationship between one metric independent variable and one metric dependent variable. Similarly, in a SEM model, we have independent and dependent constructs. Endogenous constructs play a role of dependent variables. In a path diagram, endogenous constructs have arrows pointing towards them. Exogenous constructs play a role of independent variables. In a path diagram, exogenous constructs have arrows pointing away from them (See figure 1). In SEM terminology, variables (latent or observed) that only exert an *"effect"* on other variables are called exogenous variables, while those that receive an effect from any others are called endogenous variables (Crowley and Xitao, 1997).

Figure 1 : Relationship Between Exogenous And Endogenous Constructs

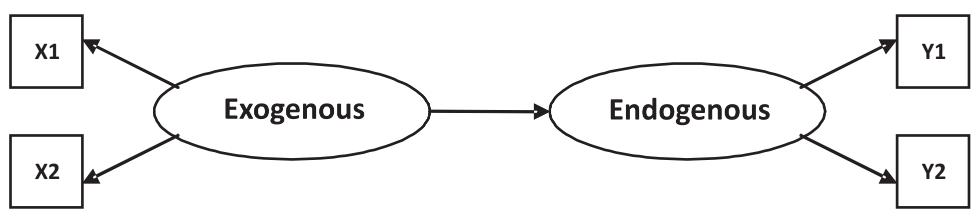


Figure 1 shows a dependence relationship between exogenous (independent) construct and an endogenous (dependent) construct. Similarly, the exogenous construct is associated with measured variables X1 and X2, and the endogenous construct is associated with measured variables Y1 and Y2.

SAMPLE SIZE

One of the challenges in using SEM technique is to decide the appropriate sample size. Although, there is no consensus on what should be the sufficient sample size, experts have offered a suggestion to decide one. Boomsma, 1987 has recommended a bottom-line number of 200. Jodie B. U (2006), stated, *"SEM is based on covariance, and covariances are less stable when estimated from small samples. Parameter estimates, and chi-square tests of fit are also very sensitive to sample size. So, generally, large samples are needed for SEM analysis. However, if variables are highly reliable, it may be possible to estimate small models with fewer participants"*. Though SEM is a large sample technique, test statistics developed by Bentler and Yuan (1999) is based on small sample size. Hair J. F., et al., (2008) have made the following suggestions for sample size decision based on model complexity and basic measurement model characteristics:

The SEM model containing five or fewer constructs, each with more than three items (observed variables), and with high item communalities (0.6 or higher), it can be adequately estimated with a sample as small as 100-105. Communality is the variance explained in the measured variable by the construct. In CFA, it is referred to as square multiple correlation. If item communalities are modest (0.45-0.55), or the model contains constructs with fewer than three items, then the required sample size is more on the order of 200 . If the communalities are lower, or the model includes multiple under identified (fewer than three items) constructs, then minimum sample sizes of 300 or more are needed to be able to recover the population parameters.

Table 1 : Sample Sizes Used In Previous Studies Based On SEM		
Sample size	Number of constructs	Source
281	4	Poznanski and Dennis, 1997
153	4	Nor A. O., et al., 2007
96	5	Njite D. and Parsa., 2005
521	6	Ann M. F., et al., 2004
780	6	Kevin E. D., et al., 2008
206	7	Ann M. F., et al., 2005
416	7	Mayfied J. and Milton, 2007
206	8	Brain D'Netto, et al., 2008
201	8	Fen-Hui Lin and Jen-Her, 2004
495	8	Kaili Yieh, et al., 2007

When the number of factors is larger than six, some of which use fewer than three measured items as indicators, and multiple low communalities are present, sample size required may exceed 500. The Table 1 shows sample size adopted for different studies done previously using SEM. The above statistics show that the sample size used for SEM ranges between 96-780. There is no single or standard sample size that is the most appropriate, rather size of the sample depends upon the complexity of the model.

