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A Monte Carlo Simulation of Observable Versus Latent Variable Structural Equation Modeling Techniques

In this study, three approaches commonly used by communication scientists to specify structural relationships using full-information maximum likelihood structural equation modeling are investigated. Specifically, a simulation study using Monte Carlo techniques was conducted to compare the structural paths generated by each of the three structural equation model types. Two of the three approaches utilized forms of latent variable modeling, and the third approach employed observed variables only. Of the three, the observed variable approach produced the most conservative structural path coefficients, whereas the hybrid latent variable approach generated the least attenuated coefficients. The appropriateness of each technique in modeling structural relationships is discussed and an argument is made for greater use of latent variable structural equation modeling in the field of communication.

Keywords: *structural equation model; latent variable; Monte Carlo; media effects; media exposure*

Structural equation modeling (SEM) has evolved into a practical multivariate tool employed by communication scholars to understand a multitude of issues, including the process of deliberative democracy (McLeod, Scheufele, & Moy, 1999), the effects of television on children's leisure-time reading (Koolstra & Van der Voort, 1996), and strategies for inducing resistance to alcohol use among adolescents (Godbold & Pfau, 2000). With little doubt, the use of this technique has provided the discipline with a greater

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understanding of communication within a broad set of processes and phenomena.

Interestingly, a recent review of communication-related research that used SEM revealed the lack of a universal technique for estimating and testing structural relationships between variables (Holbert & Stephenson, 2002). Instead, communication researchers have employed three different methods to specify the structural component of a structural equation model.¹ Each approach retains inherent strengths and weaknesses, and each may be acceptable under a given set of circumstances. However, the different techniques may generate contrasting estimates of the structural relationships between variables when looking at the same model with the same data. In short, researchers may draw different conclusions about the role communication plays in a given context solely due to the type of structural equation model used to test a set of relationships. These issues and differences warrant further attention.

This study is a comparative analysis of three approaches of SEM. Our goal was to assess the variation in the structural path estimates generated by each approach. We identified the three model types as: observed variable (OV), latent composite (LC), and hybrid (HY) (Holbert & Stephenson, 2002). To compare each type, we conducted a simulation study using Monte Carlo techniques. We specified and analyzed a single structural equation model using the same simulated data set for each of the three methods. We wanted to determine if the structural relationships among the same set of variables differed significantly by model type. Prior to our evaluation, we summarized each of the three techniques used to test the structural parameters in a structural equation model, focusing on the unique relationships established between measurement error and structure in each.

SEM Techniques in the Communication Sciences

OV Models

The OV approach specifies relationships solely among observed (measured) variables (see Figure 1).² Two types of variables are analyzed through this approach, either single-item measures or composites of multiple items directly measured by the researcher. Single-item measures function in the same capacity as composites in OV models.

Historically, the OV model was utilized by Sewell Wright (1921, 1934) as he pioneered what we know as partial-information path analysis (Blalock, 1971; Pedhazur, 1982). SEM is believed to have advanced traditional path analytic techniques by allowing for the estimation of a model via full-

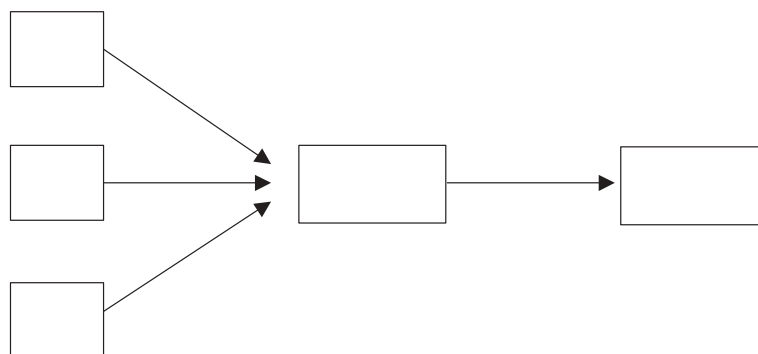


Figure 1. Observed Variable Structural Equation Model

information procedures (Bollen, 1989; Jöreskog, 1970, 1971). The full-information OV approach remains a commonly used, valid, and viable statistical technique. Indeed, the OV approach was the most frequently employed approach in communication-related journals in the latter half of the 1990s (Holbert & Stephenson, 2002).

Conceivably the greatest liability to using the OV method in SEM is that measurement error is retained within the observable variables in the structural model. As MacCallum (1995) stated, "The presence of such error in the measurements will contaminate estimates of model parameters" (p. 21; see also Bentler, 1995; Bollen, 1989; Hoyle & Kenny, 1999). Although the OV approach benefits from full-information estimation, it limits the SEM technique because measurement error is retained within the measured variables. Unless one employs SEM with latent variables (as opposed to observed variables), measurement error cannot be extracted.

