A comparative study on parameter recovery of three approaches to structural equation modeling

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Traditionally, two approaches have been employed for structural equation modeling: covariance structure analysis and partial least squares. A third alternative, generalized structured component analysis, was introduced recently in the psychometric literature. The authors conduct a simulation study to evaluate the relative performance of these three approaches in terms of parameter recovery under different experimental conditions of sample size, data distribution, and model specification. In this study, model specification is the only meaningful condition in differentiating the performance of the three approaches in parameter recovery. Specifically, when the model is correctly specified, covariance structure analysis tends to recover parameters better than the other two approaches. Conversely, when the model is misspecified, generalized structured component analysis tends to recover parameters better. Finally, partial least squares exhibits inferior performance in parameter recovery compared with the other approaches. In particular, this tendency is salient when the model involves cross-loadings. Thus, generalized structured component analysis may be a good alternative to partial least squares for structural equation modeling and is recommended over covariance structure analysis unless correct model specification is ensured.

Keywords: structural equation modeling, covariance structure analysis, partial least squares, generalized structured component analysis, Monte Carlo simulations

A Comparative Study on Parameter Recovery of Three Approaches to Structural Equation Modeling

Structural equation modeling, also known as path analysis with latent variables, is used for the specification and analysis of interdependencies among observed variables and underlying theoretical constructs, often called latent variables. Since its introduction to marketing (Bagozzi 1980), structural equation modeling has become a remarkably popular tool for many reasons, including its analytic flexibility and generality (Baumgartner and Homburg 1996; Steenkamp and Baumgartner 2000).

Traditionally, two approaches have been used for structural equation modeling (Anderson and Gerbing 1988; Fornell and Bookstein 1982; Jöreskog and Wold 1982): One is covariance structure analysis (Jöreskog 1973), and the other is partial least squares (Lohmöller 1989; Wold 1975). Covariance structure analysis is exemplified by many available software programs, including LISREL (Jöreskog and Sörbom 1993), AMOS (Arbuckle 1994), EQS (Bentler 1995), and Mplus (Muthén and Muthén 1994), and partial least squares can be implemented by the software programs LVPLS (Lohmöller 1984), PLS-Graph (Chin 2001), SmartPLS (Ringle, Wende, and Will 2005), and VisualPLS (Fu 2006). Recently, a third approach—namely, generalized structured component analysis—has been published in the

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psychometric literature (Hwang and Takane 2004). Generalized structured component analysis is implemented by the software program GeSCA (Hwang 2009a).

However, to date, no study has investigated the relative performance of these three approaches to structural equation modeling. Therefore, the objective of this article is to evaluate the three approaches in terms of parameter recovery capability using a Monte Carlo simulation study.

The structure of this article is as follows: We briefly review generalized structured component analysis and discuss theoretical differences and similarities among the three approaches. Then, we describe the design of the simulation study and report the results. Finally, we discuss the implications of the study and also provide recommendations for marketing/applied researchers based on the parameter recovery capability of the three approaches.

BACKGROUND

Vast literature provides the technical underpinnings of covariance structure analysis (e.g., Bollen 1989; Kaplan 2000) and partial least squares (e.g., Lohmöller 1989; Tenenhaus et al. 2005). However, generalized structured component analysis is still novel to marketing researchers. Thus, we present a brief description of generalized structured component analysis and then discuss theoretical characteristics among the three approaches.

Generalized Structured Component Analysis

As its name explicitly suggests, generalized structured component analysis represents a component-based approach to structural equation modeling (Tenenhaus 2008). Thus, this approach defines latent variables as components or weighted composites of observed variables as follows:

$$\boldsymbol{\gamma}_i = \mathbf{W}\mathbf{z}_i, \tag{1}$$

where $\mathbf{z}_i$ denotes a vector of observed variables for a respondent i (i = 1, …, N), $\boldsymbol{\gamma}_i$ is a vector of latent variables for a respondent i, and $\mathbf{W}$ is a matrix consisting of component weights assigned to observed variables. Moreover, generalized structured component analysis involves two additional equations for model specifications: One is for the measurement, or outer, model, which specifies the relationships between observed and latent variables, and the other is for the structural, or inner, model, which expresses the relationships among latent variables. Specifically, in generalized structured component analysis, the measurement model is given by the following:

$$\mathbf{z}_i = \mathbf{C}\boldsymbol{\gamma}_i + \boldsymbol{\varepsilon}_i, \tag{2}$$

where $\mathbf{C}$ is a matrix of loadings relating latent variables to observed variables and $\boldsymbol{\varepsilon}_i$ is a vector of residuals for $\mathbf{z}_i$. The structural model is defined by the following:

$$\boldsymbol{\gamma}_i = \mathbf{B}\boldsymbol{\gamma}_i + \boldsymbol{\xi}_i, \tag{3}$$

where $\mathbf{B}$ is a matrix of path coefficients connecting latent variables among themselves and $\boldsymbol{\xi}_i$ is a vector of residuals for $\boldsymbol{\gamma}_i$.

Then, the generalized structured component analysis model is derived from combining these three equations into a single equation as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{z}_i \\ \boldsymbol{\gamma}_i \end{bmatrix} &= \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix}\boldsymbol{\gamma}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}\mathbf{z}_i &= \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix}\mathbf{W}\mathbf{z}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \mathbf{V}\mathbf{z}_i &= \mathbf{A}\mathbf{W}\mathbf{z}_i + \mathbf{e}_i, \end{aligned} \tag{4}$$

where

$$\mathbf{V} = \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}, \mathbf{A} = \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix}, \mathbf{e}_i = \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix},$$

and $\mathbf{I}$ is an identity matrix (Hwang, DeSarbo, and Takane 2007; Hwang and Takane 2004). Although Equation 4 represents the original generalized structured component analysis model that Hwang and Takane (2004) propose, this model can also be expressed as follows:

$$\begin{aligned} \begin{bmatrix} \mathbf{z}_i \\ \boldsymbol{\gamma}_i \end{bmatrix} &= \begin{bmatrix} \mathbf{C} \\ \mathbf{B} \end{bmatrix}\boldsymbol{\gamma}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}\mathbf{z}_i &= \begin{bmatrix} \mathbf{0}\ \mathbf{C} \\ \mathbf{0}\ \mathbf{B} \end{bmatrix}\begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}\mathbf{z}_i + \begin{bmatrix} \boldsymbol{\varepsilon}_i \\ \boldsymbol{\xi}_i \end{bmatrix} \\ \mathbf{u}_i &= \mathbf{T}\mathbf{u}_i + \mathbf{e}_i, \end{aligned} \tag{5}$$

where

$$\mathbf{u}_i = \begin{bmatrix} \mathbf{I} \\ \mathbf{W} \end{bmatrix}\mathbf{z}_i, \text{ and } \mathbf{T} = \begin{bmatrix} \mathbf{0}\ \mathbf{C} \\ \mathbf{0}\ \mathbf{B} \end{bmatrix}.$$

