APPLICATION OF STRUCTURAL EQUATION MODELLING IN CONSTRUCTION INDUSTRY RESEARCH: CONCEPT AND PROSPECTS

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ABSTRACTS: Research in social sciences deals with constructs that cannot be directly measured. In light of this, the authors offer a consumer's guide to the concept, application and prospects of using structural equation modelling in construction industry research as a potential methodology for the modelling of relationships among constructs. Consequently, the study dwells on the underlying concept surrounding the use of SEM with in-depth discussions on the general uses of SEM, steps involved in SEM (model specification, identification, estimation, evaluation and modification) and two-stage SEM approach. The study concludes with presentation of various examples where SEM was used in construction industry research to argument the already discussed concept and principles of SEM.

Keywords: SEM, Structural Equation Modelling, Construction Research, Measurement Model, Structural Model
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INTRODUCTION

In introductory books and other scholarly journals, a simple and accurate definition of SEM can hardly be found. However, Kaplan, (2000), as quoted by Nachtigall et al (2003) defines SEM as "a class of methodologies that seeks to represent hypotheses about the means, variances and covariances of observed data in terms of a smaller number of 'structural' parameters defined by a hypothesized underlying model"

Being a multivariate analytical technique, structural equation modelling (SEM) is a second generation statistical method used in analysis of interrelationships among variables in a model (Awang, 2012; Diamantopoulos et al. 2008; Nachtigall et al. 2003; Sosik et al. 2009; Hair et al. 2012). SEM utilizes various types of models to depict relationships among observed variables, with the basic aim of providing a quantitative test of a theoretical model hypothesized by the researcher (Schumacker& Lomax, 2010). SEM therefore is a hypothesis-testing approach for the analysis of a structural theory on certain phenomenon (Byrne, 2010). Accordingly, Graph, (2013) observed that the evolution of structural equation modelling (SEM) methodology is perhaps the most significant and powerful statistical development in the social sciences in recent years. The term structural equation modelling basically expresses two important aspects of the procedure: (1) that the causal process under study are represented by a series of structural (regression) equations, and (2) that these structural relations can be modelled pictorially to allow a clearer conceptualization of the theory under study.

Consequently, the hypothesized model can then be tested statistically in a simultaneous analysis of the variables to assess the extent to which it fits the data. These abilities of SEM along with others make it increasingly popular among researchers (Kline, 2011) in various disciplines who work with theories concerning the relationships among their hypothetical constructs (Awang, 2012). SEM stands distinctively different from the first generation regression models such as linear regression, LOGIT, ANOVA and MANOVA which can analyse only one layer of linkages between independent and dependent variables at any given time. In SEM statistical methodology: (a) multiple equations can be estimated simultaneously (b) latent variables can be constructed (c) non-recursive models are possible (d) correlations among disturbances are possible (e) formal specification of a model is required (f) measurement and structural relations are separated, with relations among latent variables rather than measured variables (g) assessment of model fit is not as straight forward

Basically, SEM tests various theoretical models such as regression, path analysis and confirmatory factor analysis models. In essence, SEM is based on the assumption of causal relationships where a change in one variable (x1) results in a change of another variable (y1), in which (y1) affects (x1). SEM analysis procedure goes through various stages (Kline, 2011). Kline listed the stages thus: (1) review the relevant theory and research literature to support model specification (2) specify a model (3) determine model identification (4) select measures for the variables represented in the study (5) collect data (6) conduct preliminary descriptive statistical analysis such as data screening, missing values, normality distribution, collinearity issues, outlier detection etc. (7) estimate parameters in the model (8) assess model fit (9) re-specify the model if meaningful (10) interpret and present result.

The Basic Concepts of SEM

Research in social sciences deals with constructs that cannot be directly measured. SEM utilizes two major variables: *latent variables* and *observed variables*. Latent variables also called factors or constructs are abstract phenomena that are not directly observable or measured (Schumacker& Lomax, 2010; Byrne, 2010). Hence they are inferred from a set of observed variables that the researcher actually measure using tests or surveys. Latent variables are normally operationalized in terms of behaviour expected to represent it. Latent variables can either be exogenous or endogenous latent variables. Exogenous latent variables are synonymous with independent variables; they cause fluctuations in the values of other latent variables in the model.

