Fully Mediated Effects of Formative Measures Using MIMIC Constructs

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Abstract

Formatively-measured constructs are increasingly applied in information system research models. Recent work shows that exogenous formatively-measured constructs suffer from a number of problems that include interpretational confounding and a lack of external consistency. Yet replacement by reflectively-measured constructs can lead to bias if not theoretically appropriate. One solution may be to use a MIMIC construct composed of the formative measures as well as two additional reflective measures. A simulation study indicates that a MIMIC so composed mitigates the problems of interpretational confounding and poor external consistency allowing use broader use in a variety of structural models.

Keywords: Formative measures, endogenous variables, research methodology, structural equation models, simulation, MIMIC models

Introduction

Formatively-measured constructs increasingly appear in the information systems (IS) literature both in terms of application in research models and concern for methodological issues (Petter et al., 2007; Kim et al., 2010; Diamantopoulos, 2011; Bagozzi, 2011; MacKenzie et al., 2011; Bollen, 2011; Treiblmaier et al., 2011). Formatively-measured constructs differ from reflectively-measured constructs in that the observable items comprising formative measures are considered causes of a latent variable while reflective items are considered observable consequences of a latent variable. Though formative measures hold potential value in building research models, concerns about their use in theory testing and structural equation modeling (SEM) abound, particularly in consideration of formative exogenous variables (Wilcox et al., 2008; Franke et al., 2008; Kim, et al., 2010; Diamantopoulos, 2011; Bollen, 2011; Treiblmaier et al., 2011). The essential question was posed by Wilcox, et al. (2008, p.1219) who stated "… reflective measurement has filled the role of creating measures of constructs that can be used in different studies by different researchers to test different theories. But can formative measurement fill the same need? Does formative measurement allow researchers to use the same 'off-the-shelf' measure in different contexts to test different theories?"

In order to confidently use formatively-measured constructs in the same fashion that researchers have employed for reflectively-measured constructs, one must overcome known concerns about formative measures. As research investigates formative measurement, many concerns have been addressed while others still require further examination and resolution (Diamantopoulos et al., 2008; Diamantopoulos, 2011; Bagozzi, 2011; MacKenzie et al., 2011; Bollen, 2011). Known challenges when employing formatively-measured constructs in a research model include vulnerability to multicollinearity, the requirement for emanating paths from the formatively-measured construct for model identification, and an inability to validate the construct with techniques commonly employed for reflectively-measured constructs. Past work has examined these issues, though not all researchers are content with the idea of formative measurement (Diamantopoulos et al., 2008). Of continuing concern are issues of interpretational confounding and a lack of proportional structural effects when used as an exogenous variable (Franke, et al., 2008; Kim, et al, 2010). Interpretational confounding occurs "as the assignment of empirical meaning to an unobserved variable which is other than the meaning assigned to it by an individual a priori to estimating unknown parameters. Inferences based on the unobserved variable then become ambiguous" (Burt, 1976, p.4). Proportional structural effects are preserved when the construct functions as a point variable such that measures correlate with other constructs in proportion to their correlation with their own construct. This implies that a formatively-measured construct must fully mediate the effects of its measures in order to be representative (Franke, et al., 2008).

In IS research models, the inclusion of a formatively-measured construct as an antecedent can lead to both interpretational confounding and inconsistent proportional structural effects (Kim, et al., 2010; Bagozzi, 2011; MacKenzie et al., 2011). Researchers in other disciplines also report these issues (Franke et al., 2008). To counter these and other possible problems with formatively-measured constructs, a technique gaining ground among some researchers is the Multiple Indicators Multiple Causes (MIMIC) construct created by adding two reflective items to any variable measured formatively (Diamantopoulos and Winklhofer, 2001; Diamantopoulos et al., 2008; Bagozzi, 2011; Diamantopoulos, 2011). Whether the MIMIC modeling guidelines can address issues of interpretational confounding and structural proportionality has not been explored in the literature. The purpose of this study is, therefore, to examine whether a MIMIC model reduces interpretational confounding and exhibits consistent proportional structural effects for exogenous formatively-measured constructs.

Consistency of weights of the formative measures, parameter estimates for structural paths, and mediation of the formative measures are examined with simulation techniques to consider whether the MIMIC model can limit these crucial problems for formatively-measured constructs.

Background

Information system scholars have adopted structural equation modeling (SEM) as a common technique to investigate theoretical models of interest (Petter et al., 2007; MacKenzie et al., 2011; Bollen, 2011). Structural relationships are proposed among latent variables and tested by either covariance based techniques or component based techniques (Fornell and Bookstein, 1982). The latent variables are measured by observable measures that measure the unobservable variable (Borsboom et al., 2003). The argument is that any change to the latent variable will also occur to the measures. Most commonly, researchers view that interventions that change the latent variable can be detected by endogenous measures (Coltman et al., 2008). This relationship is termed reflective, a consideration of the change in each measure being a reflection of the change in the latent variable. Causality is implied from the variable to the measures and the measures are understood to be positively correlated (Bollen, 1989).

From a theoretical view, however, it is just as conceivable that a variable is formed by multiple measures that are not correlated with each other (Blalock 1964; Diamantopoulos and Winklhofer 2001; Edwards and Bagozzi 2000). This is termed a formatively-measured construct. Causality is presumed to flow from the measures to the latent variable. Further, formative measures in a construct need not covary (Bollen and Lennox, 1991), and hence may not have the same antecedents, consequences, or relationships to other variates (Jarvis et al., 2003). If any formative measure increases, the latent variable increases even if all the other measures remain stable. This implies that if the latent variable increases, not all measures in a formatively-measured construct need to increase unlike in a reflectively-measured construct where all reflective measures are assumed to change accordingly.

Reflectively-measured constructs with items seen as outcomes of the latent variable have been popular in the IS literature for many years in some of the more common models (Petter et al., 2007). As an example, the original Technology Acceptance model contains a latent variable in the structural equation model called ease of use (Davis, 1989). If a system is perceived to be easy to use, there will be expectations of the system that reflect such a perception (easy to learn, controllable, clear and understandable, flexible, easy to become skillful, easy to use). The items should all be related in order to add to consistency and reliability of the construct plus are part of the nomological net of the theory since they are direct consequences of the latent variable. On the other hand, formative items causing the latent variable in the construct need not be part of the same nomological net nor necessarily correlated with one another (Bollen and Lennox, 1991; Diamantopoulos and Winklhofer, 2001). For example, governance characteristics in outsourcing contracts are formed by the presence of distinct clauses in the contract that include a communication plan, a measurement charter, a conflict resolution charter, and an enforcement plan (Goo et al., 2009). These items need not be correlated among themselves, could come from different sources and/or different nomological nets, and should completely define the latent variable as we understand it. These are components that come together to form the latent variable rather than being observed consequences of having governance clauses in a contract.

Figure 1 shows a formatively-measured construct with three measures. The measures (xi) may or may not be correlated (Φ ij). Each is related to the latent variable (η) with a path coefficient (γi). The latent variable is thus formed as a linear combination of the measures such that:

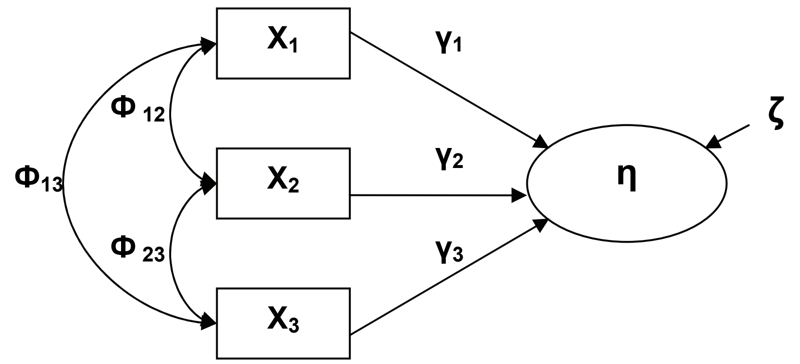

Figure 1 - Formatively-measured construct

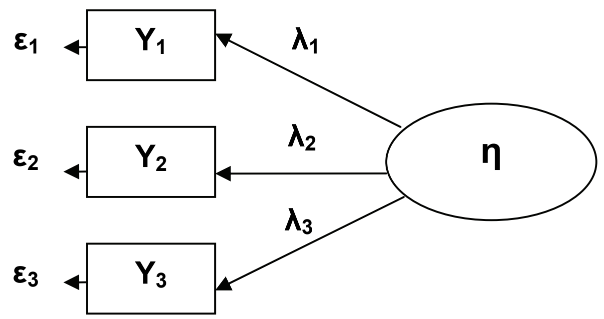

Figure 2 - Reflectively-measured construct

Eq. 1: $\eta = \gamma_1 X_1 + \gamma_2 X_2 + \gamma_3 X_3 + \ldots + \gamma_n X_n + \zeta$

This differs from reflectively-measured constructs where each measure has a separate linear relation with the latent variable as shown in Figure 2 with the equation appearing:

Eq. 2: $Y_i = \lambda i * \eta + \varepsilon_i$

where Yi is the ith reflective measure, λi is coefficient representing effect of latent variable on measure, η is reflectively-measured construct, and ε i is measurement error for reflective measure i.

Rather than having an error term for each measure as in the reflectively-measured construct, the formatively-measured construct has a single error term (ζ). This error is considered to represent the impact of all remaining causes not represented by the measures included in the construct (Diamantopoulos, 2006; 2011). Given this interpretation of the error term, as long as all possible causes of the latent variable are included in the construct, the error term could be excluded. However, when not all possible causes are explicitly incorporated as formative measures (which is common in practice), the error term must be included as a parameter and estimated along with the other parameters to ensure correct model specification.