Thus, the generalized structured component analysis model is essentially of the same form as the reticular action model (McArdle and McDonald 1984), which is mathematically the most compact specification among various formations of covariance structure analysis. With respect to the reticular action model, the only difference in model specification is that generalized structured component analysis defines latent variables as components—that is, $\boldsymbol{\gamma}_i = \mathbf{W}\mathbf{z}_i$.

The unknown parameters of generalized structured component analysis ($\mathbf{W}$ and $\mathbf{A}$) are estimated such that the sum of squares of all residuals ($\mathbf{e}_i$) is as small as possible across all respondents. This problem is equivalent to minimizing the following least squares criterion:

$$\phi = \sum_{i=1}^{N} (\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i)'(\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i), \tag{6}$$

with respect to $\mathbf{W}$ and $\mathbf{A}$, subject to $\sum_{i=1}^{N}\gamma_{id}^2 = 1$, where γ_{id} is the dth element of $\boldsymbol{\gamma}_i$. An alternating least squares algorithm (De Leeuw, Young, and Takane 1976) was developed to minimize this criterion. This algorithm alternates two main steps until convergence: In the first step, for fixed $\mathbf{W}$, $\mathbf{A}$ is updated in the least squares sense, and in the second, $\mathbf{W}$ is updated in the least squares sense for fixed $\mathbf{A}$ (for a detailed description of the algorithm, see Hwang and Takane 2004).

Generalized structured component analysis estimates model parameters by consistently minimizing the global optimization criterion. This enables the provision of measures of overall model fit. Specifically, generalized structured component analysis offers an overall measure of fit, called FIT, which is the proportion of the total variance of all endogenous variables explained by a given particular model specification. It is given by FIT = $1 - [\sum_{i=1}^{N}(\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i)'(\mathbf{V}\mathbf{z}_i - \mathbf{A}\mathbf{W}\mathbf{z}_i)/\sum_{i=1}^{N}\mathbf{z}_i'\mathbf{V}'\mathbf{V}\mathbf{z}_i]$. The values of FIT range from 0 to 1. The larger this value, the more variance in the

variables is accounted for by the specified model. The FIT measure is a function of the sum of the squared residuals that summarizes the discrepancies between the model and the data. However, FIT is affected by model complexity—that is, the more parameters, the larger is the value of FIT. Thus, another index of fit was developed that takes this contingency into account. It is referred to as adjusted FIT, or AFIT (Hwang, DeSarbo, and Takane 2007), given by AFIT = $1 - (1 - \text{FIT})(d_0/d_1)$, where $d_0 = NJ$ is the degrees of freedom for the null model ($\mathbf{W} = \mathbf{0}$ and $\mathbf{A} = \mathbf{0}$) and $d_1 = NJ - G$ is the degrees of freedom for the model being tested, where J is the number of observed variables and G is the number of free parameters. The model that maximizes AFIT is considered the most appropriate among competing models.

In generalized structured component analysis, the bootstrap method (Efron 1982) is employed to calculate the standard errors of parameter estimates without recourse to the assumption of multivariate normality of observed variables. The bootstrapped standard errors or confidence intervals can be used for assessing the reliability of the parameter estimates.

Similarities and Dissimilarities Among the Three Approaches

In this section, we compare the theoretical characteristics of generalized structured component analysis with those of covariance structure analysis and partial least squares. Table 1 provides a summary of the comparisons among the three approaches in terms of model specification and parameter estimation.

Comparisons in model specification. With respect to model specification, generalized structured component analysis defines latent variables as components or weighted sums of observed variables, as shown in Equation 1. This is similar to partial least squares, in which latent variables are also regarded as components. Conversely, in covariance structure analysis, latent variables are equivalent to common factors. Thus, generalized structured component analysis and partial least squares are viewed as component-based approaches to structural equation modeling, whereas covariance structure analysis is viewed as a factor-based approach (Chin 1998; Velicer and Jackson 1990). In turn, this implies that latent variables in covariance structure analysis are random, whereas in partial least squares and generalized structured component analysis, they are fixed. Consequently, this leads to the specification of different sets of model parameters for latent variables (i.e., factor means and/or variances in covariance structure analysis versus component weights in partial least squares and generalized structured component analysis).

Another point of comparison in model specification rests in the number of equations to be used in specifying models. As Equations 2 and 3 show, generalized structured component analysis entails the specifications of measurement and structural models. This is the case in both covariance structure analysis and partial least squares. However, covariance structure analysis and generalized structured component analysis integrate the two submodels into a unified algebraic formulation (i.e., a single equation), such as the reticular action model in covariance structure analysis and Equation 4 in generalized structured component analysis. Conversely, partial least squares does not combine the two submodels into a single equation and thus addresses the two equations separately. This difference in the number of equations for the specification of structural equation models contributes to characterizing the parameter estimation procedures of the three approaches, as we discuss subsequently.