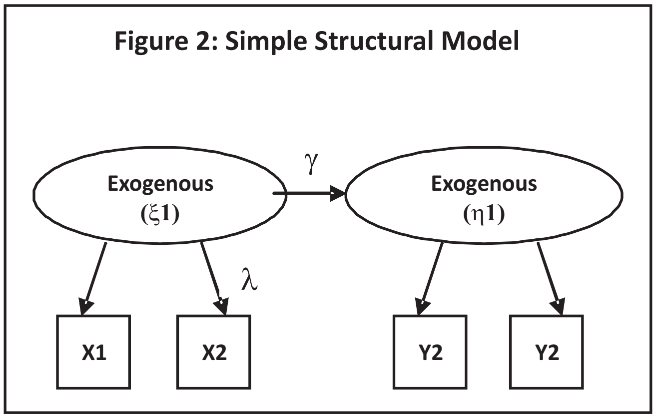
MODEL - THE PATH DIAGRAM

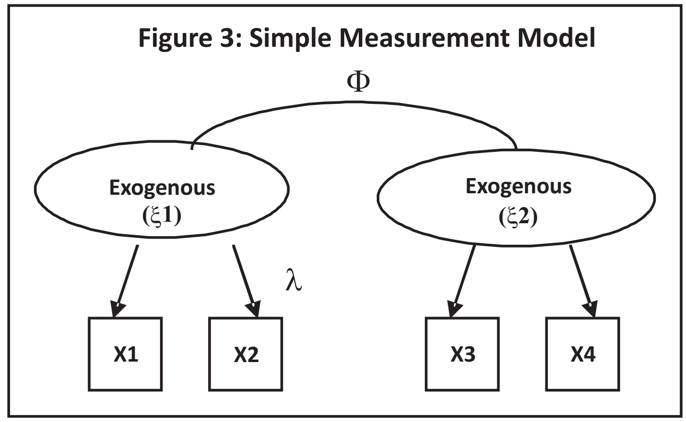
The purpose of SEM is to develop a model based on the theory and then test this model for validity. SEM is a theory testing technique. For representation of the theory, the researcher needs a model. A theory is a hypothesized phenomenon demonstrated by a group of latent variables and relationship between them. A Model is the graphical presentation of the researcher's theory, demonstrating a relationship between variables. Model development in SEM requires two steps by the researcher - developing and testing the measurement model and developing and testing the structural model. Once the measurement model is tested valid, the researcher goes ahead with testing the structural model. As suggested by Hair J. F., et al., 2008, three approaches can be used in model development: Confirmatory Model, Competing Models and Model Respecification. *Confirmatory* is a single original model developed by the researcher to see how well it fits the data using SEM. However, in reality, several alternative models may as well have a good fit to the data. These alternative models serve as competing model for the original one. Finally, model respecification can be done through modifications of measurement or structural models.

MEASUREMENT MODEL (CFA) AND STRUCTURAL MODEL (PATH ANALYSIS)

SEM has a two-step approach (G. J. Medsker, et al., 1994, Anderson J. C. and Gerbing D. W., 1988). SEM is a powerful statistical technique that combines the measurement model (confirmatory factor analysis) and the structural model (regression or path analysis) into a simultaneous statistical test (Aaker D. A. & Bagozzi R. P., 1979, Bagozzi R., 1980, Bagozzi R. P., 1981). In the first step, the researcher tests the measurement model through CFA. In this step, the researcher tests construct validity by testing construct unidimensionality, reliability, convergent validity, discriminant validity and predictive validity (Anderson J. C. & Gerbing D. W., 1988). Once the measurement model is validated, the researcher conducts the second step, testing the structural model, estimating structural relationship (regression or path analysis) between latent variables. It is in the second step where the theoretical model is tested (Idem, 1988).

The Measurement model describes how well the observed indicators serve as a measurement instrument for the latent variable (Joreskog K. & Sorbom D., 1993). Thus, the measurement model is an important tool to assess construct validity (Garver & Mentzer, 1999) Measurement model validates the relationship between construct and indicators i.e. between observed variables and latent variable (factor/construct). The Measurement model allows all latent variables to correlate freely. Structural model validated relationship between constructs themselves. In short,





researcher may specify whether the SEM undertaken is a one-step model or a two-step model. In the first step, CFA is conducted, in the second step, the structural model is examined. The Figure 2 represents a simple structural model. A straight arrow is used to show a dependent relationship. It is necessary to specify independent and dependent latent variables (construct). The Figure 3 shows a simple measurement model. Curved arrow is used to show the correlation between constructs. In correlation, it is not necessary to distinguish between the independent and dependent variables because the purpose is to study correlations among variables.

CONFIRMATORY FACTOR ANALYSIS (CFA)

CFA stands for Confirmatory Factor Analysis and is a model in SEM. It deals with the relationship between observed variables and factors (constructs). Putting it in simple words, CFA tests how well the measured variables represent the construct. Conducting CFA in SEM is like doing Factor Analysis. In statistical terms, Factor Analysis is also referred to as Exploratory Factor Analysis (EFA). The objective is to have as few factors as possible, yet account for a reasonable amount of the information contained in the original variables. Though, both CFA and EFA have the same task of testing construct validity, they are different from the theoretical and mathematical perspective (Crowley & Xitao, 1997).

EFA is data-driven (Bollen K. A., 1989; Pedhazur & Schmelkin, 1991), whereas CFA is theory-driven. EFA is a data reduction technique. Variables are reduced to a lesser number of factors using the factor loading technique. Factors are known only after the analysis, and then they are named. EFA is conducted without knowing how many factors will be resulting in after the analysis, and also which variable will belong to which factor. Whereas in CFA, the researcher has to specify the number of factors, and the number of variables required for the theory building and also, which variable relates to which factor. In other words, EFA is an exploratory set of variables, which explores factors. CFA is a confirmatory factor, which confirms a set of variables. In EFA, variables lead to factors. In CFA, it is tested how well the factors explain the variables.

SEM has two theories, a measurement theory and a structural theory. Researchers will now need a measurement model that graphically represents the measurement theory. CFA confirms the measurement theory. Measurement theory specifies the relationship between measured variables and construct i.e. how well the measured variables represent the construct. In CFA, there is no need to distinguish between exogenous and endogenous construct because the overall objective is to test the construct validity. (No dependence relationship between construct is specified). Since measurement theory examines a relationship between construct and indicators, the construct becomes independent variable, and the indicators become dependent variables (reflective relationship). Construct validity is essential in confirming a measurement model. Construct validity is the extent to which the measured variable actually represents the latent construct (Hair J. F., et al., 2008; Bagozzi R. P., et al., 1991). CFA is a powerful method for addressing construct validity (Bagozzi, R. P., et al., 1991). Construct validity is elaborated in the following discussion.

CONSTRUCT VALIDITY

The basic reason behind a researcher using SEM is to test his theory. A theory involves a linkage between latent variables (constructs) that together explain a phenomenon. As said earlier, constructs are unobserved variables and cannot be measured directly. Thus, a researcher needs to develop a set of measured items that capture the domain of the latent construct. As constructs cannot be measured directly and are dependent upon measured variables for their definition, measuring the validity becomes necessary. The validity of construct is a condition for theory development and testing and ,therefore, construct validity lies at the very heart of scientific progress in marketing. (Jan-Benedict, et al., 1991).