Recent papers have examined the IS literature to determine the pervasiveness of formatively-measured constructs and concluded their use is expanding (Petter et al., 2007; Kim et al., 2010). Appendix A indicates the papers that have employed formative measures in a SEM study from 2009 through

2011 in the six core MIS journals (Management Information Systems Quarterly, Information Systems Research, Journal of the Association for Information Systems, Journal of Management Information Systems, European Journal of Information Systems, and Information Systems Journal). In all, 50 papers have used formative measures compared to 133 papers in the same period that employ only reflectively measured constructs. The fact that a high incidence of MIS research in recent years in the top six journals has used formatively-measured constructs suggests the increasing popularity of this form of measurement. Therefore, it is important to address the use of formative measurement in SEM studies. Furthermore, of the 109 formatively-measured constructs, 63 of them (58%) were exogenous variables within the research model. Our focus in this article is limited to formative constructs as exogenous variables as the issues differ from formative constructs as endogenous variables (MacKenzie et al., 2005).

Reasons for employing formatively-measured constructs in research include increased explanatory power and avoidance of misspecification bias. Formatively-measured constructs are unique because they represent latent variables perceived to be composites of specific components (Edwards and Bagozzi, 2000). This presents unique opportunities for the interpretation of results where changes to the latent variable have measures that might predict the change. Should the latent variable be one of interest to practice, reflective items present no guidance as to how to alter the variable of interest since they occur as a result of change to the latent variable. Formative items, however, allow researchers to legitimately draw advice from the relationship of the measures. Incorrectly specified directionality, in either direction, can lead to extreme bias in the estimate of structural parameters, even to the point of indicating relationships are significant when they in fact are not (MacKenzie et al, 2005; Petter et al., 2007; MacKenzie et al., 2011).

However, formatively-measured con-structs present a number of issues that must be resolved prior to their incorporation in SEM-based research. Specification of the construct requires the items be distinct from the latent variable, the items covary with the latent variable, temporal conditions hold, and rival explanations are eliminated (Edwards and Bagozzi, 2000). The latter condition is a major argument as to why formative items must be a complete set, fully explaining the latent variable without omission of any actual causes. Failure to include any relevant facet of the variable alters the content domain and excludes part of the construct itself resulting in conceptual and theoretical changes to the structural model (Diamantopoulos and Winklhofer, 2001; Diamantopoulos, 2011). Inclusion of a large number of measures potentially results in multicollinearity problems that must be addressed through item purification procedures (Bollen and Lennox, 1991; Diamantopoulos and Winklhofer, 2001; Diamantopoulos, 2011). Formative latent variables are under identified in SEM without having at least two emitting paths (MacKenzie et al., 2005). Of more recent concern in the IS literature is issues associated with interpretational confounding (Kim et al., 2010) and proportional structural effects (Franke et al., 2008). For the remainder of the paper we focus our attention on these concerns. In particular, our focus in this article is limited to exogenous formatively-measured constructs as the issues differ from endogenous formatively-measured constructs (MacKenzie et al., 2005).

Interpretational Confounding

The nominal meaning to a construct is assigned without reference to empirical information. The construct's empirical meaning derives from its relations to one or more observed variables in an experimental setting. Empirical meaning applies to both the construct itself and to its relationships to observable measures of other constructs in a structural model. Interpretational confounding occurs "as the assignment of empirical meaning to an unobserved variable which is other than the meaning assigned to it by an individual a priori to estimating unknown parameters. Inferences based on the unobserved variable then become ambiguous and need not be consistent across separate models" (Burt, 1976, p.4).

Interpretational confounding is evident when the coefficients linking measures and the latent formative variable significantly change with changes to the endogenous variables in a model or when the path coefficient from the latent formatively-measured construct to an endogenous variable changes if another endogenous variable is replaced (Bollen, 2007; Howell et al., 2007; MacKenzie et al., 2011). In the former case, the change to the coefficients of the formative items indicates that the meaning of the items as part of the measurement construct differs from any meaning later attached to the items in a structural model. In the latter case, the measurement model is inconsistent in structural model applications, furthering interpretational confounding in the current study and making comparison across studies problematic. In Figure 3, the value of $\gamma 13$, $\gamma 13$, and $\gamma 13$ depend on the relationships to the variables $\eta 2$ and $\eta 3$. Changing out $\eta 3$ for another endogenous variable possibly changes the values of $\gamma 13$, $\gamma 13$, $\gamma 13$, and $\beta 12$ showing how the structural model and measurement model are related with a formative exogenous variable. Since the dependent variable in Eq. 1 is latent, the downstream variables are necessary to estimate the coefficients on the paths form the formative items to the latent variable in a formatively-measured construct. Studies have demonstrated that the nature of the latent construct depends on the dependent constructs included in the model (Kim, et al., 2010; Howell, et al., 2007; Hardin et al., 2008a; Hardin et al., 2008b; MacKenzie et al., 2011).

Proportional Structural Effects

Proportional structural effects state that the measures "must have effects on the outcomes that are proportional to their effects on the formatively-measured construct itself" (Franke et al. 2008, p 1229). This has a direct impact on external consistency, which is realized when the items measuring the construct have a similar relationship to the antecedents and consequences as to the construct itself. In other words, external consistency is lacking if items of a formatively-measured construct have different relationships with the endogenous variables than the formative latent construct itself (Blalock, 1969; Bollen and Davis, 1994; Hayduk, 1987). Recent studies have demonstrated the lack of point variability of the traditional formatively-measured construct (Kim et al., 2010; Franke et al., 2008).

External consistency is usually defined as a preservation of the ratios of the correlations of the items to the latent variable and the items to the measurement items of other variables in the model (Anderson and Gerbing, 1982). This is considered similar to the concept of a point variable where the latent variable is expected to serve as a single point in relationships to other variables in the model (Howell et al., 2007). The implications of a point variable are that the structural proportion of the measures to their latent variable as to other variables, meaning that a formatively-measured construct fully mediates the effects of its measures on other variables (Blalock, 1969; Bollen and Davis, 1994; Hayduk, 1987; Diamantopoulos, 2011). The presence of structural proportionality is a sufficient, but not necessary, condition for external consistency (Anderson and Gerbing, 1982).

Figure 4 shows a set of possible relationships in a model with one formatively-measured construct as an antecedent to two reflectively-measured constructs. If $\eta 1$ mediates the relationships of its measures to $\eta 2$ and $\eta 3$, then the proportional structural effects ensure external consistency exists for the formatively-measured construct. In other words, in Figure 4, there should not be a direct effect between any $X1j$ and $\eta 2$ or $\eta 3$. All $\beta 1jk$ should be close to zero. This premise is assumed in previous discussions and applications of formative models but not demonstrated to hold (Diamantopoulos, 1999; 2011; MacCallum and Browne, 1993).

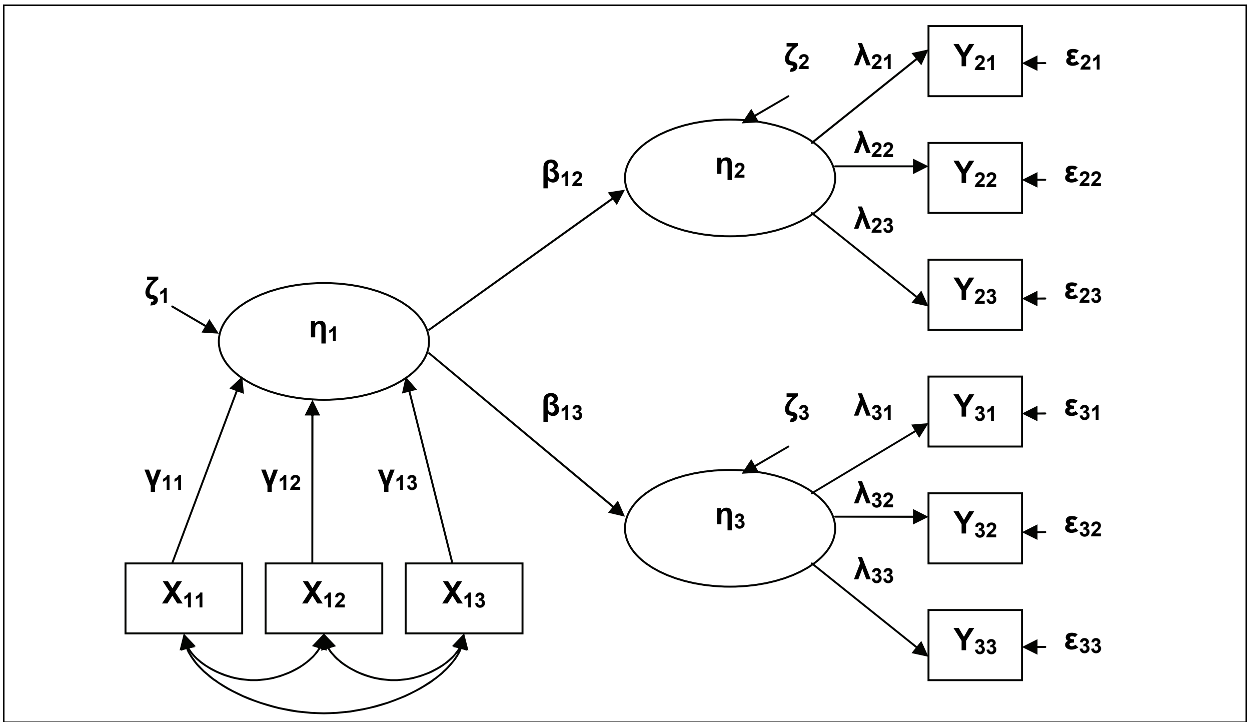

Figure 3 - Formatively-measured construct in a structural model with reflectively-measured endogenous variables