Comparisons in parameter estimation. As the name suggests, covariance structure analysis is run on covariances or correlations among observed variables as input data. Specifically, in covariance structure analysis, the population covariance matrix of observed variables is modeled as a function of the parameters of a hypothesized structural equation model. This modeled population covariance matrix is often referred to as the implied population covariance matrix. If the model is correct and the population covariance matrix is known, the parameters can be estimated by minimizing the difference between the population and the implied covariance matrices. In practice, the population covariance matrix is substituted for by the sample covariance matrix because the population covariance matrix is usually unknown (Bollen 1989). Under the assumption of multivariate normality of observed variables, Jöreskog (1973) developed a maximum likelihood method for parameter estimation for covariance structure analysis. This procedure is by far the most widely used (Bollen 1989), though there are alternative estimation methods that include generalized least squares and unweighted least squares.

Conversely, partial least squares and generalized structured component analysis employ individual-level raw data as input data for parameter estimation. Moreover, the two approaches estimate parameters with a least squares estimation method: the fixed-point algorithm for partial least squares (Wold 1965) and the alternating least squares algorithm for generalized structured component analysis. Because of the adoption of a least squares estimation method, partial least squares and generalized structured

Table 1

SIMILARITIES AND DISSIMILARITIES AMONG THE THREE APPROACHES TO STRUCTURAL EQUATION MODELING

	Covariance Structure Analysis	*Partial Least Squares*	*Generalized Structured Component Analysis*
Model Specification			
Latent variables	Factors	Components	Components
Number of equations	One	Two	One
Model parameters	Loadings, path coefficients, error variances, factor means and/or variances	Loadings, path coefficients, component weights	Loadings, path coefficients, component weights
Parameter Estimation			
Input data	Covariances/ correlations	Individual-level raw data	Individual-level raw data
Estimation method	Maximum likelihood (mainly)	Least squares	Least squares
Global optimization function	Yes	No	Yes
Normality assumption	Required for maximum likelihood	Not required	Not required
Model fit measures	Overall and local	Local	Overall and local

component analysis do not require the normality assumption for parameter estimation. Note that in covariance structure analysis, this distributional assumption can also be relaxed through the use of unweighted least squares or asymptotically distribution-free estimators (e.g., Browne 1982, 1984).

Although covariance structure analysis and generalized structured component analysis use differing estimation methods (maximum likelihood versus least squares), they remain comparable in the sense that both approaches aim to optimize a single optimization function for parameter estimation. Specifically, maximum likelihood estimates parameters by consistently maximizing a single likelihood function, which in turn is derived from a single formulation of structural equation modeling. Similarly, the alternating least squares algorithm of generalized structured component analysis also estimates parameters by consistently minimizing a single least squares optimization function, which in turn is directly derived from a single equation. Conversely, because of the absence of such a global optimization function stemming from a unified formulation of the two submodels, the fixed-point algorithm inherent to partial least squares involves minimizing separate local optimization functions by solving a series of ordinary regression analyses. Consequently, covariance structure analysis and generalized structured component analysis define convergence as the increase or decrease in the function value beyond a certain threshold. In contrast, partial least squares defines convergence as a sort of equilibrium—that is, the point at which no substantial difference occurs between the previous and the current estimates of component weights. Thus, the algebraic formulations underlying the three approaches seem to result in substantial differences in the procedures of parameter estimation.

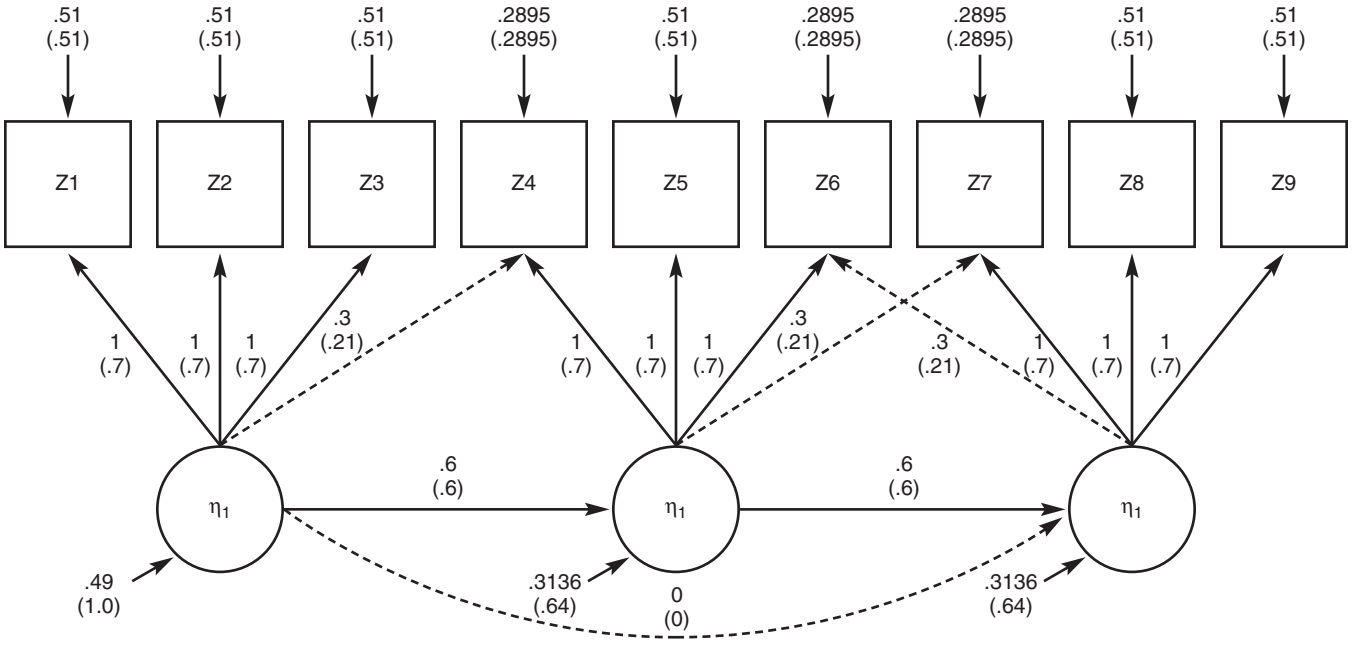
Importantly, the availability of measures of overall model fit relies on whether some global optimization criterion is present. Indeed, because generalized structured component analysis and covariance structure analysis involve a global optimization criterion, they can provide measures of overall and local model fit. In contrast, partial least squares entails the estimation of two submodels to capture the same relationships, and each is linked to a separate local optimization criterion. Thus, partial least squares is incapable of providing a measure of overall model fit. This forces partial least squares users to rely solely on local fit measures to evaluate a model. Despite the importance of measures of local fit in evaluating the suitability of models (Bollen 1989), they provide little information on how well a model fits the data as a whole. Moreover, they are of little use for comparisons of a focal model to alternative model specifications.