Construct validity is the degree to which a construct achieves empirical and theoretical meaning (Bagozzi R. P., 1980; Peter, 1981), the extent to which a set of measured variables actually represents the theoretical latent construct they are designed to measure (Hair J. F., 2008, p. 731). According to Churchill G. A., Jr. 1979; Churchill G. A., Jr. 1992, construct validity examines the degree to which the scale measures what it is intended to measure. It is most directly concerned with the question of what the instrument is, in fact, measuring (Churchill Gilbert A. Jr., 1999), the extent to which the scale measures the construct it was intended to measure (Dunn S. C., et al., 1994). Construct validity includes content validity, substantive validity, unidimensionality, reliability, convergent validity, discriminant validity, and predictive validity (Garver & Mentzer, 1999). Nomological validity is another sub-dimension of construct validity (Dunn S. C., et al., 1994; Hair J. F., 2008).

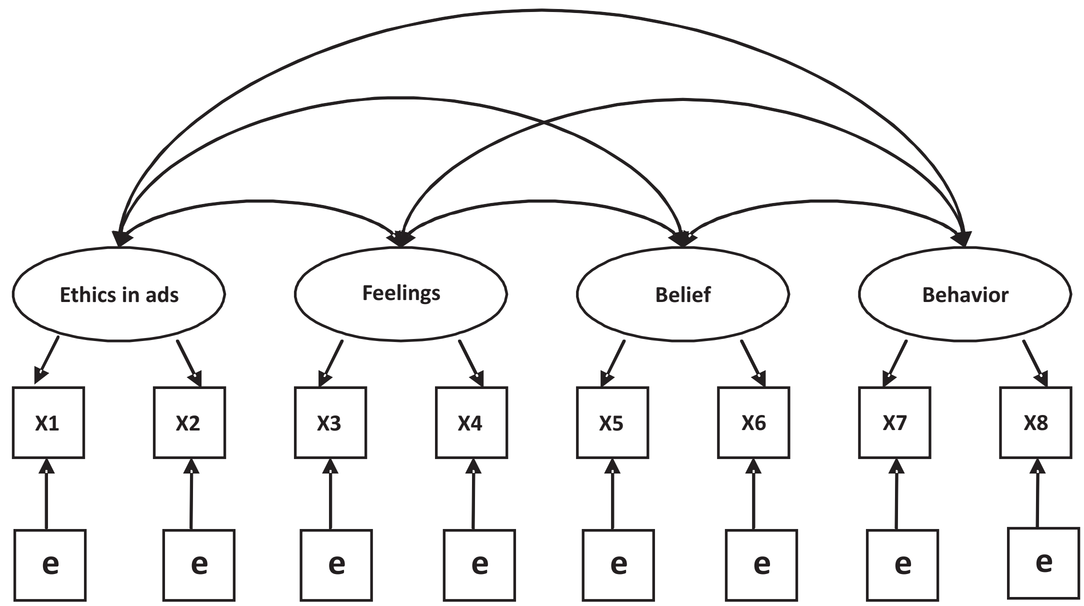
Content validity is also called as face validity. Content validity deals with the meaning and scope of the construct as covered by measured items. Content validity focuses on the adequacy with which the domain of the characteristic is captured by the measure (Churchill Gilbert A. Jr., 1999). It answers the question how well the measured variables of a particular construct represent the construct? I.e. how well the content of the scale covers the entire domain of the construct being measured? Face validity is the extent to which the contents of the items are consistent with the construct definition (Hair J. F., et al., 2008). Substantive validity refers to the theoretical linkage between the construct and its items (Dunn S. C., et al., 1994). The difference between content validity and substantive validity is that the former deals with a set of items, and the latter deals with each individual items of the construct (Idem, 1994). Testing for content and substantive validity is mostly subjective, yet it requires extensive knowledge and insight into the conceptual nature of the construct within a given context (Garver & Mentzer, 1999). Unidimensionality is another dimension of construct validity. Unidimensionality is the degree to which items represent one and only one underlying construct (Idem, 1999). Reliability is the consistency of responses to a question (Burns Alvin C. & Ronald F. Bush, 1998, p. 307). It is the extent to which a scale produces consistent results if repeated measurements are made on the characteristics (Malhotra N. K., 2004, p. 267). Reliability assesses the consistency, not accuracy of the measurement scale (Churchill G. A. & J. P. Peter, 1984). According to Garver. & Mentzer (1999), it is the ability of the scale to produce consistent results if the scale is administered overtime. Convergent validity is the extent to which the latent variable correlates to items (Dunn S. C., et al., 1994). Do the items intended to measure a latent variable statistically converge together? (Garver & Mentzer, 1999). Convergent validity focuses on how well the construct's measurement positively correlates with different measurement of the same construct (Hair, et.al., 2002, p. 379). To quote Malhotra N. K. (2004), p. 269, *"convergent validity is a measure of construct validity that measures the extent to which the scale correlates positively with other measures of the same construct"*.

Discriminant validity simply means that the different constructs should differ. It is the extent to which a construct truly differs from other constructs (Hair J. F. et al., 2008). As confirmed by Bagozzi R. P., et al., 1991; Davis, 1989, it is the degree to which measures of two constructs are empirically different. Malhotra Naresh K. (2004), p. 269 considers discriminant validity as a type of construct validity that assesses the extent to which a measure does not correlate with other constructs from which it is supposed to differ. Where as Hair, et al., 2002, p. 380 says it assesses that the construct being investigated does not significantly correlate with other constructs that are operationalized as being different.