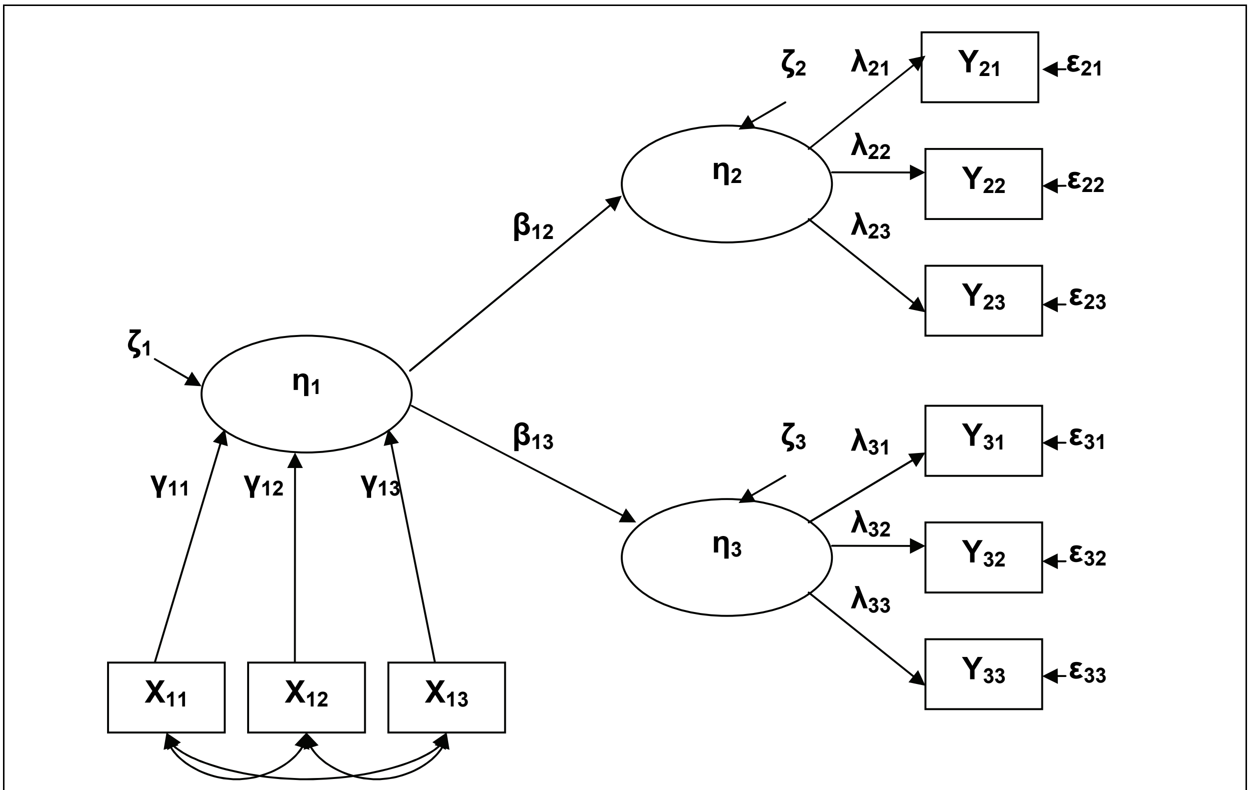

Figure 4 - Formatively-measured construct in a structural model with reflectively-measured endogenous variables

The Mimic Construct

The Multiple Indicators Multiple Causes (MIMIC) construct is created by adding two reflective items to any variable measured formatively (Diamantopoulos and Winklhofer, 2001). Such a construct is one of the choices for fully specifying formatively-measured construct which requires two emitted paths, the other being two reflectively-measured constructs, or one reflectively-measured construct and one reflective item (Jarvis et al., 2003; Diamantopoulos et al., 2008; Diamantopoulos, 2011). Figure 5 shows a MIMIC construct. The idea behind the MIMIC construct is to allow complete specification of the formative measures so that they need not be dependent on the other constructs in a SEM study. This allows separation of measurement and structural issues that formatively-measured constructs do not otherwise permit. The construct could replace formatively-measured constructs in a SEM. Doing so for the model in Figure 3 would result in the model of Figure 6.

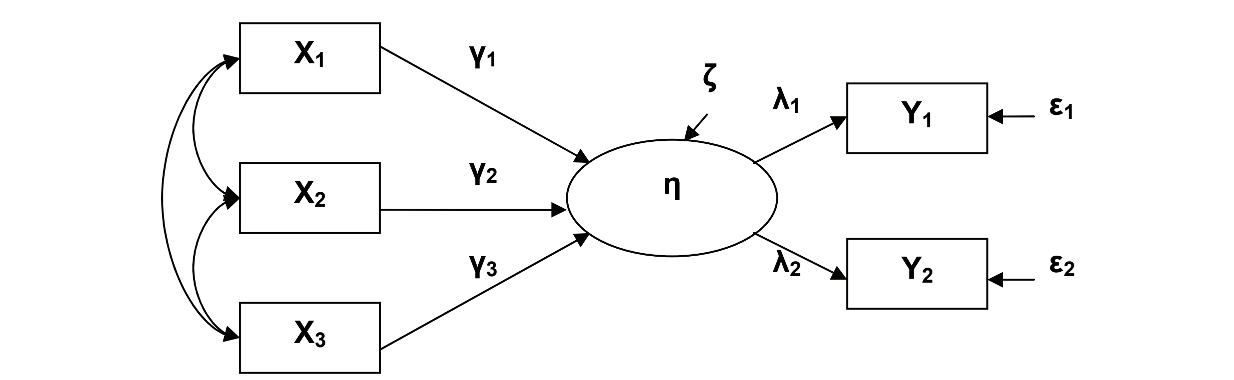

Figure 5 - A MIMIC construct with three formative measures (X_i) and two reflective measures

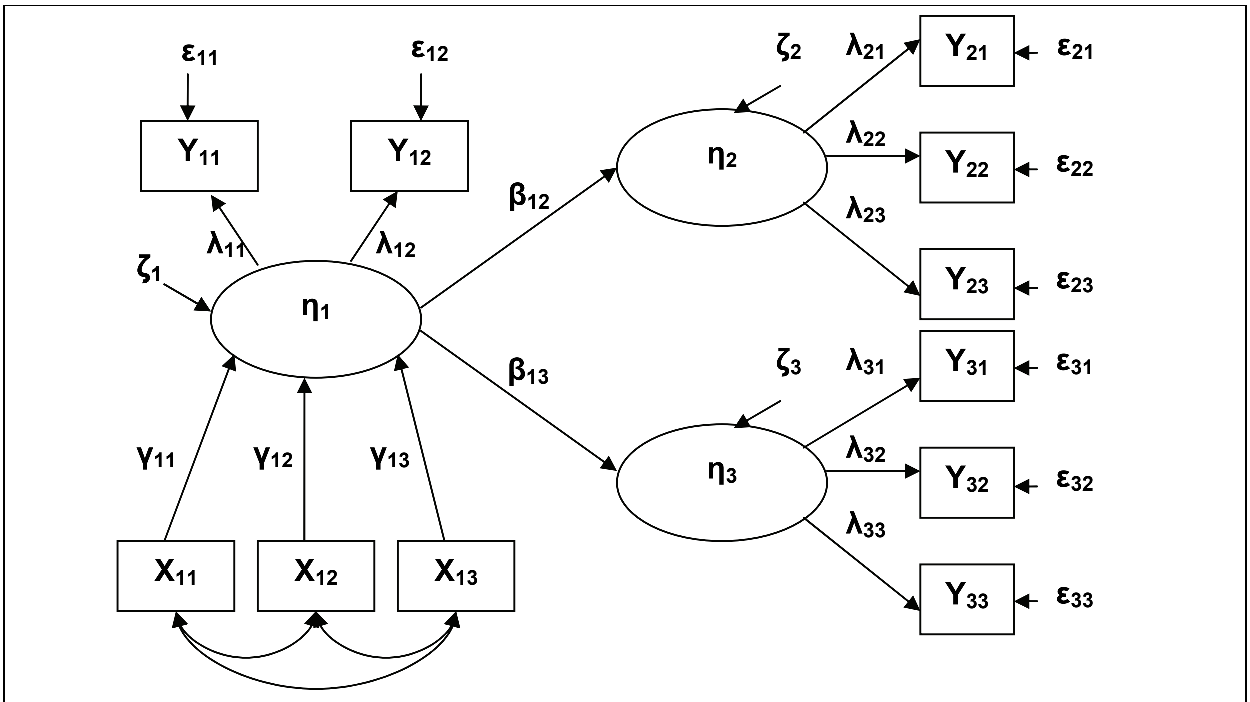

Figure 6 - A MIMIC construct in a structural equation model

The MIMIC construct still requires a complete set of formative predictors, but is considered to address issues of interpretational confounding and external consistency (Jarvis et al., 2003; MacKenzie et al. 2005; Diamantopoulos et al., 2008; Diamantopoulos, 2011). Consider the model in Figure 7 where all direct paths to the dependent reflectively-measured constructs are shown. The underlying reason to use a MIMIC formatively-measured construct is to completely mediate the effects of the formative measures on other variables (Franke et al., 2008). If the formative measures have direct as well as indirect (partially mediated) effects on the outcome variables, then the proportionality constraint would not necessarily hold and external consistency could not be established, calling the meaning and value of the formative conceptualization into question.