SIMULATION DESIGN

The experimental conditions we considered in the simulation study are as follows: approach (covariance structure analysis, partial least squares, and generalized structured component analysis), sample size (N = 100, 200, 300, 400, and 500), model specification (correctly specified versus misspecified), and data distribution (normal versus nonnormal). These experimental conditions are commonly encountered in simulations based on structural equation modeling (Paxton et al. 2001).

We specify a structural equation model for this study that involves three latent variables and four observed variables per latent variable. This model is essentially the same as that which Paxton and colleagues (2001) specify in their simulations. Figure 1 displays the correct specification and a misspecification of the model along with their unstandardized and standardized parameter values. In the misspecified

Figure 1
THE SPECIFIED MODEL FOR THE SIMULATION STUDY ALONG WITH STANDARDIZED PARAMETERS (IN PARENTHESES)



Notes: The model misspecification indicates omission of dashed loadings and inclusion of the dashed path coefficient.

model, we omit cross-loadings and specify an additional path coefficient, as indicated by the dashed lines.

We draw individual-level multivariate normal data from $N(\mathbf{0}, \mathbf{\Sigma})$, where $\mathbf{\Sigma}$ is the implied population covariance matrix derived from a covariance structure analysis formulation (i.e., the reticular action model) using the unstandardized parameter values. For a nonnormal distribution, we adopt skewness = 1.25 and kurtosis = 3.75. We use these levels of skewness and kurtosis to closely reflect a nonnormal condition typically encountered in marketing research (e.g., Hulland, Ryan, and Rayner 2005). To generate the intended nonnormality (i.e., the intended skewness and kurtosis values), we apply Fleishman's (1978) power transformation approach to normal data. We generate 500 samples at each level of the experimental conditions. Subsequently, we fit all 10,000 samples (5 sample sizes × 2 distributions × 2 model specifications × 500 replications) by the three approaches.

SIMULATION RESULTS

To evaluate the recovery of parameter estimates under the three approaches, we computed the mean absolute differences of parameters and their estimates as follows:

$$\text{MAD} = \frac{\sum_{j=1}^{P} |\hat{\theta}_j - \theta_j|}{P}, \tag{7}$$

where $\hat{\theta}_j$ and θ_j are an estimate and its parameter, respectively, and P is the number of parameters (e.g., Mason and Perreault 1991). We removed any simulated sample involving nonconvergence within 100 iterations or convergence to improper solutions from the calculation of the absolute differences.

As we discussed previously, the three approaches estimate different sets of model parameters. Thus, in this study, we evaluate and report the recovery of the estimates of a common set of parameters (i.e., loadings and path coefficients) and the recovery of the standard errors of those parameter estimates. Covariance structure analysis typically provides unstandardized parameter estimates and their standard errors, whereas generalized structured component analysis and partial least squares result in standardized parameter estimates and their standard errors. Thus, we rescaled all estimates by dividing them by the corresponding (unstandardized or standardized) parameters to ensure equal-scale comparisons across the three approaches.

Recovery of Parameters

An analysis of variance for examining the recovery of parameters. We performed an analysis of variance (ANOVA) that included the mean absolute differences of the estimates of loadings and path coefficients as the dependent variable and the four experimental conditions as design factors. Table 2 presents the results of the ANOVA. A number of the main and interaction effects of the design factors were statistically significant. However, this may be largely due to the large number of observations stemming from the replications under multiple conditions (the total number of observations was 28,267). Thus, it is important to report and interpret the meaningfulness of such effects using an effect size (Paxton et al. 2001). We focus only on effects whose sizes were at least medium (i.e., $\eta^2 \geq .06$) (Cohen 1988).

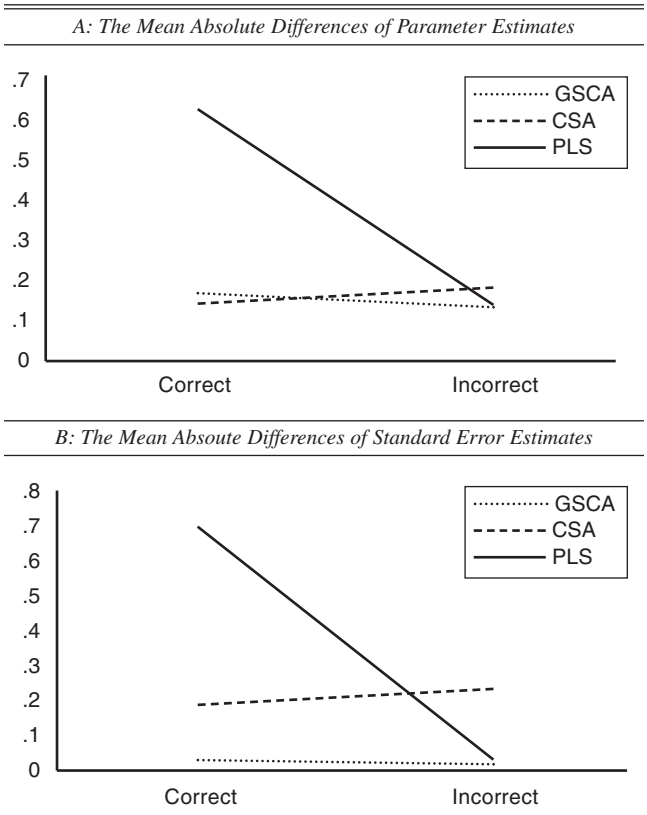
First, model specification ($\eta^2 = .08$) and approach ($\eta^2 = .14$) had a medium and large main effect, respectively. Thus, it is likely that the levels of the mean absolute differences of parameter estimates were higher when the model was correctly specified (.31) than when the model was misspecified (.15). Moreover, there are likely meaningful differences in the mean absolute differences among the three approaches. It appears that there were little differences in the mean absolute differences between covariance structure analysis (.16) and generalized structured component analysis (.15), whereas partial least squares was associated with a higher level of the mean absolute differences (.38).