Predictive validity is ascertained by how well the measure predicts the criterion (Churchill Gilbert A. Jr., 1999). It estimates whether or not the construct of interest predicts or covaries with construct that is supposed to predict or covary (Dunn S. C. et al., 1994). Whereas, Nomological validity is the test of validity that examines whether the correlations between the constructs in the measurement theory make sense (Hair J. F., et al., 2008). Nomological validity refers to whether the construct performs as expected within its nomological network (Schwab, 1980). Nomological validity of a construct exists when the construct relates to the other research constructs in a way that is consistent with the underlying theory (Peter, 1981).

The Figure 4 shows the CFA Model with error terms pointing towards measured variables X1 - X8. Ethics is

Figure 4: CFA Model



advertising as perceived by respondents, feelings generated eventually, beliefs formed and behavior intentions are four latent constructs with measured variables Xs.

ITEMS PER CONSTRUCT

How may number of items (measured variables/indicators) are required to define a construct is a commonly asked question. Fortunately, the answer is not very difficult. A researcher should select something between too many indicators and very few indicators. More items do produce higher reliability and generalizability (Bacon, et al., 1995), but more items are not necessarily better (Hair J. F., 2008, p. 807). More items also require larger sample sizes and can make it difficult to produce truly unidimensional factors (Idem, 2008, p. 807). On the other hand, using one or two indicators increases the possibility of interpretational confounding (Burt R S, 1976). However, good practice dictates a minimum of three items per factor, preferably four (Hair J. F., 2008, p. 807). A general rule of thumb is that measurement models have difficulty estimating over 5 parameters (Indicators) for a given latent variable. Three indicators per latent variable is ideal, whereas two indicators may cause an identification problem and certainly cause reliability measurement problems (Garver & Mentzer, 1999).

FIRST-ORDER MEASUREMENT MODEL AND SECOND-ORDER MEASUREMENT MODELS

CFA may include a first-order measurement model or a second-order measurement model. A first-order measurement model has one layer of latents construct and the second-order measurement model has two layers of latent construct. Whether the measurement model is first or second order test of construct validity is required. Whether specifying constructs in the measurement model as a first order or second order factor, it is imperative that both the first and second order measurement models are tested for unidimensionality and reliability (Anderson J. C. & Gerbing D. W., 1988). The question that pops up is: *"How would the researcher know whether a first order or second order factor model is required?"* As an answer to this question, Garver & Mentzer, 1999, said, *"Researchers should examine the correlation coefficient between first order factors. If the correlations are relatively high, above 0.7, then, from a statistical perspective, the respondents are viewing this phenomenon at the second order factor level... However, researchers should also bring theoretical interest to this issue. Would the first or second order factor model better answer the research question? Both theoretical and statistical considerations should be considered when determining the level of factors to be specified in the measurement model."*

Figure 5: First- Order Measurement Model

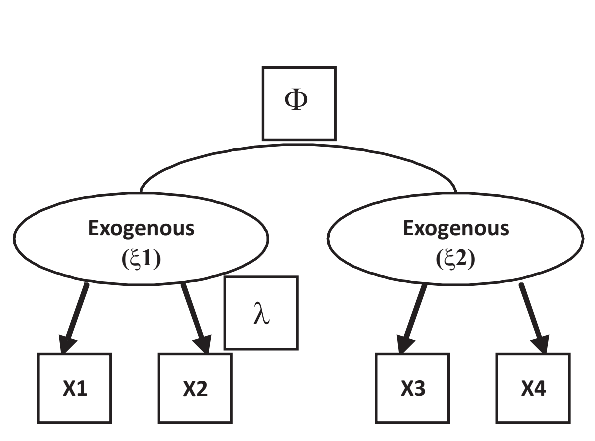


Figure 6: Second- Order Measurement Model

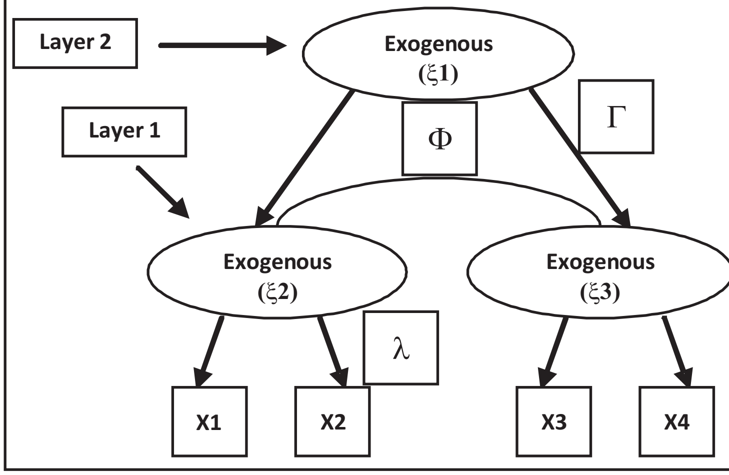


Figure 5 show First-order Measurement Model with one layer of latent constructs, and Figure 6 show second-order Measurement Model with two layers of latent constructs.

FORMATIVE VERSUS REFLECTIVE RELATIONSHIP

Indicators (measured variables) can be formative or reflective. It will be more appropriate to say that relationship between the latent variable (construct) and the measured variables (indicators) can be formative or reflective. A formative relationship is one where the measured variables cause the latent variable, (e.g. education, wealth, status decide the social class). Here, we have the arrow drawn from the measured variable pointing to the latent variable. A reflective relationship is one where the latent variable causes the measured variable (e.g. decease causes symptoms). Here, we have the arrow drawn from the latent variable pointing to the measured variable. In most social sciences studies, one will find a reflective relationship; measured variables are caused by the factor. However, considering the importance of the research validity, one has to ascertain that the relationship is correctly defined. A study done by Jarvis, et al., (2003) found that 28% of the research work has misrepresented measured variables as reflective. They further state as follows, *"measurement indicators are formative* ***(1)*** *If they define characteristics of the latent construct;* ***(2)*** *Cause a change in the construct rather than vice - versa;* ***(3)*** *Does not share a common theme among themselves;* ***(4)*** *Is fundamental to the definition of the construct, rather than parallel or substitute reflection of it;* ***(5)*** *Does not necessarily covary;* ***(6)*** *does not have the same antecedents and consequences"*.