The most appropriate use of the OV method occurs when a researcher wants to model any number of single-item measures. It is difficult to argue that a single measured item completely captures the essence of a latent variable. As a result, one is justified in modeling single items via the OV method. A second reasonable use of this approach, demonstrated by Hoyle and Kenny (1999), is when one's measures are highly reliable. As coefficient alpha increases, the parameter estimates generated by a latent variable model will become increasingly similar to those generated by an OV model. Thus, the OV approach is the only real alternative for researchers constrained by single-item measures, although there is some justification that the OV approach may be a reasonable alternative to other model types if the reliabilities of all multiple-item indices are very high (at least $\alpha > .90$; see Hoyle & Kenny, 1999).

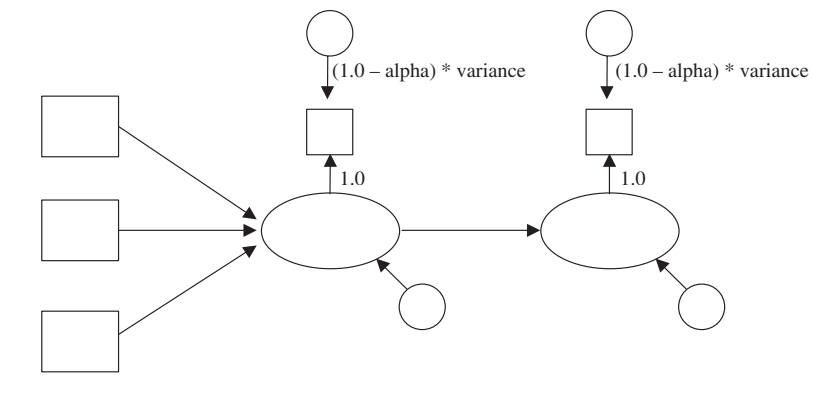


Figure 2. Latent Composite Structural Equation Model

LC Models

Those who wish to use a composite measure, but take advantage of latent variable modeling, may employ the LC approach (see Figure 2). Unlike the OV model, the LC approach acknowledges both random and systematic error. Exogenous latent variables, those that are not influenced by other variables in the model (akin to independent variables), have a variance parameter reflecting unreliability through measurement error. Endogenous latent variables, generally those that are influenced by other variables in the model (akin to dependent variables), also have variances. Endogenous variances, however, are functions of other parameters in the model. Specifically, endogenous variable error terms reflect the “part of the [latent variable] not accounted for by the linear influences specified in the model” (MacCallum, 1995, p. 21).

The specification of an LC model is slightly different than what is required to specify an OV model. Structural models must be overidentified, meaning that they have more equations than they have unknown parameters. Yet because the LC model introduces latent variables and error terms of exogenous and endogenous variables, there are multiple unknowns to be estimated. Therefore, an overidentified LC model is attained in two steps in most SEM programs. First, fix the path from the latent construct to its observed variable to 1.0. Second, fix the error variance of the observed index to $(1 - \text{reliability})$ multiplied by the variance of the indicator (see Bollen, 1989 for another demonstration of this technique). Step two reflects the proportion of variance in the index that is attributable to measurement error. SEM software subsequently estimates the fit of this model to its population (sample)

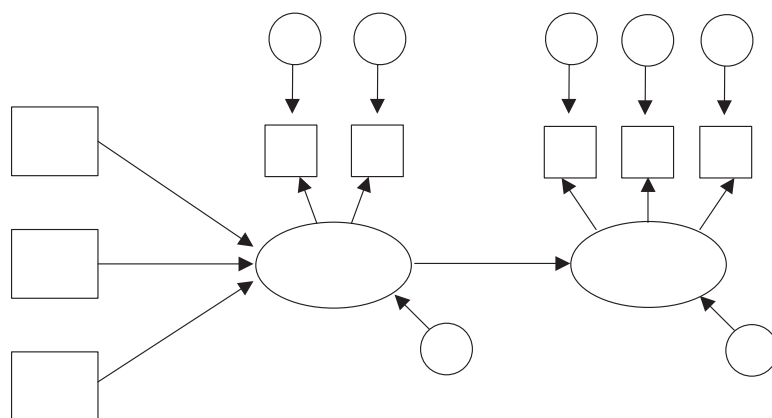


Figure 3. Hybrid Structural Equation Model

covariance matrix. Bollen (1989) provided an informative comparison of the OV and LC approaches, particularly in regard to how error can misrepresent relationships between variables (see pp. 151-176).