Second, the two-way interaction effect between model specification and approach was large ($\eta^2 = .16$). Figure 2 displays the average values of the mean absolute differences of the three approaches under the two levels of model specification (correct versus misspecified). When the model was correctly specified, covariance structure analysis was associated with the smallest level of the mean absolute differences (.15), generalized structured component analysis was associated with the second smallest (.16), and partial least squares was associated with the largest (.62). Con-

Table 2
THE RESULTS OF AN ANOVA FOR THE MEAN ABSOLUTE DIFFERENCES OF PARAMETER ESTIMATES

Source	*Sum of Squares*	*d.f.*	*Mean Square*	*F*	*Significance*	η^2
Distribution (A)	.41	1	.41	8.13	.00	.00
Model specification (B)	179.20	1	179.20	3521.36	.00	.08
Sample size (C)	8.70	4	2.17	42.72	.00	.00
Approach (D)	325.05	2	162.53	3193.77	.00	.14
A × B	.75	1	.75	14.80	.00	.00
A × C	.13	4	.03	.62	.65	.00
A × D	.10	2	.05	.96	.38	.00
B × C	.25	4	.06	1.23	.30	.00
B × D	391.09	2	195.54	3842.60	.00	.16
C × D	6.80	8	.85	16.71	.00	.00
A × B × C	.39	4	.10	1.89	.11	.00
A × B × D	.35	2	.17	3.40	.03	.00
A × C × D	.28	8	.04	.69	.71	.00
B × C × D	1.09	8	.14	2.67	.01	.00
A × B × C × D	.73	8	.09	1.78	.08	.00
Error	1435.40	28,207	.05			

Figure 2
THE AVERAGE VALUES OF THE MEAN ABSOLUTE DIFFERENCES OF THE ESTIMATES OF PARAMETERS AND STANDARD ERRORS OBTAINED FROM THE THREE APPROACHES ACROSS TWO LEVELS OF MODEL SPECIFICATION



Notes: GSCA = generalized structured component analysis, CSA = covariance structure analysis, and PLS = partial least squares.

versely, when the model was misspecified, generalized structured component analysis involved the smallest level of the mean absolute differences (.13), partial least squares had the second smallest (.14), and covariance structure analysis yielded the largest (.18). Thus, the somewhat counterintuitive nature of the main effect of model specification may be due to the poor parameter recovery of partial least squares under correct specification.

Overall finite-sample properties of parameter estimates under model specification levels. The ANOVA showed that the parameter recovery of the three approaches was distinct between the two levels of model specification. To obtain a greater understanding of how differently they behave under this condition, we further investigated the overall finite-sample properties of the parameter estimates of the three approaches across the model specification levels. Figures 3 and 4 display the average relative biases, standard deviations, and mean square errors of parameter estimates obtained from the three approaches under the two model specifications. Among these properties, in particular, the mean square error is the average squared difference between a parameter and its estimate, indicating how far an estimate is, on average, from its parameter—that is, the smaller the mean square error, the closer the estimate is to the parameter. Specifically, the mean square error is given by the following:

$$\text{(8)}\qquad \mathrm{MSE}(\hat{\theta}_j) = \mathrm{E}\left[(\hat{\theta}_j - \theta_j)^2\right] = \mathrm{E}\left\{\left[\hat{\theta}_j - \mathrm{E}(\hat{\theta}_j)\right]^2\right\} + \left[\mathrm{E}(\hat{\theta}_j) - \theta_j\right]^2.$$

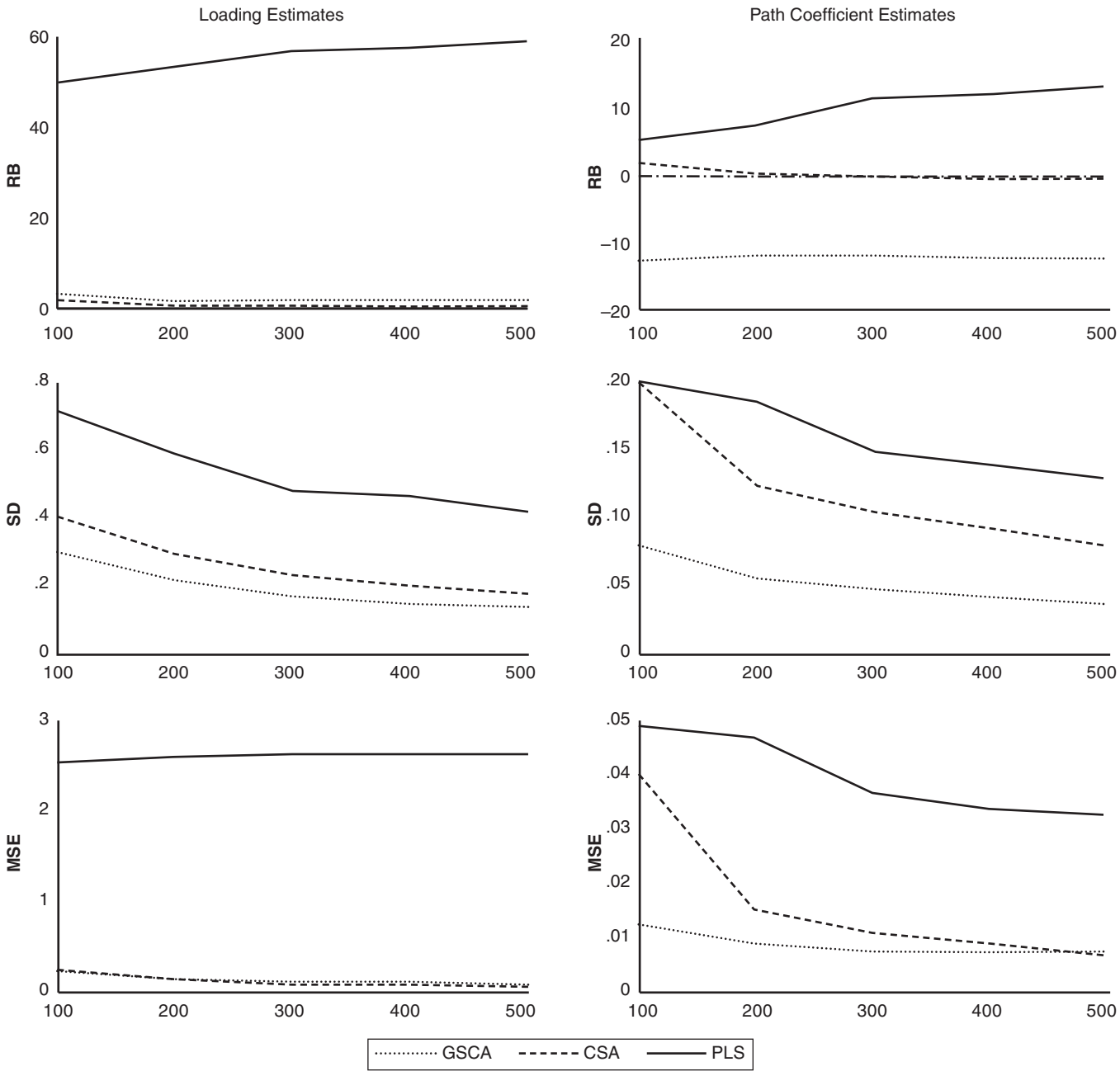
As Equation 8 shows, the mean square error of an estimate is the sum of its variance and squared bias. Thus, the mean square error entails information on both bias and variability of the estimate (Mood, Graybill, and Boes 1974).