Endogenous latent variables, on the other hand, are synonymous with dependent variables and are influenced by the exogenous latent variables in the model, either directly or indirectly Byrne, (2010). Latent variables are mostly represented in oval shapes in a computer application for SEM such as AMOS, LISREL, EQS and Mplus. Observed variables also called measured, manifest or indicator variables are set of variables used to define, measure or infer the latent variables. Observed variables are represented in rectangular shape. SEM performs two types of modelling: (1) measurement model and (2) structural model. The measurement model (mostly referred to as confirmatory factor analysis) focuses wholly on the relationships between latent variable and its indicators whereas a structural model allows for the specification of regression structure among latent variables i.e. the impact of one latent variable on the other (Bryne, 2010, Schumacker& Lomax, 2010; Hair, 2010; Coltman et al. 2008; Hair et al. 2012; Kline, 2011; Graph, 2013; Diamantopoulos et al. 2008; Lei et al. 2007; Peltier et al. 2012; Chen & Lin, 2010; Koh, 2012; Sosik, 2009; Burger-Helmchen, 2009).

SEM Statistical Techniques

The primary analysis that SEM is capable of performing is carried out through one of two distinct statistical techniques (Gefen, 2000; 2011):

(i) Covariance-based analysis – as employed in LISREL, EQS and AMOS and
(ii) (Component-based SEM) Partial Least Squares-based analysis – as employed in PLS and PLS-Graph

Various review researchers (Gefen et al. 2011; Hair et al. 2011; Bollen& Davies, 2009; Chin, 2010) have examined the major differences between the two SEM statistical techniques. The fundamental differences between the two SEM techniques are objectives in analysis, the statistical assumptions they are based on and the nature of the fit statistics they produce. For instance, whereas the statistical objective of PLS-based SEM is, basically, the same as that of linear regression, the covariance-based SEM shows that the null hypotheses – the *a priori* research model with all its paths is insignificant. In essence, the main objective of covariance-based SEM is to show that the operationalization of the theory under consideration is corroborated and not disconfirmed by the data (Hair et al, 2011; Gefen, 2000; Gefen et al. 2011). Additionally, covariance-based SEM technique, unlike PLS-based SEM, enables an assessment of *unidimensionality*– the degree to which items load only on their respective construct with no parallel correlation pattern.

Most researchers prefer the covariance-based approach in conducting their analysis because of many reasons. Firstly, covariance-based SEM addresses the problem of measurement error by clearly modelling measurement error variance/covariance structure and relying on a factor analytic measurement model (Gefen et al, 2011). Secondly, the covariance-based SEM is most appropriate where a study is based on a strong and sound theoretical consideration inclining it to confirmatory methodology rather than exploratory method specialized by PLS-based SEM. Thirdly, PLS-based analytical technique does not have a global overall inferential test statistic of the kind provided by Covariance-based SEM (such as x^2, GFI, AGFI, NFI, NNFI, RMSEA etc) to adequately assess model fit. Fourthly, PLS-based path modelling parameter estimates are generally known to be biased. On the contrary, parameters estimates obtain from covariance-based SEM are not biased when distribution assumptions hold and are still robust to a mild violation of those assumptions Hsu et al. (2006). Fifthly, the covariance-based SEM is most preferred when the constructs in a study used reflective scales and not formative scales. The use of formative scale is best accomplished with PLS-based SEM (Gefen, 2011) and creates identification problem in covariance-based SEM. Finally, while PLS path modelling makes very limited distributional assumptions of ordinary least squares regression (Hair et al. 2011; Gefen, 2011), covariance-based SEM relies on maximum likelihood estimation which is the method used most often in SEM Kline, (2011).

Steps in Structural Equation Modelling

Experts in structural equation modelling (Lei & Pennsylvania, 2007; Schumacker& Lomax, 2010; Kline, 2011; Iriondo et al. 2003) generally agree on five distinct but interrelated steps to analysis in SEM. The basic steps are: model specification, model identification, model estimation, model evaluation and model modification. Each one of these steps is briefly discussed below.