Figure 7: Formative Relationship

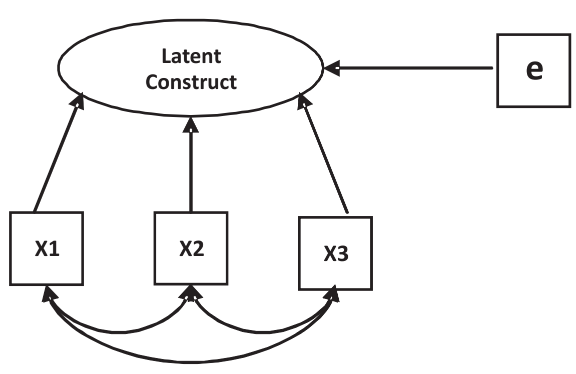


Figure 7 show a formative relationship between measured variable and latent construct. Arrows are pointing from measured variables to latent construct. This latent construct also has an additional arrow of error term.

PATH ANALYSIS

As said earlier, SEM combines measurement model and structural model. After testing the measurement model, the researcher goes further with testing the structural theory or structural model. CFA has a limitation that it cannot go beyond examining a relationship between measured variables and constructs as well correlations between constructs. In other words, it cannot measure the dependence relationship between constructs. Structural model is the graphical representation of the structural theory. It is a set of structural equations. Structural theory is the conceptual representation of the relationship between constructs. Structural theory examines the dependence relationship between the latent variables. Thus, it is necessary to specify a dependent variable and independent variable as we do in multiple regression analysis. Changing correlations relationship between constructs to a dependence relationship changes a measurement model to a structural model.

Figure 8: Full Structural Model

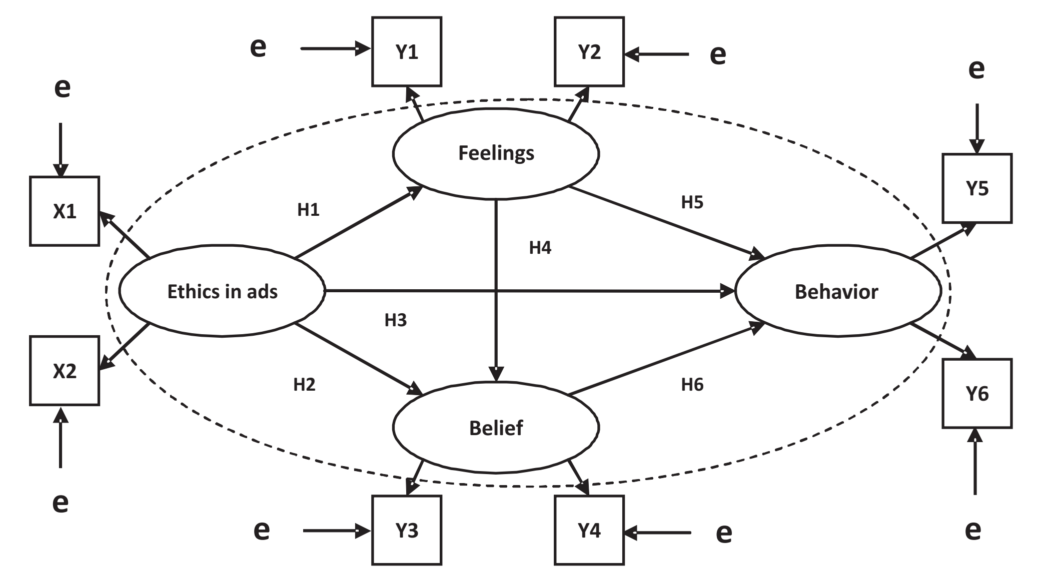
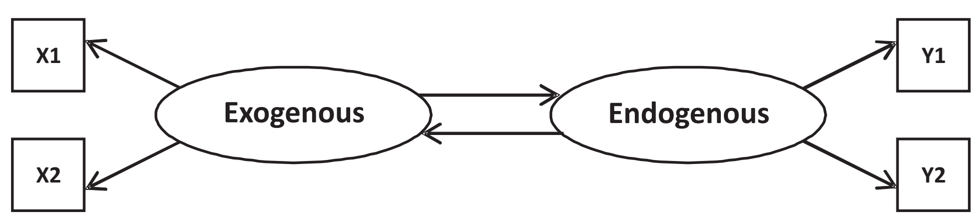


Figure 8 shows the Full Structural Model. The part outside the oval represents the measurement model describing the relationship between latent constructs and their indicators. Part inside the oval represents the structural model describing the relationship among four latent constructs: *'Ethics in ads'*, *'Feelings'*, *'Belief'* and *'Behavior'*. *'Ethics in ads'* is an exogenous construct. *'Feelings'*, *'Belief'* and *'Behavior'* are endogenous constructs. *'Feelings'* and *'Belief'* later becomes an exogenous construct in a subsequent relationship.