In the study, we regard absolute values of relative bias greater than 10% as indicative of an unacceptable degree of bias (Bollen et al. 2007; Lei 2009). As Figure 3 shows, under correct model specification, on average, covariance structure analysis yielded unbiased estimates of loadings and path coefficients across all sample sizes. Generalized structured component analysis led to unbiased loading estimates, but it yielded negatively biased path coefficient estimates, regardless of sample size. Partial least squares showed a high level of positive bias in loading estimates, which appeared to increase with sample size. This approach also tended to result in positively biased path coefficient estimates as sample size increased. When the model was correctly specified, overall, the parameter estimates of generalized structured component analysis were consistently associated with smaller standard deviations than estimates obtained from the two traditional approaches. The estimates of partial least squares involved larger standard deviations than those under covariance structure analysis. As sample size increased, these standard deviations tended to decrease across all the approaches.

On average, covariance structure analysis showed the smallest mean square errors of loading estimates, and generalized structured component analysis involved the second smallest mean square errors of loading estimates, though both approaches showed similar levels of the mean square errors until N = 300. Conversely, partial least squares exhibited the largest mean square errors of loading estimates across all sample sizes. Finally, generalized structured component analysis involved the smallest mean square errors of path coefficient estimates until N = 400, whereas covariance structure analysis resulted in the smallest mean square error of path coefficient estimate at N = 500, though the differences in the mean square errors between generalized structured component analysis and covariance structure analysis became small as N > 100. Conversely, partial least squares was associated with the largest mean square errors of path coefficient estimates across all sample sizes.

As Figure 4 shows, under model misspecification, all three approaches yielded positively biased loading estimates across sample sizes, though the amount of bias tended to decrease with sample size in covariance structure analysis. Conversely, generalized structured component analysis and partial least squares led to a negative but tolerable degree of bias for path coefficient estimates, whereas covariance structure analysis yielded positively biased path coefficient estimates that were slightly less than 10% of relative bias. In addition, under misspecification, the parameter estimates under generalized structured component analysis were consistently associated with smaller standard deviations than those under the other approaches, though the differences

Figure 3
OVERALL FINITE-SAMPLE PROPERTIES OF THE PARAMETER ESTIMATES OF THE THREE APPROACHES UNDER CORRECT SPECIFICATION ACROSS DIFFERENT SAMPLE SIZES



Notes: RB = relative bias, SD = standard deviation, and MSE = mean square error. A —·—·— line indicates no relative bias. GSCA = generalized structured component analysis, CSA = covariance structure analysis, and PLS = partial least squares.