In order to demonstrate whether a MIMIC model is a full mediator, one needs to show the direct impact of each Xij on ηk (where k = 2 or 3) is zero in the model of Figure 7. Likewise, the direct impact of each Xij on ηk (where k = 2 or 3) in Figure 8 would be identical to the indirect impact of Xij on ηk (where k = 2 and 3). In Figure 8, for example, the estimated value of β112 would be equal to the estimated value of γ11 + β12 in Figure 6. As Franke et al. (2008) and Aguirre-Urreta and Marakas (2012) noted, the scaling used for a formative construct can reveal instability in the construct. Scaling occurs in covariance-based SEM when a path in the measurement model is set to 1 for identification purposes. In a MIMIC model, the path that is set to 1 would be one of the reflective measures as it is a unidimensional measure of the construct, thus mitigating the variation in proportional effects.

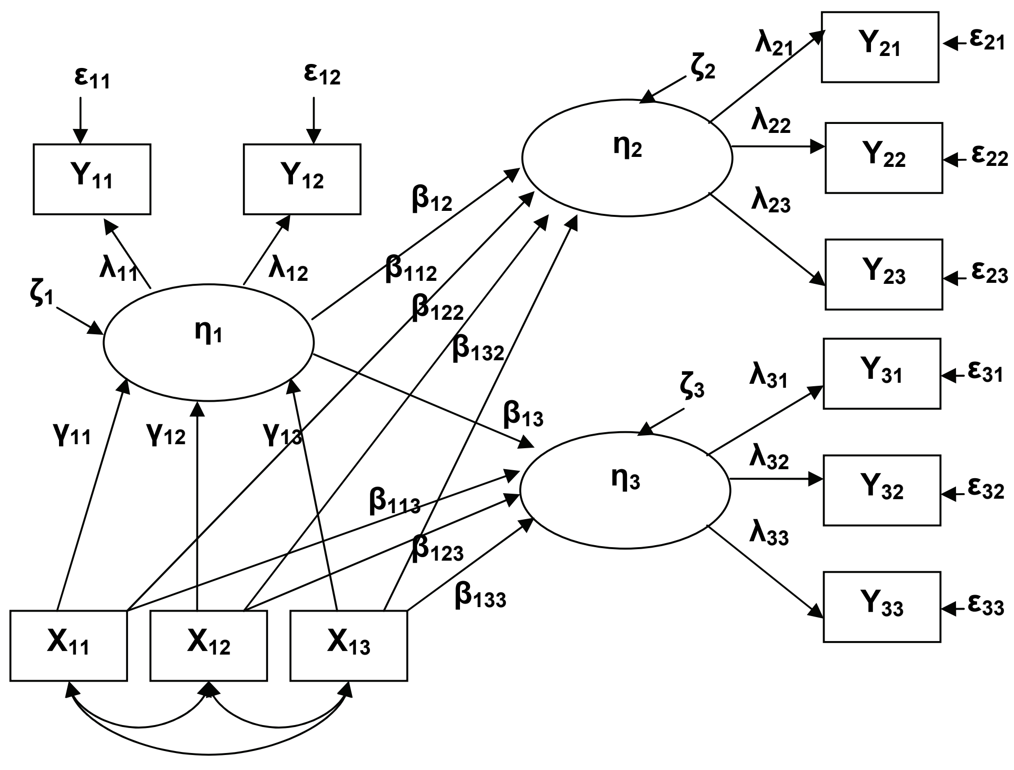

Figure 7 - MIMIC construct with relationships from the formative measures to the endogenous variables

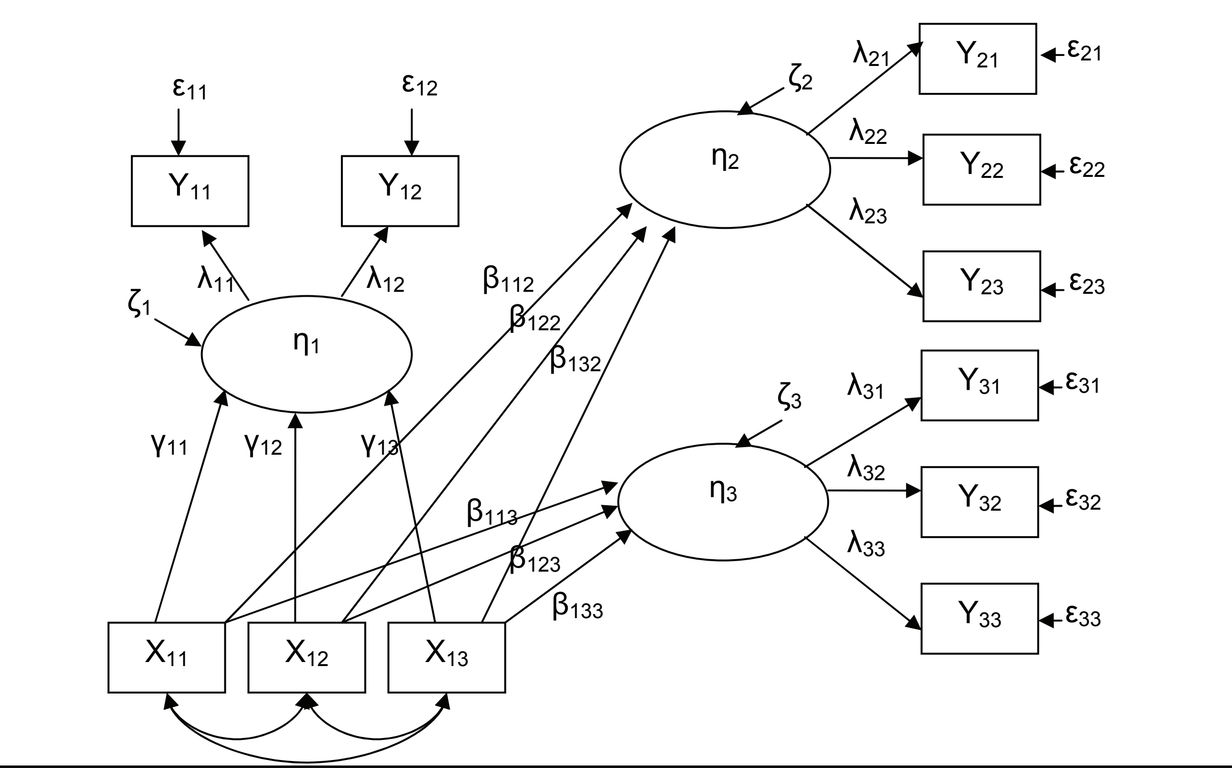

Figure 8 - Depicts a set of the formative measures lead to two outcomes variables directly

Simulation

We conducted a Monte Carlo simulation to examine the issues of interpretational confounding and proportional structural effects. The models of the simulation test for interpretational confounding by examining the stability of the path coefficients when changing the dependent variables. Figure 9 shows the assumed “true” relationships as specified in the simulation.[1] The effectiveness of the formative latent variable as a mediator is also examined using the simulation results to establish whether a MIMIC construct serves as an effective point variable for purposes of proportional structural effects, thereby external consistency.

Simulation Models

To evaluate the ability of a MIMIC construct to reduce interpretational confounding, we compare the **Base Model** to **Model A_{CV}**. The base model uses a traditional formatively-measured construct that has paths to two endogenous, reflectively-measured constructs. Model A_{CV} includes the addition of two reflective items for the formatively-measured construct, thus creating a MIMIC model for the formatively-measured construct. By comparing the stability of the formative measure weights and parameter estimates across the Base Model and Model A_{CV} when the endogenous variables change (i.e., from η_3 in Figure 9a to η_4 in Figure 9b), we can assess if a MIMIC construct can address the concern of

[1] The values chosen for the “true” relationships are generally consistent with the weights and structural parameters in Kim et al. (2010). The model used to generate the covariance matrix for the measurement and structural estimates shown in Figure 9 was actually a single model that included the MIMIC construct for η_1, and three endogenous variables (η_2, η_3, η_4). When performing the actual simulations, only a subset of this generated covariance matrix was used based on the model tested. The reason for combining the four constructs in a single model for generating the original covariance matrix for simulation was to ensure that the covariances for the formatively-measured construct (and MIMIC construct) were consistent throughout all simulations and did not introduce any bias when a different endogenous variable appeared in the model.

interpretational confounding for formatively-measured constructs.

To examine external consistency, this simulation separated the total effects into indirect and direct effects to demonstrate the magnitude of the mediating effect of the formative latent variable (i.e., η_1). The mediating effect of formative MIMIC model was examined by calculating and comparing the indirect and direct effects of its formative measures on the different sets of endogenous constructs. We used two reflective endogenous constructs (η_2 and η_3) as an example and depicted the specified models (Model A_{CV}, Model B_{CV} and Model C_{CV}) in Figure 10. **Model A_{CV}** only allowed the formative MIMIC construct to have direct links to two endogenous constructs and is identical in structure to the model of Figure