RECURSIVE VERSUS NON- RECURSIVE MODELS

Structural models can be recursive or non- recursive. According to Hair J. F., 2008, a model is considered recursive if the paths between the constructs all proceed only from the independent construct to the dependent construct i.e. no pair of construct has arrows going both ways between them. In contrast, a non-recursive model contains feedback

Figure 9: A Non- Recursive Model



loops. A feedback loop exists when a construct is seen as both - a predictor and an outcome of another single construct, i.e. one pair of construct will have arrows going both ways between them (See Figure 9).

MODEL RESPECIFICATION

Model resepecification becomes necessary for improvement in fit. Very often, the original model does not show a good fit, thus necessitating a modification. The hypothesized model is modified by adding or deleting paths until the *'best'* model is not identified (Wynne W. Chin et al., 2008). Model respecification entails paths' addition or deletion or both. Indeed, by changing paths, or permitting manifest variable or construct error variances to covary, virtually any theoretical model can be sufficiently distorted to fit existing data. (McQuitty, 2004). At a minimum, modifying an initially estimate structural equation model reduces its generality and requires that it be validated with an independent sample. (Wynne W. Chin, et al., 2008).

RESULT INTERPRETATION USING CFA

In SEM, there are some statistical outputs, which can be used to measure the construct reliability. They include square multiple correlations R^2 for each measurement item, composite reliability, and variance extracted for each factor (Nor A. O., et al., 2007). As a rule of thumb, measurement variables are reliable when the square multiple correlations R^2 of each is greater than 0.5 (Byrne, 2001). Composite reliability should be greater than 0.7, and variance extracted (AVE)>0.5 to indicate reliable factors (Hair et al., 1998).
Traditionally, Coefficient alpha (Cronbach's alpha) is used to test reliability of scale. Alpha scores with over 0.7 are considered as reliable. However, coefficient alpha has certain limitations, and SEM is a tool that overcomes these limitations (Garver & Mentzer., 1999). Results of the measurement models present output such as the standardized factor loading, standard errors (SE), t values, average variance extracted, and squared multiple correlations. Squared multiple correlations for items should be over 0.5. Average variance extracted should also have a value over 0.5. The threshold value for average variance extracted is 0.50 (Fornell and Larcker, 1981). t value should be greater than or equal to 1.96.
CFA is a powerful tool to assess the convergent and discriminant validity of the latent constructs (Anderson J. C. and Gerbing D. W., 1988). Convergent validity is assessed using three criteria: **(1)** Individual lambda coefficient (standardized factor loading). This value should be greater than 0.7; **(2)** A significant *t* static for each path (Gefen D., 2000); **(3)** Path loading greater than twice its standard error (Anderson J. C. and Gerbing D. W. 1988). Discriminant validity is seen if the inter-correlation is less than 0.60 (Carlson et al., 2000). In other words, latent variables to pass the convergent validity test, each item lambda coefficient (Factor loading) should be above 0.7 and *t* value should reach the significant level ($*p < 0.05$ or $**p < 0.01$ or $***p < 0.001$) and to pass the discriminant test, the inter-correlations should be smaller than 0.60.

EVALUATING THE MODEL FIT

Finally, it is necessary to see how closely the data fits the model. The null hypothesis in SEM is that the model fits the data. The overall objective of structural equation modeling is to establish that a model derived from the theory has a close fit to the sample data in terms of the difference between the sample and model-predicted covariance matrices (Paul A. Dion, 2008). Several fit indices are used to test this hypothesis that there is no difference between model and observed covariance matrices. Fit indices determine whether the pattern of variances and covariances in the data is consistent with a structural model specified by the researcher (Kevin E. Dow, et al., 2008). The fit indices tell the researcher about the model fit. Two decisions are important in studying the model fit: (1) Selecting fit indices, which represent different families of fit indices (Hair J. F. J., et al., 1995; Bollen K. A. and S. J. Long, 1992) and (2) Specifying a stringent criterion and selecting fit indices that best represent these criteria (G. J. Medskar, et al., 1994; Marsh H. W., et al., 1988).
When evaluating a model, the researcher is often faced with a decision of which fit indices to see and how many. A lot of uncertainty prevails with regards to the reply to these two basic questions. Crowley and Xitao (1997), p. 515 believe that there is no universally accepted criterion to judge how well the model fits the data, thus leaving much room for subjective opinions and consequently, disagreements. Considering these facts of modeling testing, it makes more sense to look at a few indices from different families of fit indices. Moreover, researchers propose a large

number of fit indices and this number is increasing. Thus, a researcher is not required to see all the fit indices. Hair J. F., 2008 suggests one should rely on at least one absolute fit Index, one increment fit index (also referred as comparative fit index), one badness-of-fit index besides chi-square and degree of freedom. ***Absolute fit indices*** assess how well a researcher's theory fits the sample data. No comparison with any other model is done (Idem, 2008). ***Incremental fit indices*** measure the proportionate improvement in fit by comparing a target model with a more restricted, nested baseline model (Daniel R. Williams et al, 1999). Incremental fit indices assess how well a specified model fits relative to some alternative baseline model (null model) (Hair J. F., 2008). The ***parsimonious indices*** are used when competing models are compared. Parsimonious indices help a researcher in knowing which model amongst the alternative has better fit to the data (Crowley and Xitao, 1997). In simple sense these indices measures which model is the best amongst a set of competing models. The following discussion includes a detailed explanation on various fit indices, their significance and the fit criteria.