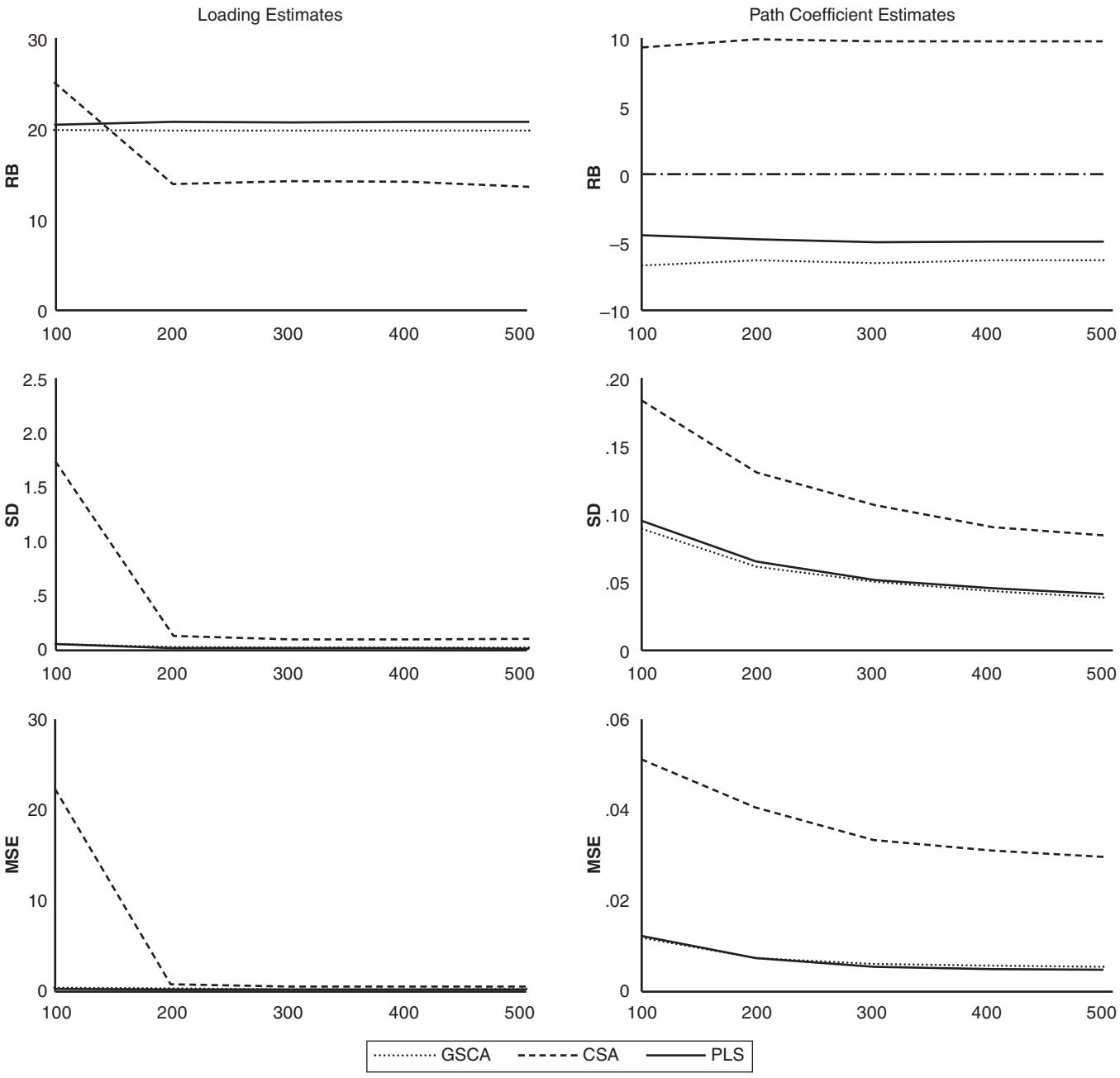
between generalized structured component analysis and partial least squares were small. The parameter estimates from covariance structure analysis showed the largest levels of standard deviations over sample size.

On average, generalized structured component analysis had the smallest mean square errors of both loading and path coefficient estimates across all sample sizes. However, the differences in the mean square errors of the parameter estimates were negligibly small between generalized structured component analysis and partial least squares. Conversely, covariance structure analysis resulted in the parameter estimates with the largest mean square errors over sample size, though the mean square errors of the loading estimates appeared close to those of generalized structured component analysis and partial least squares when sample size increased.

Recovery of Standard Errors

An ANOVA for examining the recovery of standard errors. To evaluate the recovery of the standard errors of parameter

Figure 4
OVERALL FINITE-SAMPLE PROPERTIES OF THE PARAMETER ESTIMATES OF THE THREE APPROACHES UNDER MISSPECIFICATION ACROSS DIFFERENT SAMPLE SIZES



Notes: RB = relative bias, SD = standard deviation, and MSE = mean square error. A —·—·— line indicates no relative bias. GSCA = generalized structured component analysis, CSA = covariance structure analysis, and PLS = partial least squares.

estimates, we first obtained the true standard errors empirically as follows:

$$\text{SE}\left(\hat{\theta}_j\right) = \sqrt{\frac{\sum_{i=1}^{B}\left(\hat{\theta}_j - \bar{\hat{\theta}}_j\right)^2}{B-1}}, \quad (9)$$

where $\bar{\hat{\theta}}_j$ is the mean of a parameter estimate across B replications (e.g., B = 500) (Sharma, Durvasula, and Dillon 1989; Srinivasan and Mason 1986). We then calculated the mean absolute differences of the standard errors of loading and path coefficient estimates across different experimental conditions. In covariance structure analysis, we obtained the standard errors from the asymptotic covariance matrix of parameter estimates under asymptotic normal theory (e.g., Bollen 1989), whereas in generalized structured component analysis and partial least squares, we estimated them on the basis of the bootstrap method with 100 bootstrap samples.

We performed an ANOVA to examine the main and interaction effects of the design factors on the mean absolute differences of the standard error estimates. Table 3 shows the results of the ANOVA. Again, most of the main and interaction effects of the design factors turned out to be statistically significant. Nonetheless, only two design factors showed sufficiently large main effects: model specification ($\eta^2 = .14$) and approach ($\eta^2 = .27$). Thus, these suggest meaningful differences in the mean absolute differences of standard errors between the two model specifications (correct = .03, and misspecified = .01) and the three approaches (generalized structured component analysis = .00, covariance structure analysis = .02, and partial least squares = .04).

Moreover, the two-way interaction between model specification and approach had a large effect size ($\eta^2 = .36$). Figure 2 displays the average values of the mean absolute differences of the three approaches under the two levels of model specification. Under both levels, generalized structured component analysis resulted in the smallest level of the mean absolute differences of standard errors (correct = .00, and misspecified = .00). Conversely, covariance structure analysis provided a smaller level of the mean absolute differences than partial least squares under correct specification (covariance structure analysis = .02, and partial least squares = .07), whereas partial least squares yielded a smaller level of the mean absolute differences than covariance structure analysis under misspecification (covariance structure analysis = .02, and partial least squares = .00). In particular, there seemed to be a large difference in the mean absolute differences of the standard errors of partial least squares across the two specifications. Again, this may explain why the level of the mean absolute differences was, on average, lower under misspecification, as we concluded with respect to the main effect of model specification.

Overall finite-sample properties of standard error estimates under model specification levels. Figures 5 and 6 show the average relative biases, standard deviations, and mean square errors of the standard errors estimated from the three approaches under the two model specifications over sample size. As Figure 5 shows, when the model was correctly specified, on average, generalized structured component analysis yielded unbiased standard errors of both loading and path coefficient estimates across all sample sizes. Covariance structure analysis led to positively biased standard errors of the parameter estimates. Partial least squares resulted in unbiased standard errors of loading estimates, while providing biased standard errors of path coefficients when $N \leq 200$. Under correct specification, the standard errors of loading and path coefficient estimates under generalized structured component analysis were associated with the smallest levels of standard deviations, except for those of loading estimates at $N \geq 300$. Conversely, the standard errors of both sets of parameter estimates obtained from partial least squares had the largest levels of standard deviations over sample size.