Most agree, with respect to measurement error, that the LC approach is a marked improvement over the OV approach (Bentler, 1980; Bollen, 1989; Hoyle, 1995; Loehlin, 1998). The liabilities associated with these approaches are described by Bagozzi and Heatherton (1994). They agreed that these approaches are warranted for more global representation of constructs. However, the composites generally fail “to represent the unique properties of subdimensions, if any, and obscure both the differential dependence and the effects of subdimensions on other constructs of theoretical interest” (Bagozzi & Heatherton, 1994, p. 39). The alternative to either approach requires one to specify a complete measurement model. This is more representative of the third approach, the HY model.

HY Models

The HY approach represents a full latent variable model consisting of measurement and structural parameters (see Figure 3). The measurement model concerns the “within-construct relations” (Hoyle, 1991, p. 67) by specifying relationships between the measured variables (i.e., scale items, item parcels) and their respective latent constructs (Pedhazur, 1982). The structural model represents “the magnitude and direction of the relations among a collection of measured or latent constructs” (Hoyle, 1991, p. 67) and allows one to assess and evaluate the hypothesized relationships in the proposed model.

Carmines (1986) provided this explanation of the relationship between measurement and structural models:

The structural model without its measurement component makes the unrealistic assumption of perfect measurement. The measurement model without the structural component does not allow for causal relationships among the unobserved theoretical constructs. Only when the two submodels are fully integrated to form the general model for the analysis of covariance structures is it possible to analyze the most realistic case—a structural model with causal relationships among the unobserved theoretical constructs, recognizing that they are measured imperfectly. (p. 31)

Kaplan (2000) has most recently articulated that the problem inherent in HY models is the substantial increase in degrees of freedom, “leading to the rejection of otherwise well-fitting structural models” (p. 188). To some extent, our own data support this assertion. Almost 80% of the HY models found in communication-based academic journals from 1995 to 2000 produced a significant χ^2 test, implying the models were not consistent with the data.³ Kaplan argued that this problem is a result of the restrictions placed on one’s data—that there are a specific number of factors and that a simple structure exists that underlies the relationship between the measured variables and the latent factors in a specific population. The most credible response to Kaplan is that the evaluative χ^2 test is χ^2 distributed under only the most ideal conditions that are rarely achieved (Bentler, 1990; Bollen, 1989; Hu & Bentler, 1995). As a result, many have turned to alternative fit indices that are based on the noncentral χ^2 distribution (Browne, 1984; Fan, Thompson, & Wang, 1999; Gerbing & Anderson, 1993; Marsh, Balla, & McDonald, 1988).

Intradisciplinary and Interdisciplinary Comparisons

Of the three model types, the OV model was the overwhelming choice in the communication sciences and the LC was the least (Holbert & Stephenson, 2002). Specifically, between 1995 and 2000, 57.6% of SEM-related studies employed the OV model, 35.6% utilized the HY model, and 6.8% used the LC technique. We concluded that although there was a critical mass of studies employing full-information maximum likelihood SEM in the communication discipline, the majority underutilized the statistical technique by not taking advantage of latent variable modeling.

In fact, it is clear that communication researchers lag behind other disciplines in advancing the use of SEM due to their heavy reliance on OV models. For comparative purposes, consider MacCallum and Austin’s (2000) analysis

of SEM articles in 16 psychology journals published between 1993 and 1997. They concluded that only 25% of the articles they analyzed employed observed variables (measured rather than latent). Perhaps even more enlightening is that other analyses of SEM studies, one in psychology by Breckler (1990) and one in marketing by Baumgartner and Homburg (1996), did not even consider an article to have conducted SEM unless the study employed latent variables. In fact, many continue to label the use of observable variables as path analysis; and further, "some researchers do not consider path analysis models to be typical SEM models" (Raykov & Marcoulides, 2000, p. 3). This evidence indicates a clear discrepancy in the use of SEM by communication scholars relative to their peers in other social scientific disciplines.

Measurement Error as a Source of Variability

The fundamental difference in the three approaches is how each accounts for random measurement error that, as we know, attenuates the magnitude of the relations between variables (Judd & Kenny, 1981). Measurement error is manifest in a construct's reliability, with greater reliability an indicant of "the relative absence of errors of measurement in a measuring instrument" (Kerlinger, 1964, p. 430). Classical test theory demonstrates how reliability is the proportion of true variance to total variance generated by a measure (e.g., Lord & Novick, 1968). A true score "is the variable that results from all the systematic factors in the observed variable" as it reflects "what remains when the errors of measurement are removed" (Bollen, 1989, p. 208). When measures are stable, consistent, and accurate, they are reliable and therefore more likely to approximate the true score of a measure. As stated by Kerlinger (1964): more error, greater unreliability; less error, greater reliability.

