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Abstract
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Keywords
component, marketing, modeling, sem, complex

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Complex Modeling in Marketing Using Component Based SEM

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Abstract

Structural equation modeling (SEM) is an important tool for marketing researchers to estimate a network of causal relationships linking two or more complex concepts. The PLS approach to SEM, also known as component based SEM, is becoming more prominent in estimating complex models due to its soft modeling assumptions. This study elucidates the use of component based SEM in estimating a complex higher order model with a small sample size. The utility of the approach is illustrated empirically by estimating a third-order, reflective, hierarchical service quality model in the context of mHealth. The findings of the study confirm the conceptual and methodological advances of component based SEM to establish rigor in complex modeling.

Keywords: Complex model, component based SEM, Service Quality, Hierarchical Modeling.

Complex Modeling in Marketing Using Component Based SEM

Introduction

There is little doubt that quantitative research has made a great impact in marketing since John Stuart Mill and the 19th century experimental positivists. The whole beauty of this research paradigm lies in embracing inferential statistics and related cause and effect modeling to validate theories that explain complex concepts. In this context, the emergence of structural equation modeling (SEM) over the last three decades has brought a new level of sophistication in quantitative modeling by its versatile applications to address a variety of substantive and methodological issues. SEM, a second generation multivariate technique, allows the simultaneous modeling of associations among multiple independent and dependent variables. Coupling the econometric perspective of prediction and the psychometric perspective of construct validity, it enables the measurement of unobservable (latent) variables using observable measures (or, manifest variables, items or indicators) by explicitly modeling measurement error (Chin, 1998a). It is widely used for its inherent flexibility in testing a theoretical model with multiple predictors and criterion variables against empirical data. In SEM, the dominant paradigm is the covariance based approach which uses maximum likelihood (ML) function to minimize the difference between the sample covariances and those predicted by the research model. As such, the resultant covariance matrix assumes to be based on sufficient interdependent observations based on multinormal distribution. Though covariance based SEM (CBSEM) is the dominant approach in such modeling; however, it involves various constraints regarding the distributional properties (multivariate normality), measurement level, sample size, model complexity, identification, and factor indeterminacy (Chin, 1998b; 2010; Hair et al. 2011; Hulland, 2010; Fornell & Bookstein, 1982). In case of complex models, CBSEM typically results in positively biased model fit indices as the degrees of freedom increase with the increasing number of indicators and latent variables (Akter et al. 2011a; Chin & Newsted, 1999; Mulaik et al., 1989). As such, most CBSEM studies seem to focus on simple theoretical framework, which restrict the development of complex models (Chin et al., 2008). We define a complex model as the larger model with many latent variables and manifest variables, such as, a model with 10 or more constructs and 50 or more items (Chin, 2010; Akter et al., 2011a). In this particular case, component based SEM surpasses CBSEM to establish rigor in complex modeling by removing the uncertainty of improper solutions.

For empirical illustration, this study applies component based SEM to develop and validate a complex model for mHealth using a small sample size (n=100). This study develops the quality model for mHealth because it is an emerging healthcare paradigm which is under researched and still most of the research in this domain is largely fragmented. The study specifies the service quality of mHealth as a complex, hierarchical model which is composed of large number of latent variables capturing several dimensions under multiple hierarchies. Therefore, the main objective of the study is to demonstrate that component based SEM (or, component based SEM) can effectively be used to estimate the parameters of a complex model, using third order, reflective, hiearchical mHealth service quality model as an empirical illustration. Theoretically, this demonstration extends quality modeling in service research and methodologically, it confirms the utility of component based SEM in developing and validating complex models.

Literature Review

Complex Modeling and Component based SEM

The idea of complex modeling is deeply rooted in the objective and requirements of the research philosophies. Based on the concept of verisimilitude (i.e., trust likeness or nearness to the truth), Meehl (1990, p. 14) states that models always suffer imperfection in capturing reality, which necessitate them to rely on two principles, that is, incompleteness and falseness. Whereas incompleteness refers to the capacity to capture complex reality, falseness represents how well the contradictions between the model and the real world are matched. Though these two principles are critical to approximate reality, however, "Most SEM studies seem to focus on the falsity of a model as opposed to its completeness. In part because of algorithmic constraints, few SEM models are very complex (i.e., have a large number of latent variables). Emphasis on model fit tends to restrict researchers to testing relatively elementary models representing either a simplistic theory or a narrow slice of a more complex theoretical domain" (Chin et al. 2008, 294).