Model Specification

This is the first step in SEM and basically involves using all the available and relevant theory, research and other information to develop a theoretical model (Kline, 2011). The researcher specifies which relationships are hypothesized to exist among both the observed and unobservable variables (Weston & Gore, 2006) so that any unspecified relationships among the variables are supposed to be equal to zero.Specification is done prior to data collection and the *a priori* model should then be confirmed using variance-covariance data. This is the hardest part of structural equation modelling (Kline, 2011) since the hypothesized model, if properly specified, is deemed consistent with the true population model. All later steps are dependent on this step and researchers are advised to thoroughly gather adequate theoretical insights about the causal relationships among variables. Model misspecification can occur especially when a certain variable does not fully account for the relationships between some variables (Weston & Gore, 2006). At this point, possible changes to the initial model would be required according to justified theory or any empirical findings since not all specified model can be identified and estimated (Lei & Pennsylvania, 2007).

Model Identification

After properly specifying the model, the model is identified prior to the estimation of parameters (Schumacker& Lomax, 2010). Here, the aim is to find the most parsimonious summary of the interrelationships among both observed and unobserved variables that precisely depicts the associations observed in the data (Weston & Gore, 2006). According to Lei and Pennsylvania, (2007), one basic principle in model identification is that a model should not have a higher number of unknown parameters to be estimated than the number of distinctive pieces of information offered by the data. The second basic principle is that all unobserved variables must be scaled so that their values can be interpreted. When a model is properly identified, every model parameter can be distinctively estimated. A model can be over-, under- or just identified. An over-identified model contains fewer parameters to be estimated than the number of variance and covariances whereas an under-identified model has number of variances and covariances less than the number of parameters to be estimated. A just-identified model contains the same number of variances/covariances as the number of parameters

Model Estimation

Since the specified and identified structural equation model has some fixed and free parameters to be estimated from the data (Lei & Pennsylvania, 2007), model estimation involves determining the values of the unknown parameters and the error terms associated with the computed value (Weston & Gore, 2006). Here, a SEM computer tool is used to conduct the analysis (Kline, 2011) and as in regression analysis, both unstandardized and standardized parameter estimates and coefficients are included as output (Weston & Gore, 2006). In the case of this thesis, Amos (analysis of moment structures) version 22.0 was used to estimate model parameter values using maximum likelihood fitting function as stated in the previous sections. Model fit is evaluated after estimation to determine how well the model explains the data in addition to estimate interpretations.

Model Evaluation

At this juncture of model development, the focus here is to determine how well the data fits the model (Schumacker& Lomax, 2010) by examining the fit of different parameters in the model. The entire model goodness of fit is reflected by the magnitude of discrepancy between the sample covariance matrix and the covariance matrix implied by the model with the parameter values. Standardized parameter values are often reported for ease of interpretation (Lei & Pennsylvania, 2007). According to Weston & Gore, (2006), SEM experts agree that researchers should estimate model fit in relation to: (a) significance and strength of estimated parameter values (b) variance accounted for in endogenous observed and unobserved variables (c) how well the overall model fits the data, as shown by a variety of fit indices such as chi square, GFI, AGFI, RMSEA, p-value etc.

Model Modification

Usually, the fit of the initially estimated model is not as strong as one would like (Schumacker& Lomax, 2010; Weston & Gore, 2006). Consequently, the next operation would be to modify the model and evaluate the new modified model Schumacker& Lomax, (2010). Model modification is carried out through modification indices, occasionally in combination with expected parameter change statistics. Modification indices estimate the magnitude of decrease in model chi square whereas expected parameter change estimates the expected size of change in the parameter estimate when a certain fixed parameter is freely estimated.

One-Stage Verses Two-Stage Structural Equation Modelling Approach

Generally, in conducting SEM, there are two major approaches: (1) one stage approach and a (2) two stage approach. In adopting the one-stage or single stage approach, the aim is to carry out the analysis with simultaneous estimation of both the measurement and structural models. On the other hand, the second-stage approach is targeted at processing the measurement model first (through confirmatory factor analysis) and then fixing the measurement model in the second stage when the structural model is estimated. In essence, the measurement model is a confirmatory factor analysis whereby relations between unobserved variables and their indicators are defined Schumacker& Lomax 2010; Byrne, 2010. All observed variables are allowed to load on their respective factors. According to Schumacker& Lomax, (2010), in measurement model, the researcher is basically interested in answering these questions: (1) to what extent are the observed variables actually measuring the hypothesized latent variables? (2) to what extent are the observed variables actually measuring something other than the hypothesized latent variable? (3) which observed variable is the best measure of a particular latent variable. Structural model, on the other hand, defines relations among the unobserved variables i.e. it specifies the manner by which a certain latent variable influence other latent variables in the model Kline, (2011).