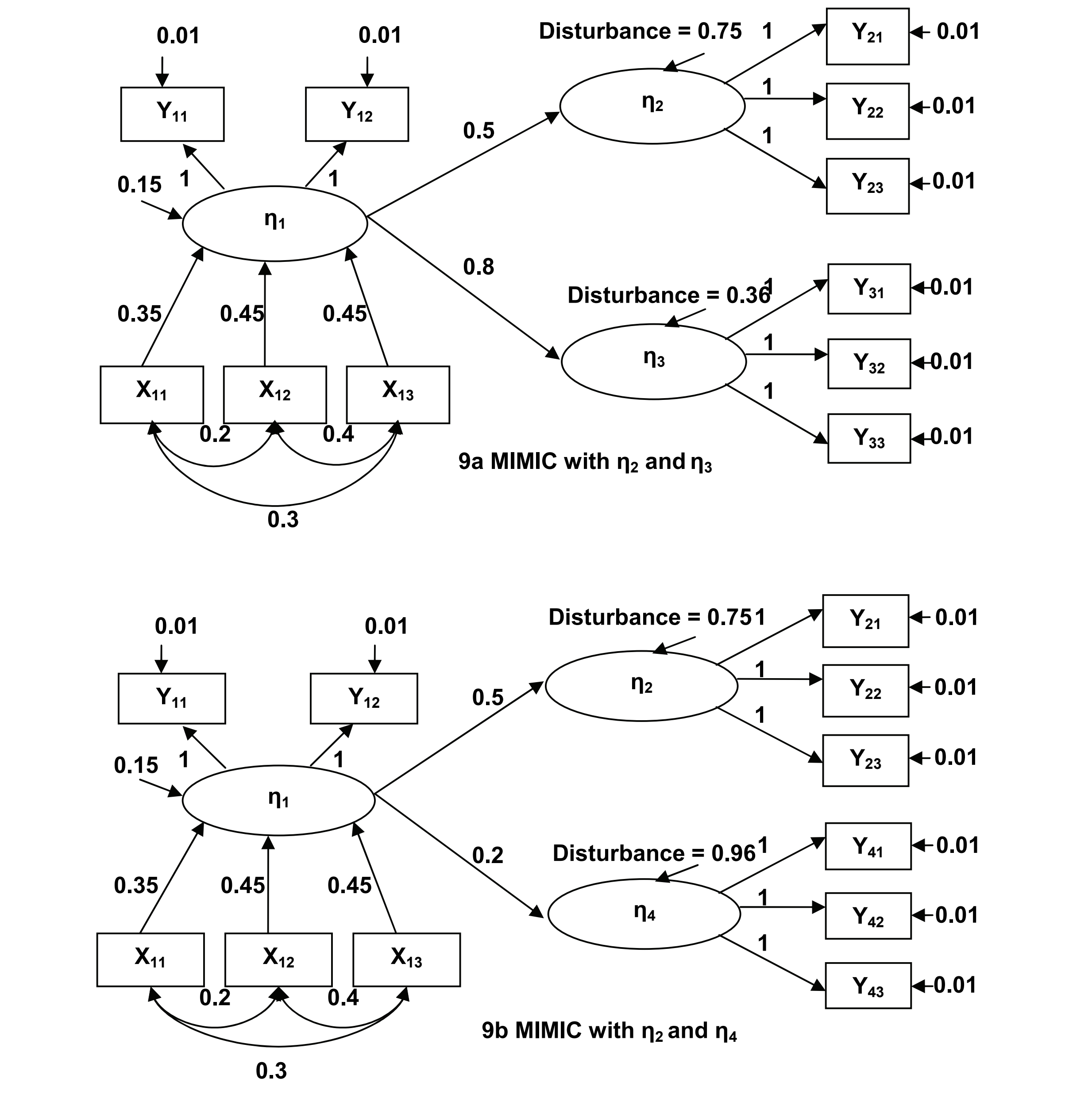

Figure 9 - True parameters model in covariance-based software

9a. **Model B_{CV}** allowed the formative MIMIC construct and its formative measures both to have direct links to the same two endogenous constructs. **Model C_{CV}** only allowed the formative measures to have direct links to the same two endogenous constructs. The same sequence was repeated for two reflective endogenous constructs (η_2 and η_4).

Assumptions

The parameters of the models are shown in Figure 9. The weight of formative measures was set to 0.35, 0.45 and 0.45. We assume a small error term for the formatively-measured construct (0.15) and all formative measure coefficients are significant, indicating a sound formative measure (Diamantopoulos, 2006). All reflective items have very low errors in defining the latent variables (0.01) to ensure the results are not influenced by poor reflective measures. The structural path between the formative MIMIC construct and η_2 remained at 0.5 for all runs, while the path to η_3 was 0.8 and the path to η_4 was 0.2. Changing from 0.8 to 0.2 in the path model for the second reflectively-measured construct should induce changes to estimates in the paths from the formative measures to the

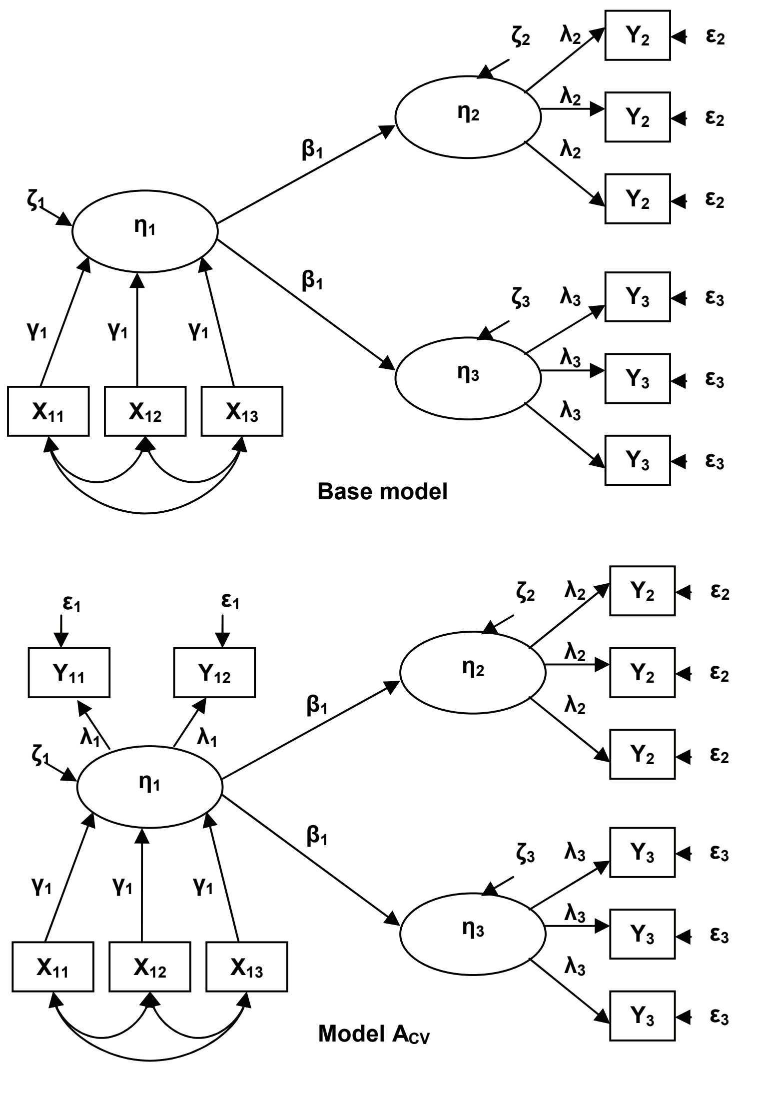

Figure 10 (part 1) - Specified models in covariance-based SEM software

formative latent variables if the MIMIC construct is unable to stabilize the measurement model.

Process

The population covariance matrix were calculated from the true parameters models shown in Figure 9, assuming a sample size of 250. We ran Monte Carlo simulations in EQS 6.1 using the population covariance matrix for each of the specific models in Figure 10 for both endogenous variable sets (η_2 and η_3; η_2 and η_4). This resulted in eight different models examined for the simulation. Consistent with Paxton et al. (2001), the analysis of the generated raw data sets, parameter estimations and fit statistics were estimated using 500 replications and only the converged samples and proper solutions were included in the analysis.

The first series of models (Figure 9A) consisted of one formatively-measured construct (η_1) with two reflective endogenous constructs (η_2 and η_3), where the structural estimation of η_1 on η_2 was 0.5, and the structural estimation of η_1 on η_3 was 0.8. In the second series (Figure 9B), we used different sets of endogenous constructs. The identical η_2 was

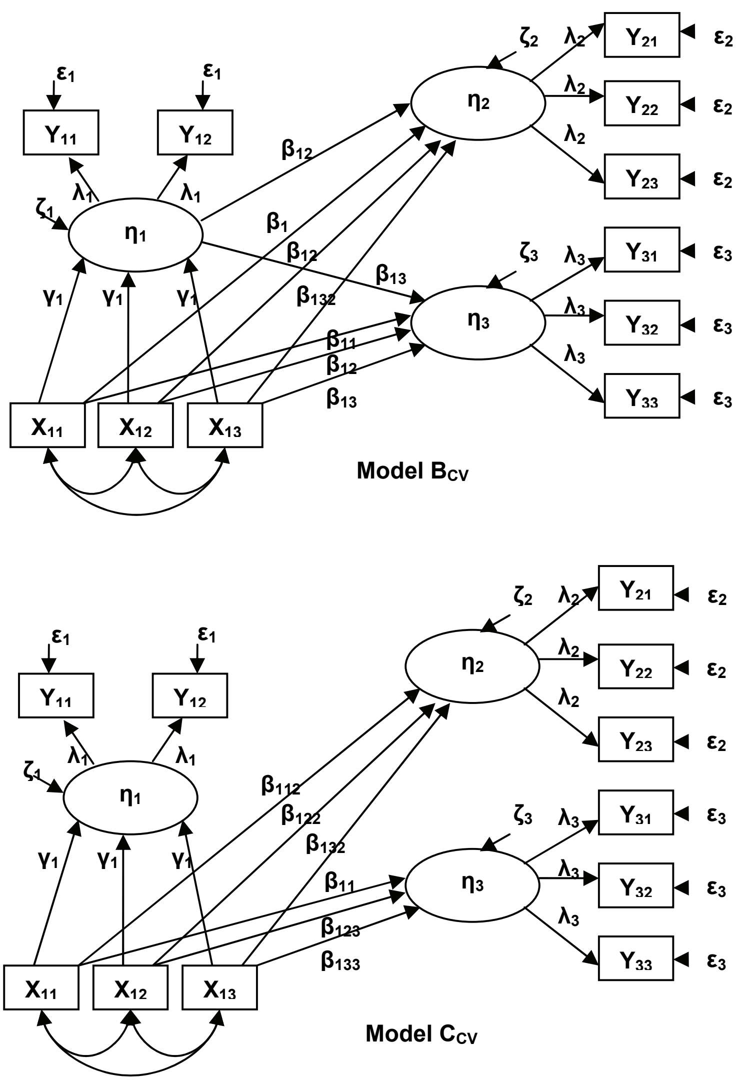

Figure 10 (part 2) - Specified models in covariance-based SEM software

still required to serve as an endogenous construct, and we replaced η_3 by η_4 as another endogenous construct. The second series of models consisted of one formative MIMIC model (η_1) with two reflective endogenous constructs (η_2 and η_4), where the structural estimation of η_1 on η_2 was 0.5 and the structural estimation of η_1 on η_4 was 0.2. Hence, each series was composed of one formative exogenous construct with two reflective endogenous constructs.