Table 2 : Fit Indices, Full Forms And Fit Criteria

Fit Indices	Full Forms	Fit criteria
Absolute fit		
X^2/df	A ratio of the chi-square to degree of freedom	Less than 3
RMR	Root Means Square Residual (measures badness of fit)	Close to 0, less than 0.05 is better
GFI	Goodness-of-fit index	GFI $\in$ (0,1) More than 0.9, Close to 1 is better
AGFI	Adjusted Goodness-of-fit index	AGFI $\in$ (0,1) More than 0.9/0.8, Close to 1 is better
RMSEA	Root Mean Square Error of Approximation	Less than 0.08 for good fit and less than 0.05
	(measures badness of fit)	for excellent fit
Comparative fit		
NFI	Normal Fit Index	More than 0.9, Close to 1 is better
NNFI / TLI	Non-Normed Fit Index also called as Tucker lewis Index	More than 0.9, Close to 1 is better
IFI	Incremental Fit Index	IFI $\in$ (0,1) Close to 1 is better
CFI	Comparative Fit Index	More than 0.9, Close to 1 is better
RFI	Relative Fit Index	More than 0.9, Close to 1 is better
ECVI	Expected Cross Validation Index	ECVI > 0, the smaller the better
Parsimonious fit		
PNFI	Parsimonious Normed Fit Index	PNFI $\in$ (0,1) Close to 1 is better
PGFI	Parsimonious Goodness-of-fit Index	PGFI $\in$ (0,1) Close to 1 is better
AIC	Akaike Information Criterion	Smaller is better
CAIC	Constant AIC	Smaller is better
Adapted from Hair J. F., et al., 2008; Fen-Hui Lin & Jen-Her Wu, 2004; AMOS 6.0 User's Guide.		

❁**Chi-square (X^2) and X^2/df :** Chi-square is the most common method of evaluating a fit (Garver & Mentzer, 1999). The X^2 value is a measure of the difference between what the actual relationships in the sample are and what would be expected if the model were assumed correct. (Paul A. Dion, 2008). However, the Chi-square technique has certain limitations.

Chi-square relates to a strict yes or no decision regarding whether the hypothesized model is correct or not (Danniel R. Williams, et al., 1999). Some are tempted to avoid Chi-square tests to assess overall fit because of their sensitivity to sample size and other biases (James, et al., 1982). This fit index is highly sensitive to sample size and the significance test can be misleading (G. J. Medskar, et al., 1994; Hulland J., et al., 1996; Marsh H. W., et al., 1988; Baumgartner H., et al., 1996). When evaluating the chi-square statistic, the analyst wants to find *"non-significance"* , which means the actual observed matrix is not considerably different from the estimated matrix. Thus, the researcher wants a low chi-square value, indicating a good fit. However, when sample size becomes large (over 200 observations), significant difference will be found for most models. (Garver & Mentzer, 1999). This is particularly troublesome since a minimum sample size of 200 observations is recommended to obtain a stable parameter estimates (G. J. Medskar, et al., 1994; Hulland J., et al., 1996; Baumgartner H., et al., 1996). Thus the chi-square test statistic should be used with caution in evaluating SEM measurement models. (Garver & Mentzer, 1999).

In these situations, it is often more useful to examine the ratio of chi-square to the degree of freedom. The model is generally considered to have a good fit to the data when this ratio is less than 3 (Bollen, 1989; Bollen & Long, 1993; Schumaker & Lomax, 1996).

❅**Root Mean Square Residual (RMR) :** The RMR (Root Mean Square Residual) is the square root of the average squared amount by which the sample variances and covariances differ from the estimates obtained under the assumption that your model is correct. The smaller the RMR, the better it is. An RMR of 0 indicates a perfect fit (AMOS 6 User's guide, pp. 508,509).

❅**Goodness-of-Fit Index (GFI) :** GFI is a measure of the relative amount of variance and covariance between variables that are predicted by sample size (Bollen, 1989). GFI ranges from 0 to 1, with close value to 1 being indicating a good fit, and 1 indicating a perfect fit (Arbuckle, 1999).

❅**Adjusted Goodness-of-Fit Index (AGFI) :** AGFI differs from the GFI only in the fact that it adjusts for the number of degrees of freedom in the specified model (Byrne, 1998). AGFI also ranges from 0 to 1, with a value close to 1 being indicating a good fit, and 1 indicating a perfect fit (Arbuckle, 1999).

❅**Root Mean Square Error Of Approximation (RMSEA) :** RMSEA is related to the difference in the sample data and what would be expected if the model were assumed correct. Because it is a model error term, lower values indicates a better fit. (Paul A. Dion, 2008). RMSEA takes into account the error of approximation in the population and asks the question, How well would the model, with unknown, but optimally chosen parameter values, fit the population covariance matrix if it were available (Byrne, 1998). A Value about 0.08 or less for the RMSEA would indicate a reasonable error of approximation (Arbuckle, 1999; Browne and Cudeck, 1993). RMSEA measures the discrepancy between the observed and estimated covariance matrices per degree of freedom (G. J. Medskar, et al., 1994). The RMSEA measures the discrepancy in terms of the population and not the sample (Hair J. F. J., et al., 1995). Thus, the value of this fit index is expected to better approximate or estimate the population and not be affected by sample size. Again, values run on a common continuum from 0 to 1, with values between 0.05 and 0.08 deemed acceptable (G. J. Medskar, et al., 1994; Hulland J., et al., 1996; Hair J. F. J., et al., 1995; Baumgartner H., et al., 1996). Browne & Cudeck, 1993 suggest that a value of 0.05 or less for RMSEA is indicative of a good fit. RMSEA focuses on the degree of fit between the data and the model at hand (Danniel R. Williams, et al., 1999).

❅**Normal Fit Index (NFI) :** It is a ratio of the difference in the X^2 value for the fitted model and a null model divided by the X^2 value for the null model. It ranges between 0 and 1, with 1 indicating a perfect fit (Hair J. F., et al, 2008, p. 773).