In most SEM researches, the two-stage approach is mostly employed since it is recommended by many researchers (Anderson &Gerbing, 1982; 1988; Schumacker& Lomax, 2010; Bollen, 1989; Kline, 2011). Many reasons were advanced for that. First, it is widely accepted and adopted in social science research (Aibinu& Al-lawati, 2010; Mayhew et al. 2009; Teo et al. 2006; Mohammed & Abdul-rahman, 2014). Secondly, in order for the structural portion of the SEM model to be identified, its measurement portion must also be fully identified first (Bollen, 1989 quoted in Kline, 2011). Thirdly, the measurement model provides an assessment of convergent and discriminant validity while the structural model provides an assessment of predictive validity (Anderson &Gerbing, 1982 quoted in Schumacker& Lomax, 2010).

To adequately buttress the significance of the two-stage approach, (Joreskog&Sorbom, 1993 pp. 113 as quoted in Schumacker& Lomax, 2010) summarized the basic points thus:

"The testing of the structural model, i.e., the testing of the initially specified theory, may be meaningless unless it is first established that the measurement model holds. If the chosen indicators for a construct do not measure that construct, the specified theory must be modified before it can be tested. Therefore, the measurement model should be tested before the structural relationships are tested".

It is only when latent variables are satisfactorily measured that it now makes sense to examine the relationships between latent variables in a structural model Schumacker& Lomax, (2010. Similarly, according to Awang, (2012), the two step approach allows the researcher assess the measurement model's unidimensionality, validity and reliability requirements before proceeding with the structural model. The figure 1 below shows a graphical procedure of the two-stage approach.

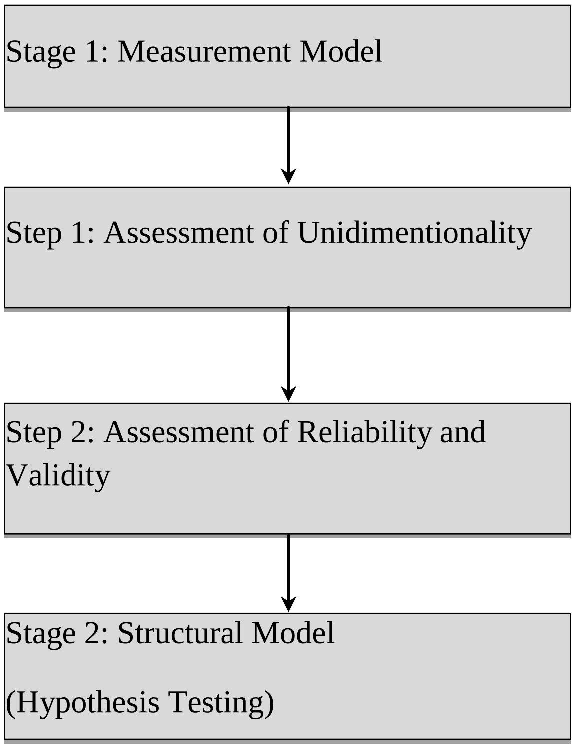

Figure 1 : Two-Stage Structural Equation Model

As can be seen from figure 1, in the first stage of model development, the constructs would be measured first with their indicators to establish unidimensionality of all the constructs. This is closely followed by an assessment of both reliability and validity assessment of factors and the model. Stage 2 involves modelling the entire constructs (structural model) to determine their effects on the dependent variable.

According to Kline, (2011), to assess unidimensionality of a construct, multidimensional measurement should be avoided by specifying that: (1) each indicator loads on a single factor and (2) error terms are independent. This is a typical CFA procedure where the analysis of *a priori* measurement model and both the number of latent variables and their correspondence with the indicators are clearly specified.