Expectations

If the MIMIC construct avoids issues of interpretational confounding, the paths from the formative measures to the latent formative variable should not change nor should the direct path from η_1 to η_2 by replacing η_3 with η_4. Variation in the estimates when an endogenous variable changes would suggest that interpretational confounding is not mitigated when a MIMIC model is used. Further, we expect the MIMIC construct to act as a point variable and fully mediate the measures to the endogenous variables, indicating proportional structural effects and external consistency.

The examination of the relationships from the formative measures of the MIMIC construct to the endogenous constructs allowed us to examine whether the indirect effects and the direct effects are the same. We can calculate and compare the indirect effect of one formative measure in Model A_{CV} and the direct effect of the same formative measure in Model C_{CV}. For example, to observe the mediating effect of the formative MIMIC construct in Model A_{CV} and Model C_{CV}, the indirect effect of X_{11} is the product of $\gamma_{11}{*}\beta_{12}$ and $\gamma_{11}{*}\beta_{13}$. These should be nearly equivalent to β_{112} and β_{113} if formative MIMIC model is a full mediator. Likewise, the direct paths to from the formative measures to the endogenous variables should be zero if the formative variable fully mediates the formative measures. This indirect effect and zero coefficients represent the meditating effect of formative MIMIC model on the relationship between its formative measures and endogenous constructs (Hair et al., 2010).

Results

Tables 1a and 1b present the results of all eight models. The columns represent the different models, varying across the structure (Base Model in Table 1a, Models A_{CV}, B_{CV} and C_{CV} in Table 1b) as well as the endogenous variable sets (η_2 and η_3, η_2 and η_4). The standard weights of the formative measures in the MIMIC construct are the first three rows of data. These should not vary or interpretational confounding is present the structural model. Further, if the path coefficient from η_1 to η_2 (β_{12}) varies when the model alters from η_3 to η_4, this would indicate a problem of interpretational confounding. As can be seen in Table 1a, the formative measure weights and structural path coefficients in the base model (using formative measures only) vary, while the formative measure weights and structural path coefficients in Table 1b do not vary to any degree across the rows when using a MIMIC construct for formative measurement. Interpretational confounding does not appear to be a problem when using a MIMIC construct with both formative and reflective measures, particularly when the reflective measures capture the construct well.

Considerations of the point variable property for external consistency considerations are evident in both Table 1 and Table 2. First, Table 1b shows that the direct paths from the formative measures to the endogenous variables are not statistically different form zero (indeed close to zero) in model B_{CV}. Further, Table 2 shows the computed values of the indirect path to η_2 in model A_{CV} to allow comparison to the direct path to η_2 in model C_{CV}. The direct path values and the indirect values should be the same if there are no proportional violations. Direct path values are those determined as the path coefficients in model C_{CV}. Indirect values are the product of the path from the measure to the latent exogenous variable and the path from the exogenous to endogenous variable (the product is shown in the third column of table 2). The changes from the direct effects to the indirect effects are very low (t = 0.473, non-significant), indicating that the MIMIC formatively-measured construct mediates the measures as desired providing a good point variable with desired external consistency for these models. Both tables lend optimism to showing formatively-measured constructs can be applied in the measurement model without leading to detriments in the structural model found by other researchers (Kim. et al, 2010).

Table 1a - Model Estimation and Fit Indices for Base Model			
Endogenous variables	**η_2, η_3**	**η_2, η_4**	**Ave % Δ**
Weights of formative measures			
$X_{11} \rightarrow \eta_1$ (γ_{11})	**0.352**	**0.308**	**-12.6**
$X_{12} \rightarrow \eta_1$ (γ_{12})	**0.448**	**0.383**	**-14.5**
$X_{13} \rightarrow \eta_1$ (γ_{13})	**0.443**	**0.399**	**-10.1**
Standard path coefficients			
η1 → η2 (β12)	**0.503**	**0.588**	**16.9**
X11 → η2 (β112)	N/A	N/A	
X12 → η2 (β122)	N/A	N/A	
X13 → η2 (β132)	N/A	N/A	
η1 → η3 (β13)	**0.805**	-----	
X11 → η3 (β113)	N/A	-----	
X12 → η3 (β123)	N/A	-----	
X13 → η3 (β133)	N/A	-----	
η1 → η4 (β14)	-----	**0.233**	
X11 → η4 (β114)	-----	N/A	
X12 → η4 (β124)	-----	N/A	
X13 → η4 (β134)	-----	N/A	
Fit Indices			
Chi-sq(df)	22.57 (22)	22.46 (22)	
GFI	0.981	0.981	
CFI	0.999	0.999	
NFI	0.995	0.995	
RMSEA	0.015	0.014	
Note: Bold items are significant at $p < 0.05$			

Table 1b - Model Estimation and Fit Indices for Model Variations

	Model A_{CV}			Model B_{CV}			Model C_{CV}		
Endogenous variables	**η_2,η_3**	**η_2,η_4**	**Ave% Δ**	**η_2,η_3**	**η_2,η_4**	**Ave% Δ**	**η_2,η_3**	**η_2,η_4**	**Ave% Δ**
Weights of formative measures									
$X_{11} \rightarrow \eta_1$ (γ_{11})	**0.352**	**0.350**	-0.5	**0.352**	**0.350**	-0.5	**0.352**	**0.350**	-0.5
$X_{12} \rightarrow \eta_1$ (γ_{12})	**0.459**	**0.452**	-1.6	**0.450**	**0.452**	0.4	**0.450**	**0.452**	0.4
$X_{13} \rightarrow \eta_1$ (γ_{13})	**0.453**	**0.453**	-0.1	**0.453**	**0.453**	0.1	**0.453**	**0.453**	-0.1
Standard path coefficients									
$\eta_1 \rightarrow \eta_2$ (β_{12})	**0.498**	**0.498**	0.1	**0.490**	**0.493**	0.5	N/A	N/A	N/A
$X_{11} \rightarrow \eta_2$ (β_{112})	N/A	N/A		0.005	0.002		**0.177**	**0.174**	
$X_{12} \rightarrow \eta_2$ (β_{122})	N/A	N/A		0.004	0.001		**0.224**	**0.224**	
$X_{13} \rightarrow \eta_2$ (β_{132})	N/A	N/A		0.003	0.006		**0.225**	**0.229**	
$\eta_1 \rightarrow \eta_3$ (β_{13})	**0.799**	-----		**0.804**	-----		N/A	-----	
$X_{11} \rightarrow \eta_3$ (β_{113})	N/A	-----		-0.001	-----		**0.283**	-----	
$X_{12} \rightarrow \eta_3$ (β_{123})	N/A	-----		-0.005	-----		**0.357**	-----	
$X_{13} \rightarrow \eta_3$ (β_{133})	N/A	-----		-0.002	-----		**0.362**	-----	
$\eta_1 \rightarrow \eta_4$ (β_{14})	-----	**0.194**		-----	**0.202**		-----	N/A	
$X_{11} \rightarrow \eta_4$ (β_{114})	-----	N/A		-----	-0.007		-----	0.063	
$X_{12} \rightarrow \eta_4$ (β_{124})	-----	N/A		-----	-0.007		-----	0.086	
$X_{13} \rightarrow \eta_4$ (β_{134})	-----	N/A		-----	0.001		-----	0.093	
Fit Indices									
Chi-sq (df)	40.14 (39)	40.41 (39)		33.93 (33)	34.15 (33)		104.35 (35)	49.06 (35)	
GFI	0.972	0.972		0.976	0.976		0.933	0.966	
CFI	0.999	0.999		0.999	0.999		0.988	0.997	
NFI	0.993	0.993		0.994	0.994		0.982	0.991	
RMSEA	0.014	0.014		0.014	0.015		0.089	0.036	
Note: Bold items are significant at $p < 0.05$									

Table 2 - Computed effect of each formative measure on endogenous construct η_2

	Model A_{CV}		Indirect effect	Model C_{CV}		Direct effect	%Δ
Endogenous variables (η_2,η_3)	$X_{11} \rightarrow \eta_2$	$\gamma_{11}*\beta_{12}$	0.175	$X_{11} \rightarrow \eta_2$	β_{112}	0.177	1.0
	$X_{12} \rightarrow \eta_2$	$\gamma_{12}*\beta_{12}$	0.229	$X_{12} \rightarrow \eta_2$	β_{122}	0.224	-2.1
	$X_{13} \rightarrow \eta_2$	$\gamma_{13}*\beta_{12}$	0.225	$X_{13} \rightarrow \eta_2$	β_{132}	0.225	-0.4
Endogenous variables (η_2,η_4)	$X_{11} \rightarrow \eta_2$	$\gamma_{11}*\beta_{12}$	0.175	$X_{11} \rightarrow \eta_2$	β_{112}	0.174	-0.1
	$X_{12} \rightarrow \eta_2$	$\gamma_{12}*\beta_{12}$	0.225	$X_{12} \rightarrow \eta_2$	β_{122}	0.224	-0.5
	$X_{13} \rightarrow \eta_2$	$\gamma_{13}*\beta_{12}$	0.226	$X_{13} \rightarrow \eta_2$	β_{132}	0.228	1.2

Illustrative Example: Web Site Service Quality

We employ a simple model as an example (Figure 11) to demonstrate the issue of interpretational confounding and external consistency. The illustrative model is largely based on the work of Cenfetelli et al. (2008); we replicated a part of their research model and collected the data from 173 Yahoo online shopping center users. In our illustrative example, service quality consists of five latent variables, which is different from the work of Cenfetelli and Bassellier (2009) in which service quality is modeled with five indicators. This illustrative model includes eight constructs: a second-order exogenous formatively measured construct (service quality) with five first-order reflectively measured constructs (assurance, empathy, reliability, responsiveness and tangibles) and three endogenous reflectively measured constructs (perceived usefulness, satisfaction and perceived value). To satisfy the sample size requirements for SEM modeling and maintain a parsimonious illustrative model, this study estimated a simple, first-order, formatively-measured. The five first-order reflectively measured constructs are converted into single measures using factor scores in order to convert service quality into a first-order formatively-measured construct.