Each of the three SEM approaches treats random error (that associated with reliability) very differently relative to the establishment of its structural relationships. The OV approach does not provide a mechanism for extracting measurement error from the variables of interest to the model. The error terms that are generated from estimating the OV model reflect the error manifest within its respective composite or single-item measure. One plausible remedy to the manifest error is to correct correlation coefficients for attenuation. This is accomplished by dividing the correlation between two variables by the square root of the product of their reliabilities. One subsequently employs the disattenuated correlations and their respective standard deviations to generate the covariance matrix for the iterative SEM

procedure (e.g., Cudeck, 1989, on the statistical problems inherent from the use of the correlation versus covariance matrix in SEM).

Although this is a viable and frequently employed procedure (Schmidt & Hunter, 1996), Cohen and Cohen (1983) discussed the need to employ “extreme caution” in correcting for attenuation and interpreting disattenuated coefficients (p. 69). McPhee and Babrow (1987) echoed this position. At issue is the fact that the parameter estimates are highly dependent on a lower-bound reliability coefficient (Cortina, 1993), but the reliability coefficient is, in turn, dependent on the sample from which it is derived. The result, according to McPhee and Babrow, is that the error in the reliability or the correlation coefficient may be magnified because the formula involves “the equivalent of dividing by a reliability value” (p. 347). Additionally, they indicated that no statistical test is available for the corrected coefficient and that “such corrections use only the internal reliability of each measure relative to other measures of the same variable, disregarding the performance of each index as an indicator of relations with other variables” (p. 346). This issue, as it pertains to SEM, is discussed in detail by Bedeian, Day, and Kelloway (1997), whereas Cortina (1993) discussed the assumptions and meaning of coefficient alpha.

Latent variable approaches to SEM were designed specifically to extract measurement error from the variables from which structural relationships are established, thereby estimating only the systematic relationship between unobserved constructs (Cudeck, du Toit, & Sörbom, 2001; Jöreskog, 1973). In latent variable modeling, a construct’s unreliability is accounted for in the measurement model. The measurement model consists of measured variables, their respective error terms, latent variables, their error terms (also called a disturbance term), and the relationships between the measured and latent variables. The error terms for measured variables estimate the unreliability (measurement error) that exists between the measured and latent variables. The disturbance term for the latent variable represents the variance unaccounted for in the latent variable by the measured variables. “In this way, uniqueness and random error are divorced from commonality in such a way that the reliability . . . is in effect 1.0” (Hoyle & Kenny, 1999, p. 203). As a result, the parameter between the measured variables and their respective latent variable reflects the systematic (true) relationship of measurement corrected for unreliability (see Bollen, 1989, especially pp. 218-221).

HY and LC approaches account for unreliability in slightly different ways. In the HY approach, the measurement model includes multiple measured indicators for each latent variable. The unreliability associated with each measured variable is thereby accounted for in the HY model. In contrast, the

measurement model for the LC approach specifies only one measured composite variable for each latent variable. Here, the unreliability of the construct is retained in the residual term.

The influence of unreliability on model type is illustrated by Hoyle and Kenny (1999). They tested a three-variable model (X, Y, and Z) where Z mediated the influence of X on Y. In a Monte Carlo simulation manipulating collinearity of X and Z, reliability of Z, sample size, and model type (only OV and HY), they detected a significant model type by reliability interaction. Hoyle and Kenny observed that “unreliability had relatively little influence on estimates of [the mediator-outcome path] in the latent variable model,” but “it had a strong influence on estimates in the composite model” (p. 206). For example, with X and Z correlated at .60, a sample of 200, and low reliability for Z ($\alpha = .60$), the path from the mediator to the outcome (Z to Y) was substantively different between the models. Specifically, the parameter estimate was .32 in the HY model but only .14 in the OV model. When Z was moderately reliable ($\alpha = .75$), the parameter estimates were .29 for HY and .20 for OV. When Z was reliable ($\alpha = .90$), the parameter estimates were .30 for HY and .25 for OV. Hoyle and Kenny found that parameter estimates for X to Z were also attenuated by unreliability. Their conclusion, that “as reliability decreases, the underestimation in the composite model was more pronounced” (p. 206), is perhaps not surprising, although it does illustrate the ill effects of measurement error on parameter estimates in different models.

Hypothesis and Research Question

To examine the effects of measurement error in three types of SEM, we conducted a simulation study using Monte Carlo techniques. The model selected for the simulation study is depicted in Figures 1, 2, and 3. The model contains three exogenous variables and two endogenous variables. A more detailed description of the origins of this model and its centrality to the study of mass communication is described later. From our review of the three distinct approaches as well as the factors potentially influencing the estimation procedures, we propose the following:

Hypothesis 1: The latent models (LC and HY) will generate significantly higher structural path estimates than the OV model.