Unlike exploratory factor analysis (EFA) where all indicators are allowed to load on every factor through rotation in an infinite number of ways, CFA factor models are restricted, identified and allowed to covary (Kline, 2011, Anderson &Gerbing, 1988; Hair, et al. 2012). EFA cannot assess unidimensionality of a scale directly but only targets to assess the factor structure of a scale (Anderson &Gerbing, 1988). Where *a priori* hypothesis about the grounded theoretical model exists and a sound theoretical evidence about a factor-indicator correspondence, CFA is the best method to use (Bollen, 2002; 2010). Additionally, unrestricted factor models (as is the case in EFA) are generally unidentified Kline, (2011).

Furthermore, where a study involves the development of a conceptual model of hypothesized relationships specified by a researcher on the basis of theoretical considerations, the two-stage approach is mostly preferred and adopted (Kline, 2011; Ullman, 2010). Consequently, confirmatory factor analysis was used to determine the extent to which indicators load on their respective constructs conforming to what was expected based on theory. When conducting confirmatory factor analysis, a standardized factor loading of .50 and above on a certain construct is considered acceptable (Hair et al, 2012). This threshold is therefore regarded as the cut off value considered in SEM analysis.

On a successful achievement of unidimensionality of all constructs, reliability and validity of those constructs should also be assessed in the second step of model development. To achieve that, confirmatory factor analysis using maximum likelihood estimation is to be performed based on (Anderson and Gerbing, 1988; Kline, 2005; 2011) recommendations. Following the establishment of reliability and validity of all constructs, the paths specifying the causal relationships among the latent variables of the study are then specified in the structural model i.e. second stage of model development.

Researches in Construction Industry Using Structural Equation Modelling Methodology

Structural equation modelling represents a multitude of techniques under one umbrella which makes it appropriate for conducting research in social sciences. For instance, Aibinu and Al-Lawati (2010) used PLS-Based SEM technique to model construction organization's willingness to participate in e-bidding in the Omani construction industry. One of the author's main objectives is to demonstrate the application of SEM to a research problem in construction. Similarly, Alashwal and Abdulrahman, (2012) used SmartPLS Package (PLS-Based SEM) to build a hierarchical model of inter-project learning that describes the interaction among experience accumulation, knowledge articulation, knowledge codification and knowledge transfer. In another research, Waziri et al, (2015) used covariance-based SEM technique to develop a model and instrument for organizational readiness for change in ICT applications adoption among construction organizations in Nigeria.The authors developed a model for IT adoption and present an instrument for use by other researchers to further studies on the problems associated with IT adoption in the Nigerian construction industry. Using data obtained from 68 valid responses, Waziri et al (2015) employed covariance-based SEM technique to examine the influence of transformational leadership style on ICT adoption among Nigerian construction organizations. The authors used the same SEM approach to establish the reliability and validity of the constructs used in the study.With a total of 245 valid responses, Idris et al (2016) developed a knowledge management environmental factor and measurement models for adoption in the Nigerian construction industry. The author reported using Amos version 22.0 (covariance-based SEM technique) in the model development processes.

In the same vain, Waziri et al (2014) explores the environmental variables influencing IT adoption among Nigerian construction organizations with the aid of a covariance-based SEM analytical approach.In their study on the impact of organizational culture on knowledge management process in construction organizations, Idris et al (2015) used 323 valid questionnaire responses to predict the effect of organizational culture on organization's knowledge management processes using structural equation modelling analytical technique. In Asia, Jin et al (2006) modelled the relationships-based determinants of building project performance in China using covariance-based analysis.

CONCLUSION

This study was set out as a guide to the concept and application of structural equation modelling in construction industry research with specific reference to basic concepts and interrelated steps of model development and subsequent interpretation. SEM allows complex variable relationships to be conveyed through hierarchical or non-hierarchical, recursive or non-recursive structural equations in order to present a more complete picture of the entire model.Researchers dealing with problems in construction can employ SEM especially where the modeller intends to develop a model in terms of a system of unidirectional effects of one variable on the other. While the use and application of SEM in construction research has greatly improved in recent years,caution is however advised not to employ SEM statistical procedure without a comprehensive understanding of its basic foundations and principles. SEM is an exciting initiative toward increasing the sophistication of research conduct even when complex variables are involved.

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