Table 1: Difference between component and covariance based SEM

Criterion	Component based SEM	Covariance based SEM
Objective	Prediction oriented	Parameter oriented
Approach	Variance based	Covariance based
Assumptions	Nonparametric	Parametric
Parameter estimates	Consistent at large	Consistent
Number of Latent variables	Any numbers	Limited numbers (max. 8)
Number of Manifest variables	At least 1	At least 2
Latent variable scores	Explicitly estimated	Indeterminate
Minimum sample size	20-100	200-800
Model complexity	High complexity	Low complexity

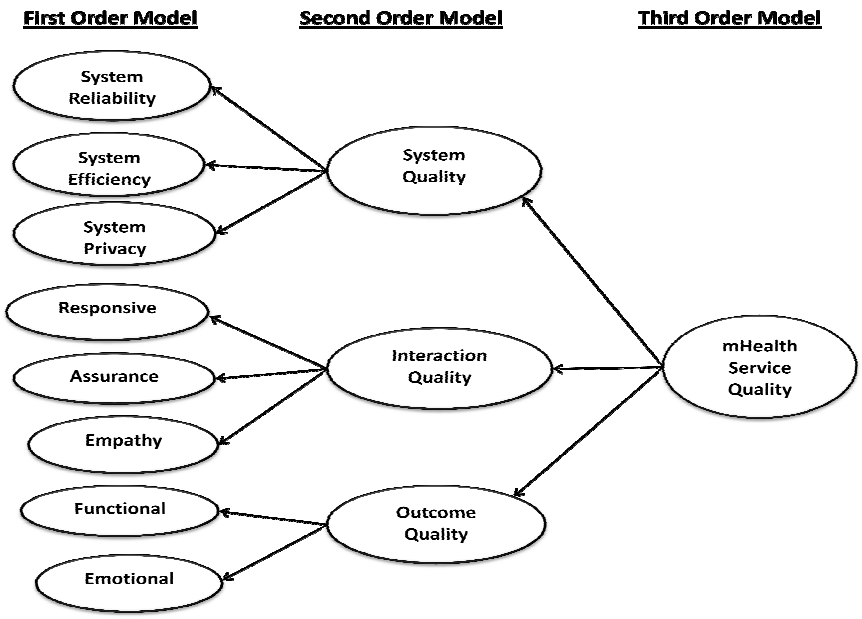
In a comparative study between component based SEM and ML, Vilares et al. (2010, p. 302) state that "ML estimators were much more sensitive to the various potential deficiencies in data and in the model specification. When asymmetric data is used and especially formative block is used, the quality of the estimates decrease drastically." Though some researchers (e.g., Marsh et al. 2004; Barendes et al. 2010) use small sample size under ML estimate; however, they restrict their models by at least 3 indicators per construct to ensure the desired model fit. Criticizing such constraints, MacCallum (2003) states that it is difficult to capture the complexity of the empirical phenomena with a small number of common factors. It is also echoed in Blalock's (1979, p.881) statement that "reality is sufficiently complex that we will need theories that contain upward of fifty variables if we wish to disentangle the effects of numerous exogenous and endogenous variables on the diversity of dependent variables that interest us". Thus, to develop and validate a complex model, component based SEM clearly surpasses CBSEM in any settings (exploratory or confirmatory) because of its flexible or soft modeling assumptions (see Table 1).

mHelth service quality: A Complex Model

mHealth, a new healthcare paradigm, is the application of mobile communications—such as mobile phones and PDAs—to deliver right time health services to customers (or, patients). This study defines service quality in mHealth as the users' judgment about the overall excellence or

superiority of mHealth platform (Zeithaml, 1987). A review of the mobile healthcare literature reveals that there are few studies which directly measured mHealth service quality in this setting. Researchers in mHealth paradigm explore that there are some predominant factors which influence the quality of this service (Varshney 2005; Akter et al. 2010). Thus, articulating all these factors, this study proposes that users perceive mHealth service quality at three dimensions; first, *System quality or quality of service delivery systems*, such as, system reliability, system efficiency, and system privacy; second, service quality or, *quality of interpersonal interaction* between physicians and users in terms of responsiveness, assurance and empathy etc; and third, *outcome quality* in terms of *functional and emotional benefits* (Parasuraman et al., 2005; Sousa & Voss, 2006) . Therefore, focusing on user's perceptions, this study develops an mHealth service quality model (Figure 1), which is a complex model because of its large number of dimensions at multiple hierarchies.

Figure 1: mhealth Service Quality Model



Nature of the Proposed Complex Model

We specify the proposed mHealth service quality model as the third-order, reflective model in which indicators are manifestations of construct (Jarvis et al., 2003; Petter et al., 2007). The extant research on mHealth quality (Fassnacht & Koese, 2006) and measurement model specifications (Wetzels et al., 2009) has always embraced such hierarchical view. We specify that the proposed research model is reflective because direction of causality is from construct to items, all the indicators in our model share a common theme, they are interchangeable, covary with each other and dropping an indicator should not alter conceptual domain of the construct (Jarvis et al. 2003; Diamantopoulos & Siguaw, 2006). Formally, if *X1* is a latent variable and Y_1, Y_2..... Y_n a set of observable indicators, the reflective specification implies the equation $Y_i = \beta_{i1} X_1 + \varepsilon_i$, where β_i is the expected effect of X on Y_i where ε_i is the measurement error for the i_{th} indicator (i= *1, 2,.....n*). It is assumed that COV (X, ε_i) = 0, and COV (ε_i, ε_j)= 0, for $i \neq j$ and E (ε_i) = 0.