Although we have sufficient evidence to hypothesize differences between the latent and observable variable models, we have less information about how differences might play out between the two latent variable models. Although there are a host of theoretical and measurement implications for

how one specifies latent variable models (see Baumgartner & Homburg, 1996, especially pp. 143-144), the outcomes of these approaches are less clear. Both latent variable approaches that we have identified extract measurement error, but will the approaches produce contrasting outcomes? Therefore, the following question can be asked:

Research Question 1: Are there significant differences in the path estimates for the two latent variable model types (the LC and HY)?

Overview of Monte Carlo Simulation

Monte Carlo simulation allows researchers the ability to track the behavior of a given statistic. This is accomplished by extracting several random samples from a simulated data set that retains certain properties defined by a researcher (Mooney, 1997). In short, it is an “empirical method for evaluating statistics” (Paxton, Curran, Bollen, Kirby, & Chen, 2001, p. 289). Monte Carlo techniques allow researchers to observe the behavior of a given statistic across several random samples, a feat that is “either impossible or extremely expensive” via any other means of analysis (Rubenstein, 1981, p. 8).

The foundation of Monte Carlo simulation is in the generation of random variables. Each variable is assigned a set of properties defined by the researcher: whether these properties are distributional in nature, how one variable is related to another variable in a given model, or how much error is associated with the measurement of a variable. Several statistical software packages are available for the generation of matrices based on a given set of properties for multiple variables (see Mooney, 1997). Once a matrix of this kind is produced, the researcher then has the ability to produce a seemingly infinite stream of observations that retain the properties of the matrix. The data used for Monte Carlo simulations are artificial and unobserved but are generated via theory and a researcher’s understanding of variables’ distributional qualities (Paxton et al., 2001).

Once this single data set is generated, several random samples are extracted from this data and used for the purpose of observation. The researcher establishes the size of the simulated data set, the number of random samples extracted from the simulated data, and the size of each of the random samples. It is important to recognize that Monte Carlo simulation is a form of experimentation. Researchers are able to establish a controlled environment through the establishment of a given set of variable properties, and can then test for the behavior of a given statistic based on those properties. Once the random samples have been extracted from the simulated data, the researcher can then track the movement of a statistic across the samples.

Although the data produced through a Monte Carlo simulation are unobserved, the generation of several hundred random samples (creating several hundred observations for a given statistic) is seen as far superior to the use of a single or small number of data sets (e.g., Smith, 1973).

Monte Carlo Simulation in SEM

Monte Carlo simulations are found in a host of disciplines (e.g., Finch, Macmillan, & Simpson, 2002; Hurley & Lior, 2002; Wick, Siepmann, & Schure, 2002) and are increasingly popular in recent SEM literature (e.g., Jackson, 2001; Oczkowski, 2002). However, Paxton et al. (2001) stated that works providing general overviews of this technique only indirectly apply to SEM (e.g., Mooney, 1997; Robert & Casella, 1999; Rubenstein, 1981). They argued that SEM offers a unique set of circumstances that must be taken into account when performing a Monte Carlo simulation. Thus, Paxton et al. offered “an introduction to the design and implementation of a Monte Carlo simulation in the area of SEM” that focuses on theory, relevance, and practicality (p. 288). We used the Paxton et al. sample introduction to performing an SEM Monte Carlo simulation as a template from which to conduct our comparison of three types of models that test the same set of structural relationships among a given set of variables (latent or observed).

One point raised by Paxton et al. (2001) that is of particular importance to our simulation concerns the creation of an appropriate model. The question of external validity is always associated with Monte Carlo experiments. Thus, authors of SEM-based simulations should, according to Paxton et al., “create a model that is representative from an applied standpoint” (p. 291). A model should be created based on what is generally found in a given literature. Paxton et al. suggested looking over previous SEM pieces in an area of study, a task we recently completed in communication (Holbert & Stephenson, 2002). We use this assessment of communication-based SEM to generate the models for this simulation to maximize the external validity of this study.

Method

Model Selection

The proposed model contains three exogenous variables and two endogenous variables. To establish the external validity and relevance to mass communication, we derived a commonly employed model that reflects a process mediated by media use. The exogenous variables represent the presence or absence of a population characteristic. The first endogenous variable represents media

use. Two observable items—media exposure and media attention—are commonly used to form the latent variable called media use (e.g., McLeod et al., 1996; McLeod et al., 1999; McLeod, Sotirovic, & Holbert, 1998). The second endogenous variable reflects a three-item theoretical outcome variable influenced by media use (see Figure 3).

