Chapter V
Theory Development in Information Systems Research Using Structural Equation Modeling:
Evaluation and Recommendations

Nicholas Roberts
Clemson University, USA

Varun Grover
Clemson University, USA

ABSTRACT

Structural equation modeling (SEM) techniques have significant potential for assessing and modifying theoretical models. There have been 171 applications of SEM in IS research, published in major journals, most of which have been after 1994. Despite SEM's surging popularity in the IS field, it remains a complex tool that is often mechanically used but difficult to effectively apply. The purpose of this study is to review previous applications of SEM in IS research and to recommend guidelines to enhance the use of SEM to facilitate theory development. The authors review and evaluate SEM applications, both component-based (e.g., PLS) and covariance-based (e.g., LISREL), according to prescribed criteria. Areas of improvement are suggested which can assist application of this powerful technique in IS theory development.

INTRODUCTION

Structural equation modeling (SEM) has become an important and widely diffused research tool for theory development in the social and behavioral sciences. One reason for the substantive use of SEM is that it enables researchers to conduct a single, systematic and comprehensive analysis by modeling relationships among multiple independent and dependent variables simultaneously (Kline, 2005). Additionally, in contrast to exploratory methods, SEM allows for the specification of a precise model that is driven by theoretical considerations (Bollen, 1989). Finally, SEM also permits researchers to model higher-order latent variables (Edwards, 2001). These inherent advantages provided by SEM have caused many researchers in the information systems (IS) field to use it for measuring constructs or developing and testing IS theories.

Despite SEM's numerous advantages, the relative sophistication of SEM also makes it prone to misuse (Anderson & Gerbing, 1988). Moreover, theory development relies upon the effective use of empirical research methods (Van Maanen, Sorensen, & Mitchell, 2007). Invalid theory development could greatly inhibit the building of a cumulative tradition of research. Thus, we believe it is important to take stock of how this powerful technique has been applied in IS research.

To strengthen ties between theory and empirical IS research, this study provides an in-depth review and analysis of a critical mass of SEM applications in three top-tier IS journals. Based on our review, we suggest specific areas for improvement. To the best of our knowledge, no comprehensive survey of contemporary SEM applications in the IS field has been reported in the literature.

OVERVIEW OF STRUCTURAL EQUATION MODELING

To provide a basis for subsequent discussion, we present a brief overview of SEM. SEM is a technique used to specify, estimate, and evaluate models of linear relationships among a set of observed variables in terms of a generally smaller number of unobserved variables. Figure 1 depicts a basic latent variable model. A circle is used to represent each of the four latent variables, and the boxes represent associated manifest or indicator variables. The relationships between the latent variables and their indicators are often referred to as a "measurement" model, in that it represents an assumed process in which an underlying construct determines or causes behavior that is reflected in measured indicator variables.

Within this context, it is important to note that the arrows go from the circles to the boxes, which is consistent with the process noted above. Thus, each factor serves as an independent variable in the measurement model, and the indicator variables serve as the dependent variables. Each indicator is also potentially influenced by a second independent variable in the form of measurement error, and its influence is represented as a cause of the indicator variable through the use of a second arrow leading to each of the indicators. Finally, the model shown in Figure 1 includes correlations (double-headed arrows) among the three exogenous constructs (LV1–LV3) and regression-like structural parameters linking exogenous and endogenous constructs (e.g., LV3, LV4). The model also acknowledges that there is unexplained variance in the endogenous latent variable. The part of the overall model that proposes relationships among the latent variables is often referred to as the structural model.

Often using a maximum likelihood function, covariance-based SEM techniques attempt to minimize the difference between the sample covariances and those predicted by the theoretical model. As a result, the parameters estimated by this procedure attempt to reproduce the covariance matrix of the observed measures. Observed measures are assumed to have random error variance and measure-specific variance components that are not of theoretical interest. Hence, this error variance is modeled separately. Following this, the covariances among the latent variables are adjusted to reflect the attenuation in the observed covariances due to excluded error variance components. Because of this assumption, "the amount of variance explained in the set of observed

Related Content

An Analytics Architecture for Procurement
Sherif Barrad, Stéphane Gagnonand Raul Valverde (2020). *International Journal of Information Technologies and Systems Approach (pp. 73-98).*
www.irma-international.org/article/an-analytics-architecture-for-procurement/252829

Olympics Big Data Prognostications
Arushi Jainand Vishal Bhatnagar (2016). *International Journal of Rough Sets and Data Analysis (pp. 32-45).*
www.irma-international.org/article/olympics-big-data-prognostications/163102

Making Sense of IS Project Stories
Darren Dalcher (2018). *Encyclopedia of Information Science and Technology, Fourth Edition (pp. 5660-5668).*
www.irma-international.org/chapter/making-sense-of-is-project-stories/184266

Digital Technologies for Teaching and Learning at the BoP: A Managerial Perspective
Alessia Pisoni, Alessandra Cortiand Rafaela Gjergji (2021). *Handbook of Research on Analyzing IT Opportunities for Inclusive Digital Learning (pp. 272-292).*
www.irma-international.org/chapter/digital-technologies-for-teaching-and-learning-at-the-bop/278964

Interpretable Image Recognition Models for Big Data With Prototypes and Uncertainty
Jingqi Wang (2023). *International Journal of Information Technologies and Systems Approach (pp. 1-15).*
www.irma-international.org/article/interpretable-image-recognition-models-for-big-data-with-prototypes-and-uncertainty/318122