Methodology

Instrumentation and Data Collection

The questionnaire consists of previously published multi-item scales with favourable psychometric properties and items from qualitative research. All the constructs in the model were measured using 7 point likert scale (e.g., strongly disagree - strongly agree). Using systematic random sampling, Data were collected 100 individuals from Bangladesh under a global mHealth assessment project from January 07 to March 17, 2010.

Estimating the complex Model using component based SEM

This study applies component based SEM in estimating the third order mHealth quality model in order to achieve more theoretical parsimony and less model complexity (Akter et al., 2011b; Chin, 2010; Edwards, 2001; Law et al., 1998; MacKenzie et al., 2005; Wetzels et al., 2009,). As we have undertaken a hierarchical approach, the manifest variables will be used three times: for the first-order latent variable (e.g., system efficiency), for the second-order latent variable (e.g., Systems quality) and for the third-order latent variable (mHealth service quality) (see Table 2). According to Wetzels et al. (2009), "This approach also allows us to derive the (indirect) effects of lower-order constructs, or dimensions, on outcomes of the higher-order construct."

Table 2: Estimation of the higher-order quality model using component based SEM

First Order model	Second order model	Third order model (Extension of second order model)
$y_i = \Lambda_y . \eta_j + \varepsilon_i$ y_i = manifest variables (*e.g., items of system reliability*) Λ_y = loadings of first order LV η_j = first order LV (e.g., system reliability) ε_i = measurement error	$\eta_j = \Gamma . \xi_k + \zeta_j$ η_j = first order factors Γ = loadings of second order LV ξ_k = second order LV *(e.g., system quality)* ζ_j = error of first order factors	$\eta_j = \beta . \eta_j + \Gamma . \xi_k + \zeta_j$ η_j = Second order factors $\beta\ \eta_j$ = Higher order LVs with loadings (i.e., from first to the nth order, except the highest order) $\Gamma\ \xi_k$ = The highest order LV with loadings (i.e., *third order service quality)* ζ_j = error of second order factors

Findings

Measurement Model

In order to assess the complex- hierarchical model, this study uses PLS Graph 3.0 (Chin 2001) to estimate the parameters in the outer and inner model. The findings confirm that all the item loadings, composite reliabilities (CRs) and average variance extracted (AVEs) of first order, second order and third order measurement models exceed the cut off values of 0.7, 0.7 and 0.5 respectively, which ensure adequate scale reliability (see Table 3). In addition, this study calculates the square root of the AVE that exceeds the intercorrelations of the construct with the other constructs in the model to ensure discriminant validity. This process also paves the way for proving the research model.

Table 3: Psychometric Properties of the measurement model

First order	Items	Loadings	CR	AVE	**Second order**	CR	AVE	**Third order**	CR	AVE
System Reliability	SR1-SR3	0.945-0.970	0. 968	0.910	System Quality	0.919	0.561	Service Quality	0.967	0.556
System Efficiency	SE1-SE3	0.915-0.956	0.959	.886						
System Privacy	SP1-SP2	0.983-0.986	0. 984	0.969						
Responsiveness	RE1-RE3	0.899-0.943	0.940	0.840	Interaction Quality	0.946	0.661			
Assurance	AS1-AS2	0.961-0.963	0.962	0.926						
Empathy	EM1-EM3	0.872-0.963	0.952	0.869						
Functional Benefits	FB1-FB3	0.798-0.894	0.889	0.728	Outcome Quality	0.949	0.755			
Emotional Benefits	EB1-EB3	0.939-0.960	0.967	0.908						

Structural Model

The degree of explained variance of the third order service quality construct is reflected in its second order components, that is, system quality (83%), interaction quality (90%), and outcome quality (91 %) (see Table 4). Accordingly, second order constructs are reflected in its first order dimensions, such as, interaction quality is reflected in responsiveness (78%), assurance (76%) and in empathy (83%). All the path coefficients from service quality to second order and first order components are significant at $P < 0.001$. Overall, the variance explained by the higher-order model in terms of R^2 is significantly large ($R^2 > 0.35$) (Cohen, 1988).

Table 4: Results of the Structural Model

Associations	Latent constructs	Dimensions	β	R^2	t-stat
Third order to second order dimensions	Service quality	System quality	0.909	0.826	56.481
		Interaction quality	0.948	0.899	121.826
		Outcome Quality	0.956	0.914	169.161
Second order to first order dimensions	System quality	System reliability	0.775	0.600	20.582
		System efficiency	0.856	0.733	38.685
		System privacy	0.734	0.539	12.812
	Interaction quality	Responsiveness	0.884	0.782	33.023
		Assurance	0.874	0.764	40.089
		Empathy	0.913	0.833	68.991
	Outcome quality	Functional Benefits	0.940	0.883	99.258
		Emotional Benefits	0.962	0.925	171.762

Conclusion

The main thrust of the study was to demonstrate that component based SEM (or, component based SEM) can effectively be used to estimate the parameters of a large-complex model. This study confirms the applications of this approach by developing and validating a third order, reflective, hierarchical mHealth quality model. This study confirms the utility of component based SEM in a complex setting by providing robust solutions to a large model with small sample size. Thus, we conclude that:

"There is nothing vague or fuzzy about soft modeling;
the technical argument is entirely rigorous"
Herman Wold (1982)

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