The framework employed in our model is represented in multiple mass communication research inquiries. For example, Holbert, Shah, and Kwak (2003) examined how prime-time entertainment television use mediated the relationships between multiple exogenous variables (age, sex, education, income) and attitudes concerning women's rights. In a more complex example, McLeod, Scheufele, and Moy (1999) evaluated how television news and newspaper use mediated the relationship between two exogenous population variables (social networks and city versus neighborhood residence) on political participation.

As the model is representative, so too are the measurement characteristics for each variable employed in the model. Exogenous variables such as biological sex or education are typically single-item measures. The mediating endogenous variable, media use, is traditionally measured by two items reflecting exposure (e.g., "How many days in the previous week did you watch local news?") and attention (e.g., "When watching local news, how much attention did you give to it?") (Chaffee & Schleuder, 1986). The second endogenous variable reflects outcome variables that would typically be influenced by media use, including any perceptual or attitudinal constructs traditionally measured with multiple items. We chose three items to load on this theoretical construct.

All three model types were overidentified, meaning that there were more equations for the model than unknown parameters (Hoyle, 1991; Raykov & Marcoulides, 2000). Unknown parameters are those for which the SEM process will generate numerical values. To be overidentified, a model must have one or more degrees of freedom. A model with zero *df* is just identified, the fit is always perfect, and the model cannot be properly evaluated (MacCallum, 1995). In this study, the HY model had 16 *df* whereas the OV and LC models each retained 3 *df*.

Samples sizes for Monte Carlo simulations should also reflect what is found in a given discipline (Paxton et al., 2001). We employed a sample size of 350 in all the simulations as this was the average sample size of all SEM studies conducted in communication during the past 6 years (Holbert & Stephenson, 2002).⁴ In some simulations, sample size is treated as a variable in a more complex factorial design. For example, Hoyle and Kenny (1999) varied sample size to assess how small one's sample could be and still obtain stable estimates of a mediated model. Hu and Bentler (1999) varied sample sizes

from 150 to 5,000 to test rejection rates of fit indices for true population models under various conditions. Although in these previous studies sample size as a variable was central to the questions raised regarding asymptotic properties of the fit indices, this is not the case here. Varying sample size would only have added a level of complexity that was not necessary to answer the questions in this study.

We chose two distinct reliabilities for the two endogenous variables in the model. Consistent with the results of Chaffee and Schleuder (1986) in their study of media use measures, the reliability for the first endogenous variable was set at .65. This lower reliability reflects the presence of greater measurement error. In general, this reliability approaches the floor for media use studies (e.g., Holbert, Shah, & Kwak, 2003). For the second endogenous variable, a coefficient alpha of .80 was selected to reflect the moderate reliability evidenced in media studies (e.g., Koolstra & Van der Voort, 1996; Semetko & Valkenburg, 1998).

Monte Carlo Simulation

This simulation study was conducted in three steps. First, a covariance matrix with coefficient alpha of .65 for the first endogenous variable and an alpha of .80 for the second endogenous variable was generated using the software package GAUSS 4.0 (see Mooney, 1997, for a brief tutorial). GAUSS creates a variance-covariance matrix based on the distributional properties of a set of variables supplied by the researcher (see the appendix for covariance matrix). Second, EQS 5.7b for Windows was employed to conduct the simulation for each of the three model types (HY, LC, OV) using full-information maximum likelihood estimation.⁵ For each model, we generated and analyzed 500 random samples with $N = 350$. From these samples, we retained the parameter estimates, the standard errors, and the diagnostic information regarding the convergence and fit of the data to the model. Finally, these data were analyzed using SPSS for Windows. In particular, we were interested in the parameter estimates for the structural paths shown in Figures 1, 2, and 3.

Results

The integrity of the simulated solutions were checked prior to running analyses comparing the three model types. Because simulations often produce models that fail to converge or are improper solutions, we generated 550 solutions for each model type. All models generated proper solutions in the LC and OV models, however there were estimation problems in 14 (2.5%) of the HY models. Following Paxton et al. (2001) and Hoyle and Kenny (1999), we

Table 1
Structural Coefficients

	Hybrid	Latent Composite	Observed Variable	F	p	η^2
Endogenous to Endogenous Path <i>d</i>	.406	.331	.211	665.9	.001	.47
Exogenous to Endogenous Path <i>a</i>	.176	.160	.165	15.8	.001	.02
Path <i>b</i>	.182	.171	.167	17.4	.001	.02
Path <i>c</i>	.168	.152	.154	29.1	.001	.04

Note. Coefficients are unstandardized. For Path *d*, $SE = .002$. For Paths *a*, *b*, and *c*, $SE = .004$. Degrees of freedom for all univariate F tests are 2, 1497.

eliminated those models that did not converge and retained the first 500 proper solutions for each model type.