❅**Tucker-Lewis Index (TLI)/NNFI :** TLI shows how effective the model is compared to a null model. The index is computed so that a higher value indicates a better fit (Paul A. Dion, 2008). TLI is also called as the Non-normed Fit Index (NNFI). It compares a proposed model's fit to a nested baseline or null model. Additionally, the TLI measures parsimony by assessing the degree of freedom from the proposed model to the degree of freedom of the null model. TLI also seems resilient against variations in sample size and, thus, is highly recommended (Marsh H. W., et al., 1988). An acceptable threshold for this index is 0.90 or greater (G. J. Medskar, et al., 1994; Hulland J., et al., 1996; Marsh H. W., et al., 1988; Baumgartner H., et al., 1996) .

❅**Incremental Fit Index (IFI) :** IFI has a value between 0 to 1, with values closer to 1 indicating a good fit. IFI is, however, affected by sample sizes and may never reach 1 with small sample sizes even if the model is correct (Njite David, et al., 2005).

❅**Comparative Fit Index (CFI) :** CFI is not affected by model complexity and has a maximum value of one. A good fitting model should have a CFI greater than 0.95 (Paul A. Dion, 2008). Bentler developed the Comparative Fit Index (CFI) as a non-centrality parameter-based index to overcome the limitation of sample size effects. (Bentler P. M., 1990). This index ranges from 0 to 1, with 0.90 or greater representing an acceptable fit. (G. J. Medskar, et al., 1994; Hulland J., et al., 1996; Baumgartner H., et al., 1996).

❅**Relative Fit Index (RFI) :** RFI is obtained from NFI. Values close to 1 indicate a very good fit (AMOS 6 User's guide, pp. 508,509).

☸**Expected Cross-Validation Index (ECVI) :** The Expected Cross-validation Index is an approximation of goodness-of-fit, the estimated model would achieve in another sample of the same size. It is most useful for comparing the performance of one model to another (Hair J. F., et al, 2008, p.772).

Table 3 : Fit Indices Used In The Past Research

Authors	Year	Model	Fit Indices used
Crowley and Xitao	1997	CFA	X^2/df, GFI, AGFI, PFI, BBI*
Poznanski, et al.,	1997	Full	X^2/df RMSR, NFI, NNFI, GFI, AGFI, PNFI
Daniel R. Williams et al.,	1999	Full	X^2/df, CFI, RMSEA
Ann Marie Fiore, et al.,	2004	Full	X^2/df, RMSEA, GFI, NFI
Ann Marie Fiore, et al.,	2005	Full	X^2/df, CFI, NFI, RFI, IFI, RMSEA
Njite David, et al.,	2005	Full	X^2/df, RMSEA, RMSR, GFI, AGFI, CFI, IFI
Wahyuningsih	2005	Full	X^2/df, RMSEA, GFI, AGFI
Dimiter M. Dimitrov	2006	CFA	X^2, RMSEA, CFI, SRMR
Jodie B. Ullman	2006	CFA	X^2, RMSEA, CFI
Nor Asiah Omar, et al.,	2007	Full	X^2/df, RMSEA, CFI, TLI, NFI, IFI, RFI
Mayfield Jacqueline, et al.,	2007	Full	X^2/df, RMSEA, NFI, NNFI, CFI, CFI, BIC
Kaili Yieh, et al.,	2007	Full	X^2/df, GFI, AGFI, CFI, NNFI, IFI, RMSEA
Teresa L. Marino, et al.,	2007	CFA	X^2/df, RMSEA, CFI, PFI
Brian D'Netto, et al.,	2008	Full	X^2/df, RMSEA, CFI, TLI,
Kevin E. Dow, et al.,	2008	Full	X^2/df, GFI, AGFI, RMSEA, CFI, NNFI

*BBI refers to Bayes Inference coefficient
Note: NNFI is also called as TFI

Analysis of the past 15 research papers based on SEM technique show that X^2/df (13), RMSEA (13), CFI (11), GFI (7), AGFI (6) and NNFT (TFI) (6) are commonly used fit indices for model testing. These results show that it is not necessary to look at all the fit indices. Rather, it is sufficient to have one or two fit indices, which represent different families of fit indices. However, the most standard fit indices are X^2/df, RMSEA, TFI and CFI (Paul A. Dion, 2008).

COMPUTER PROGRAMS FOR SEM

SEM was less popular because of the late development of computer programs. The mathematical complexity of SEM limited its application until the computer, and softwares become widely available. As computer programs were introduced, the use of SEM techniques increased. The complex tasks of SEM are now performed by computers without much difficulty. Four most widely used computer programs for SEM are LISREL (Linear Structure Relations), AMOS (Analysis of moment structures), EQS (an abbreviation of equations) and PROC CALIS (Covariance Analysis of Linear Structures). AMOS is similar, but easier to use than LISREL, EQS and PROC CALIS (Hox, 1995).

CONCLUSION

The goal of this article was to provide a general overview of SEM. SEM is a rapidly growing statistical technique. It is a powerful tool to measure dependence relationship between latent constructs. Many researchers are becoming interested in SEM. When it comes to testing relationships, they would surely like to go beyond factor analysis and multiple regressions. Researchers want to develop theories specifying hypothesized relationships between variables and test, both the measurement properties and theoretical relationships in their models.

This article has presented an introduction of SEM. Ideally, this article will serve as a necessary guideline for the researchers keen to use structural equation modeling in their studies and hopefully, persuade readers to continue studying SEM. Although SEM is not without critics, but it is a versatile instrument that answers many research questions when it comes to testing theoretical models. Its popularity will rise in years to come.

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