Firstly, we assessed the validity of the measurement items within the reflective first-order constructs. Then, we used the factor score of each of the five first-order constructs to represent the formative indicators of second-order service quality construct. In this analysis, we modeled service quality as a MIMIC model and included two reflective items, with items such as “Overall, Yahoo online shopping center provides a high level of service”. This MIMIC construct was used to test the structural relationship among service quality and perceived usefulness, satisfaction and perceived value. Descriptive statistics, convergent validity and discriminant validity of all measurement items are reported in Appendix B.

Consistent with the Base Model, ModelAcv and ModelCcv (see Figure 10), we examined the relationships between service quality and both endogenous construct sets (satisfaction and perceived playfulness; satisfaction and perceived value). As demonstrated in Table 3, when comparing the results in the Base Model and Model Acv, the standard weights of formative measures in the MIMIC construct are more stable than that of non-MIMIC construct. This demonstrates that the threat of

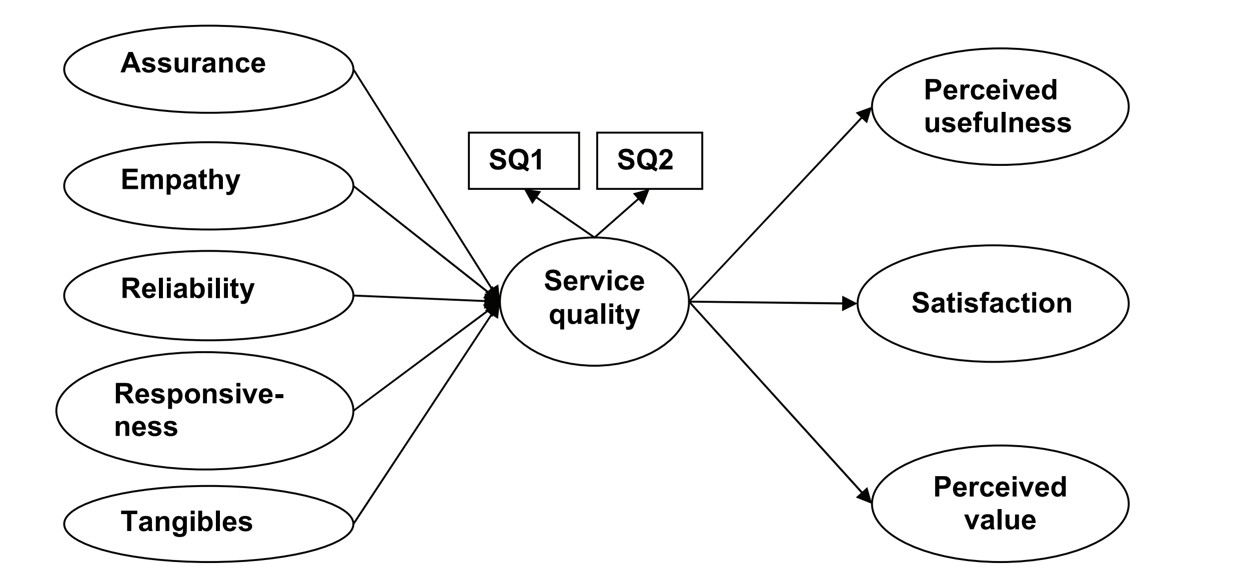

Figure 11. Illustrative Example

interpretational confounding was reduced in this example when a MIMIC model was used to model the formatively-measured construct.

The direct path values and indirect path values of the five formative indicators on satisfaction are shown in Table 4. The changes from the direct effects to the indirect effects are higher than the simulation results. We conducted t-test to compare the indirect effect and direct effect. First, we computed the change between the indirect effect in Model Acv and direct effect in Model Ccv, and the results indicated that the change rate is insignificant (t = -0.92 for endogenous variable set 1; t = -0.30 for endogenous variable set 2). Second, we computed the change between the indirect effect in Model Acv and direct effect in Model Bcv, and the results indicated that the change rate is insignificant (t = 1.66 for endogenous variable set 1; t = 1.46 for endogenous variable set 2). This suggests that the MIMIC service quality construct mediates the measures, and demonstrates the MIMIC construct provides a good point variable for external consistency.

Table 3 - Model Estimation

	Base Model			Model A_{CV}		
Endogenous variable	**SAT, PU**	**SAT, PV**	**Ave % Δ**	**SAT, PU**	**SAT, PV**	**Ave % Δ**
Weights of formative measures						
ASS→ SQ	0.06	0.10	**67**	0.09	0.10	11
EMP→ SQ	**0.10**	**0.19**	**90**	**0.13**	**0.14**	8
REL→ SQ	**0.53**	**0.42**	**-21**	**0.48**	**0.45**	-6
RES→ SQ	**0.11**	**0.15**	**36**	**0.19**	**0.19**	0
TAN→ SQ	0.02	0.10	**400**	**0.10**	**0.11**	10
Standard path coefficients						
SQ → SAT	**0.93**	**0.85**	8.6	**0.80**	**0.79**	
SQ → PU	**0.72**			**0.70**		
SQ → PV		**0.66**			**0.66**	
Fit Index						
Chi-sq(df)	68.63(42)	75.841(42)		106.39(65)	95.61(65)	
GFI	0.935	0.932		0.919	0.927	
CFI	0.982	0.975		0.978	0.983	
NFI	0.955	0.946		0.947	0.949	
RMSEA	0.064	0.072		0.064	0.055	

Notes:
Bold items are significant at $p < 0.05$
SQ = Service quality
SAT = Satisfaction
PU = Perceived playfulness
PV = Perceived value

Table 4 - Computed effect of each formative measure on satisfaction

		Model A_{CV} Indirect effect	Model C_{CV} Direct effect	%Δ	t-value	Model B_{CV} Direct effect	%Δ	t-value
SET 1 Endogenous variables (SAT, PU)	ASS→SAT	0.07	0.09	29	-0.92	0.05	29	1.66
	EMP→SAT	0.09	0.14	56		0.05	44	
	REL→SAT	0.34	0.46	35		0.12	65	
	RES→SAT	0.13	0.11	-15		0.02	-85	
	TAN→SAT	0.07	0.03	-57		0.10	43	
SET 2 Endogenous variables (SAT, PV)	ASS→SAT	0.08	0.09	12	-0.30	0.05	-38	1.46
	EMP→SAT	0.12	0.14	17		0.05	-58	
	REL→SAT	0.36	0.46	28		0.12	-67	
	RES→SAT	0.15	0.11	-27		0.02	-87	
	TAN→SAT	0.08	0.03	-63		0.10	25	

Notes:
ASS = Assurance EMP = Empathy REL = Reliability
RES = Responsiveness TAN = Tangibles SAT = Satisfaction
PU = Perceived playfulness PV = Perceived value

Conclusions

Concerns for formatively-measured constructs include issues of interpretational confounding and external consistency. Prior work establishes that these problems exist in correctly specified measurement models and not just misspecified models. A MIMIC measurement construct, with two reflective measures in addition to formative measures, might resolve these issues. The contribution of this study is to establish through simulation that the MIMIC construct serves as a point variable in a structural equation model such that interpretational confounding is avoided and external consistency is established by properties of full mediation of the measures by the construct on the endogenous variables. Formative measures can be applied in research if the measurement model is properly built to include two reflective items in a MIMIC measurement model for each formatively-measured construct.

The burden on researchers is not light when using formatively-measured constructs. The choice of using either a formatively-measured construct or a reflectively measured construct must be theoretically justified. However, automatically selecting a reflectively-measured construct when formative measurement would be more appropriate can negatively impact the understanding of the phenomenon of interest given that reflective and formative measures can provide different insights about a construct and lead to misspecification errors and estimation bias. Once the formatively-measured construct is selected, the researcher must demonstrate that all formative dimensions are included, interpretational confounding is mitigated and external consistency is present. The use of a MIMIC model with two reflective measures should be strongly considered in order to address scaling problems in an SEM. This was demonstrated even in cases where the formative measures are significant, complete, and free of multicollinearity – in other words even a well measured formative construct is subject to problems that can be enhanced by employing a MIMIC construct in the model. The reflective measures should be rigorously evaluated as appropriate for a measurement model.

From the reviewer perspective, when research employs a formatively-measured construct there must also be assurance that the known problems of interpretational confounding and external consistency are somehow alleviated. Addressing the issue of proportionality is crucial in attaining external consistency and reducing interpretational confounding. Application of the MIMIC model may not be a solution unless the reflective measures exhibit measurement properties traditionally expected on rigorous research. Further, just because a researcher has two reflective items, it does not suggest that the construct should be measured reflectively as opposed to both reflectively and formatively. While the introduction of one more reflective item would fully identify the reflectively-measured construct, the researcher may want to use formative measures to understand specific contributing factors or examine theoretical concepts related to the construct empirically.