To evaluate Hypothesis 1 and Research Question 1, we combined the data sets ($N = 1,500$) and employed MANOVA with model type as the independent variable and the four unstandardized path estimates as dependent variables. The multivariate effect was significant, Wilks's $\Lambda = .46$, $F(8, 2988) = 175.3$, $p < .001$, $\eta^2 = .32$. The univariate results are presented in Table 1.

Hypothesis 1 predicted that the latent variable models (the HY and LC) would generate significantly higher path estimates than the observable variable models. In Table 1, Path *d* provides support for this prediction. In fact, this path, which reflects the endogenous to endogenous path, reveals the most marked difference among the three model types. Scheffé's post hoc analysis revealed that the HY path is significantly greater than the LC path, which in turn is significantly greater than the OV path. Moreover, model type explains nearly half the variance in this structural parameter. Perhaps most important, significantly different path estimates were found for the three model types despite the fact that all three models employed the same data.

Paths *a*, *b*, and *c* in Table 1, which provide estimates for the exogenous to endogenous variables, also lend support to Hypothesis 1. Although the differences are small, Scheffé's post hoc test revealed that the HY model generated a statistically significant and stronger parameter estimate than the other two models. In fact, the LC and OV paths are not statistically different from each other. As with the previous hypothesis, the HY provides the least attenuated results of the three model types. The results here should be tempered by noting the ample power ($N = 1,500$) available to detect these small differences in the dependent variable.

Research Question 1 asked about the differences between the two latent variable model types, the LC and the HY. Given that both are forms of latent variable analysis, it was useful to compare any variation in the path estimates even though the same data were used. Indeed, there were differences in the estimates provided by the two models. In all four paths, the HY generated path estimates that were significantly greater than the LC model.

Discussion

In this study, we specified a single structural equation model representative of the research literature in mass communication. Then, using a Monte Carlo simulation technique, we examined how the model's path coefficients varied as a function of the approach used by communication researchers to model the data (HY, LC, or OV). The same data and the same theoretical model were used for all three approaches. The sole difference was the approach to specifying the data. But because each approach is different in managing error, we predicted that the path coefficients would vary to the degree that error was extracted from the data. In particular, we believed the latent variable techniques (HY and LC) would generate path coefficients that were greater than those produced by the OV approach.

As indicated in Table 1, our expectations were largely confirmed. In all instances, the HY model generated path coefficients that were statistically different and greater in magnitude than the OV technique. This outcome is not entirely surprising. The assumption under which one operates when using an observable variable in SEM is that the empirical construct is perfectly measured. This is rarely the case (Muchinsky, 1996). Moreover, SEM techniques cannot extract measurement error from those variables specified as observable (e.g., Rubio & Gillespie, 1995). In essence, the OV approach is the most conservative of the three. As for the ramifications of using observable variables, and as Schmidt and Hunter (1996) observed, "random error of measurement distorts virtually every statistic computed in modern studies" (pp. 199-200). When SEM consumers employ observable variables (either single-item indicators or linear composites like those used in ANOVA or regression), they forego the opportunity to incorporate and extract measurement error from the structural equation model (Rubio & Gillespie, 1995).

This finding has many implications for the field of communication. It is important to restate that nearly three out of every five studies using SEM and published from 1995 to 2000 employed observable variables (Holbert & Stephenson, 2002).⁶ From our findings, it is clear that some of the results in

these studies would differ significantly if the authors had employed latent rather than observable variables. Second, most other disciplines do not use observable variables to conduct SEM (Baumgartner & Homburg, 1996; Breckler, 1990; MacCallum & Austin, 2000). In essence, communication researchers are out of step with the more advanced SEM techniques employed in other disciplines. This is not to imply that the HY approach is the best or only approach to SEM. We earlier identified two instances in which the OV approach would be appropriate—for single-item measures or for composites with very high reliability. Alternatively, one may simply be interested in determining whether relationships exist rather than the size of the relationships. It is rarely the case that a researcher relies entirely on single-item measures or on all the indices retaining very high reliability. Still, this technique remains a viable option for these situations.

A second major issue pertaining to this study involves the comparison of the HY and LC approaches to SEM. Both are latent variable techniques that provide some mechanism for generating relatively error-free parameters (e.g., Hoyle, 1991). We knew less about the potential differences in parameter estimates of these two approaches at the outset of this study. Miller (1995) commented that the HY approach may generate problems as a result of too many parameters and nonnormally distributed indicator scores, and Kaplan (2000) claims this approach is overly restrictive. Alternatively, summing item scores into a composite for the LC technique “can reduce the number of observed variables dramatically, yielding a manageable model with roughly normally distributed variables” (Miller, 1995, p. 271). Yet Miller goes on to caution researchers that the LC approach is fault prone because of the reliance on an estimate of coefficient alpha to identify the model.

Specifically, coefficient alpha is a lower bound estimate (Cortina, 1993), whereas the true reliability is almost always greater than the reliability score generated by Cronbach’s alpha (Novick & Lewis, 1967). According to Miller (1995), when we use an unweighted composite, we assume that all pairs of items forming the composite score have equal variances (i.e., they are tau equivalent). Only when pairs of items actually produce equal variances will coefficient alpha be equal to the true reliability of the measure. In reality, this is “seldom if ever achieved” (Cortina, 1993, p. 101). This perspective sheds light on the path estimates in the LC model. Because coefficient alpha was used as the mechanism to extract measurement, the path coefficients generated by the LC approach are likely overestimated (Miller, 1995).

With the understanding of the relationship between coefficient alpha, tau equivalence, and the LC model, we begin to understand why the HY and LC

path estimates were consistently different despite their both being latent techniques. For LC models, the error variances for all item pairs in the unweighted composite are assumed to be equal (Miller, 1995). In contrast, in the HY technique “error variance is calculated for each observed measure” that loads on its respective latent variable in the HY measurement model (Rubio & Gillespie, 1995, p. 368). Unlike the LC technique, the HY measurement model allows only the variance that is shared among the observed variables to load on the latent variable. All else is specific variance and measurement error variance (Kaplan, 2000) that is contained in the uniqueness (error) term of the observed measures. The bottom line is that the LC is not an equivalent form of the HY (see Bollen & Lennox, 1991, especially pp. 309-310).

Conclusion

More than a decade has passed since McPhee and Babrow (1987) concluded that communication researchers lack a clear and coherent approach to executing and evaluating structural equation models. Despite the critical mass of research employing SEM in communication (Holbert & Stephenson, 2002), little progress has been made to further any such coherence in our field. This study advances our understanding of the three approaches used to model structural equations. Our intent is that the findings of this investigation will document how the observed and latent variable approaches can generate different path estimates. The most profound differences occurred between the OV and HY approaches. In essence, the path estimates generated by OV models are smaller than the estimates provided by the latent variable techniques. Schmidt and Hunter (1996) adequately note that “in theory-based research, the real interest is in the relationships that exist between actual traits or constructs rather than between specific measures of traits or constructs” and that “the increasing use of structural equation modeling has also contributed to this change in thinking” (p. 200). Although a case can be made for using the more conservative OV approach, latent variable techniques (the HY approach in particular) are more consistent with disciplines regarded as more advanced in this technique and allow for more precise testing of theories in communication research.

Appendix
Variance-Covariance Matrix for the Model Employing
the Hybrid Approach

	X1	X2	X3	Eta11	Eta12	Eta21	Eta22	Eta23
X1	1.989							
X2	0.703	2.572						
X3	0.318	0.812	3.495					
Eta11	0.551	0.740	0.794	2.248				
Eta12	0.436	0.607	0.656	1.002	1.930			
Eta21	0.182	0.273	0.430	0.409	0.464	2.814		
Eta22	0.167	0.147	0.126	0.255	0.300	1.839	2.398	
Eta23	0.121	0.241	0.222	0.291	0.237	1.185	0.886	1.403

Note. The matrices for the observed variable and latent composite models were calculated from data that were generated by this variance-covariance matrix.

Notes

1. We refer specifically to the structural model component that estimates the relationship among two or more variables (latent or observed). However, several communication studies employ SEM to conduct confirmatory factor analyses (e.g., Booth-Butterfield & Booth-Butterfield, 1996; Hackman, Ellis, Johnson, & Staley, 1999). These structural equation models focus solely on measurement, not the structural relationships among the host of latent variables in the model.

2. Measured or observed variables are represented in figures by boxes. Latent variables are typically depicted by large ovals or large circles. Measurement error is represented by a small circle. See Hoyle and Smith (1991).

3. The χ^2 test is often misconceived as a χ^2 statistic. In reality, this is a test statistic that when evaluated with large samples, is asymptotically χ^2 distributed. See Hu and Bentler (1995).

4. We chose to use the mean sample size of 350 rather than the harmonic mean of 204 because larger sample sizes are more desirable with maximum likelihood estimation.

5. Although there are other methods of estimation, full-information maximum likelihood estimation is the most commonly employed (Chou & Bentler, 1995). Full-information maximum likelihood estimators, however, assume multivariate normality.

6. Users of the PATH program (Hunter & Hamilton, 1995) employ observable composites corrected for attenuation due to measurement error. However, PATH is a partial-information program employing OLS estimation. In contrast, users of SEM programs (LISREL, EQS, and Amos) typically employ full-information maximum likelihood estimation or other asymptotic distribution-free estimators.

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