Several limitations to this study should be considered. First, only exogenous variables are considered. The use of formative measures in a construct has differing implications in an SEM depending on placement within a model, thus, consideration of strictly exogenous variables in this paper is appropriate. Further studies of formatively-measured endogenous constructs are essential to understand their unique implications. Endogenous, formatively-measured constructs at the path's end must accommodate the theoretical considerations of the upstream variables without violating the precept that the formative indicators completely specify the variable. The inclusion of a direct relationship leading into the formatively-measured construct adds an additional formative factor, thus, nullifying the original formatively-measured construct as valid under original measurement assumptions. Therefore, the MIMIC approach might be applied to the endogenous variables, but studies should still be conducted. Secondly, the simulation assumes the reflective measures in the MIMIC construct to have effectively no error, restricting conclusions to MIMIC constructs where the reflective items are especially representative. The degree of quality in the reflective measures and the reflective endogenous variables is a question that must be addressed in further work. Lastly, we examine MIMIC models that develop reflective measures for the construct that is consistent with the theoretical definition of the construct, while other proposed MIMIC models consider additional downstream variables. The efficacy of this alternate approach requires examination as well.

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Appendix A: Formatively-measured constructs in the 6 core journals: 2009 through 2011

Article	Formatively-measured construct name (Structural position)
Burton-Jones (2009)	• Focused immersion (exogenous) • Deep structure usage (exogenous) • Performance (endogenous)
Cenfetelli and Bassellier (2009)	• SERVQUAL (exogenous)
D'Arcy et al. (2009)	• Security policies (exogenous) • SETA program (exogenous) • Computer monitoring (exogenous)
Davis et al. (2009)	• Joint IT competence (exogenous) • Partnership-led implementation (mediator) • User satisfaction (endogenous)
Goo et al. (2009)	• Foundation characteristics (exogenous) • Change characteristics (exogenous) • Governance characteristics (exogenous)
Herath and Rao (2009)	• Subjective norm (exogenous) • Resource availability (exogenous)
Iacovou et al.(2009)	• Optimistic biasing (mediator) • Pessimistic biasing (mediator) • Project size (control variable)
Kim and Benbasat (2009)	• Consumers' trusting beliefs (endogenous)
Kim et al. (2009)	• Perceived risk (mediator) • Perceived benefit (mediator) • Perceived performance (exogenous)
Klein and Rai (2009)	• Buyer Strategic Information Flows to Supplier (mediator) • Supplier Strategic Information Flows to Buyer (mediator) • Buyer Relationship-Specific Performance (endogenous) • Supplier Relationship-Specific Performance (endogenous) • Buyer Trusting Beliefs in Supplier (exogenous) • Supplier Trusting Beliefs in Buyer (exogenous)
Lee and Larsen (2009)	• Perceived severity (exogenous) • Perceived vulnerability (exogenous) • Response cost (exogenous) • Social influence (exogenous)
Lowry et al. (2009)	• Process satisfaction (endogenous) • Task discussion effectiveness (first-order formatively-measured construct of communication quality)
Meso et al. (2009)	• National information infrastructure (exogenous) • Governance (mediator) • Social-Economic Development (endogenous)
Phang et al. (2009)	• Perceived usability (exogenous) • Perceived sociability (exogenous)

Article	Formatively-measured construct name (Structural position)
Preston and Karahanna (2009)	• Structural systems of knowing (mediator) • Demographic similarity (exogenous) • Experiential similarity (exogenous)
Rai et al. (2009)	• Top management support (exogenous) • Security safeguards (exogenous) • Organizational readiness (exogenous) – IT sophistication (first-order formatively-measured construct of organizational readiness) – Financial resources (first-order formatively-measured construct of organizational readiness) • Trusting beliefs of suppliers (exogenous) • EPI standards efficacy (exogenous) – Standards flexibility (first-order formatively-measured construct of EPI standards efficacy) – Standards comprehensiveness (first-order formatively-measured construct of standards efficacy) • Aggregated EPI Assimilation (mediator)
Sia et al. (2009)	• Trust beliefs (mediator)
Titah and Barki (2009)	• Intention to use (endogenous)
Anderson and Agarwal (2010)	• Concern regarding security threats (exogenous)
Chen et al. (2010)	• CIO human capital (exogenous) • CIO structural power (exogenous)
Choi et al. (2010)	• IT support for KM (exogenous) • Team performance (endogenous)
Johnston and Warkentin (2010)	• Social influence (exogenous)
Kim et al. (2010)	• IT infrastructure flexibility (exogenous)
Lee and Xia (2010)	• Response extensiveness (mediator) • Response efficiency (mediator)
Liang et al. (2010)	• Team climate (exogenous)
Pavlou and El Sawy (2010)	• IT capability in NPD (exogenous) • Effective use of PRMS (exogenous) • Effective use of OMS (exogenous) • Effective use of CWS (exogenous)
Posey et al (2010)	• Self- disclosure (endogenous)
Rai and Tang (2010)	• Competitive performance (endogenous) • IT integration (exogenous) • IT reconfiguration (exogenous) • Process alignment (mediator) • Offering flexibility (mediator) • Partnering flexibility (mediator) • Environmental Turbulence (moderator)

Article	Formatively-measured construct name (Structural position)
Sila (2010)	• Adoption factors (exogenous)
Siponen and Vance (2010)	• Neutralization (exogenous)
Spears and Barki (2010)	• User participation (exogenous)
Tiwana and Konsynski (2010)	• IT architecture modularity (exogenous) • IT governance decentralization (moderator)
Chengalur-Smith et al. (2010)	• Business value (endogenous)
Datta (2011)	• Performance expectancy, (exogenous) • Social influence (exogenous) • Facilitating conditions (moderator)
Gopal and Gosain (2011)	• Boundary spanning (exogenous)
Hsieh et al. (2011)	• Habitus (exogenous) • Cultural capital (exogenous) • Social capital (exogenous)
Ke and Zhang (2010)	• Satisfaction of needs (moderator)
Lowry et al. (2011)	• Information privacy concerns (mediator)
Pee et al. (2010)	• Project phase performance (endogenous) • Project complexity (control variable)
Shin and Kim (2011)	• IT management capability (exogenous) • IT personal expertise (exogenous)
Venkatesh et al. (2011)	• Electronic healthcare system use (mediator) • Quality of care (mediator) • Patient satisfaction (endogenous)
Wang and Haggerty (2011)	• Virtual media skill (first-order constructs) • Virtual daily life experience (exogenous) • Virtuality (control variable)
Warkentin et al (2011)	• Situational support (exogenous) • Vicarious experience (exogenous) • Verbal persuasion (exogenous)
Wells et al. (2011)	• Website quality (exogenous)
Wells et al. (2011)	• Web Site Quality (exogenous)
Whitaker et al. (2010)	• IT coordination applications (exogenous) • Process codification (exogenous) • Internationalization (exogenous)
Xue et al. (2011)	• Perceived justice of punishment (mediator)
Yang et al (2011)	• Service quality (mediator)
Zhao et al. (2011)	• Perceived process benefit (exogenous)

Appendix B: Illustrative Model Information

Illustrative model : Descriptive statistics and Convergent validity

	Mean (S.D.)	Item (Loading)	Composite reliability	AVE	VIF
Assurance	4.73 (1.027)	Ass1 (**0.981**) Ass2 (**0.970**) Ass3 (**0.753**)	0.932	0.823	2.582
Empathy	4.38 (0.950)	Emp1 (**0.698**) Emp2 (**0.797**) Emp3 (**0.855**)	0.828	0.618	2.317
Reliability	4.89 (0.909)	Rel1 (**0.883**) Rel2 (**0.812**) Rel3 (**0.821**) Rel4 (**0.712**)	0.883	0.655	4.434
Responsiveness	4.60 (1.058)	Res1 (**0.878**) Res2 (**0.933**) Res3 (**0.906**)	0.932	0.820	2.205
Tangibles	4.87 (1.035)	Tan1 (**0.879**) Tan2 (**0.946**) Tan3 (**0.893**) Tan4 **(0.840)**	0.939	0.793	1.478
Service quality	4.83 (0.923)	Sq1 (**0.940**) Sq2 (**0.926**)	0.931	0.871	N/A
Perceived use-fulness	5.29 (0.944)	Pu1 (**0.931**) Pu2 (**0.933**) Pu3 (**0.814**)	0.923	0.800	N/A
Satisfaction	5.07 (0.837)	Sat1 (**0.841**) Sat2 (**0.901**) Sat3 (**0.816**) Sat4 (**0.893**)	0.921	0.746	N/A
Perceived value	4.74 (0.910)	Pv1 (**0.836**) Pv2 (**0.888**) Pv3 (**0.832**)	0.884	0.727	N/A

Bold items are significant at $p < 0.05$

Illustrative model : Discriminant validity

	Ass	Emp	Rel	Res	Tan	Pu	Sat	Pv
Assurance	***0.907***							
Empathy	0.505	***0.786***						
Reliability	0.773	0.705	***0.809***					
Responsiveness	0.435	0.669	0.668	***0.906***				
Tangibles	0.446	0.449	0.544	0.472	***0.891***			
Perceived usefulness	0.401	0.368	0.522	0.402	0.439	***0.894***		
Satisfaction	0.533	0.555	0.665	0.515	0.358	0.635	***0.864***	
Perceived value	0.356	0.449	0.446	0.438	0.526	0.705	0.516	***0.853***

Note: Square root of AVE in the diagonal