On average, generalized structured component analysis showed the smallest mean square errors of the standard errors of loading and path coefficient estimates over sample size. Covariance structure analysis involved smaller mean square errors of both sets of estimates than those under partial least squares when $N \geq 200$. However, the differences in the mean square errors of the standard errors of path coefficient estimates appeared negligibly small among the three approaches as sample size increased.

As Figure 6 shows, under model misspecification, the standard errors for covariance structure analysis and generalized structured component analysis seemed to possess similar properties to those under correct specification. Conversely, the standard errors for partial least squares under misspecification appeared to have smaller biases, standard deviation, and mean square errors than those under correct specification. Moreover, under misspecification, the standard errors obtained from partial least squares and generalized structured component analysis behaved comparably.

CONCLUSIONS AND RECOMMENDATIONS

In this article, we undertook investigations of the performance of three approaches to structural equation modeling (covariance structure analysis, partial least squares, and generalized structured component analysis) through analyses of simulated data under diverse experimental conditions. This study represents the first effort toward providing systematic comparisons between the performances of three different approaches to structural equation modeling, including a recent development in the area, namely, generalized

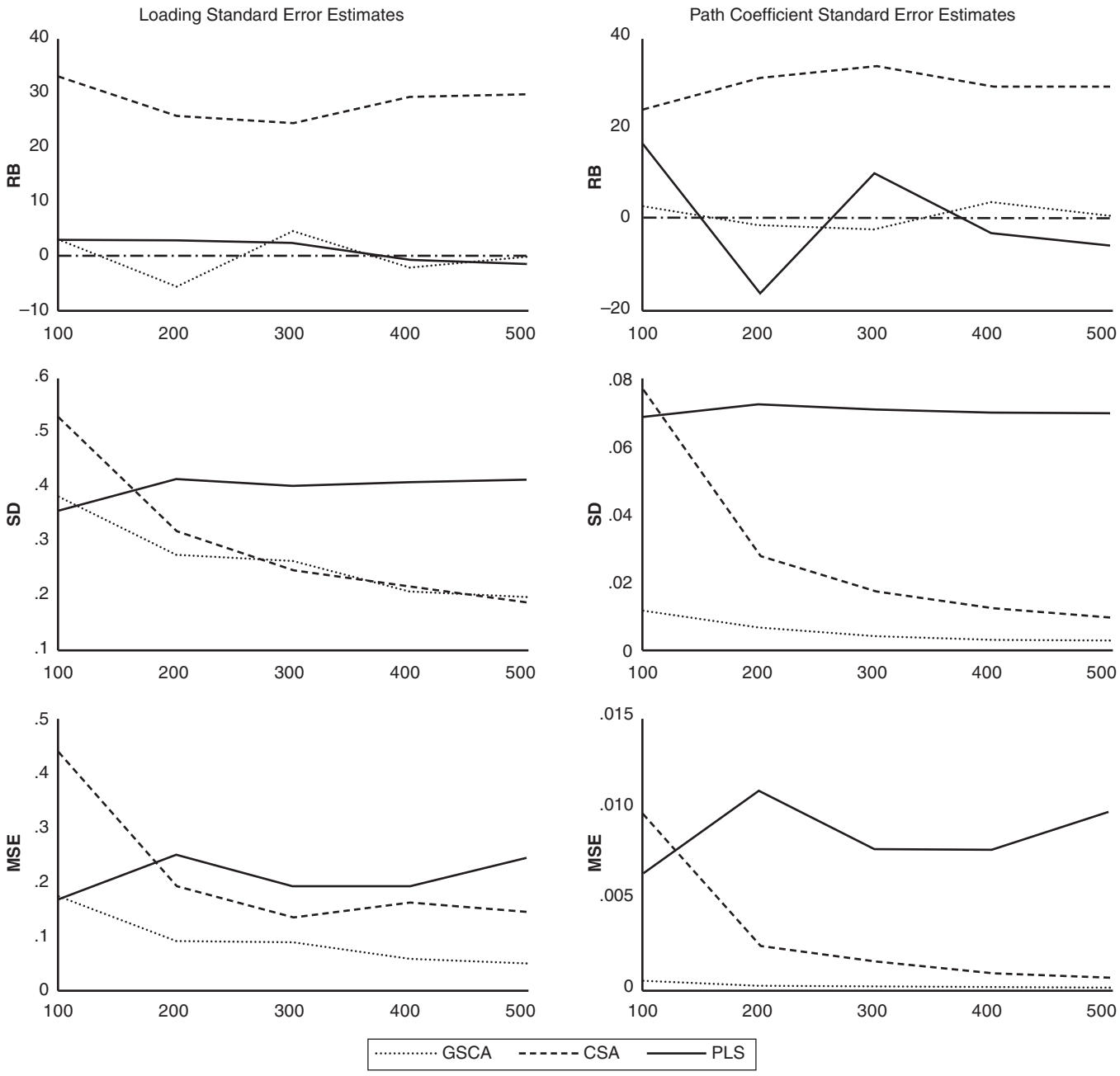
Table 3

THE RESULTS OF AN ANOVA FOR THE MEAN ABSOLUTE DIFFERENCES OF STANDARD ERROR ESTIMATES

Source	*Sum of Squares*	*d.f.*	*Mean Square*	*F*	*Significance*	η^2
Distribution (A)	.00	1	.00	.16	.69	.00
Model specification (B)	2.99	1	2.99	38,820.93	.00	.14
Sample size (C)	.63	4	.16	2040.47	.00	.03
Approach (D)	5.68	2	2.84	36,932.50	.00	.27
A × B	.04	1	.04	524.39	.00	.00
A × C	.01	4	.00	28.48	.00	.00
A × D	.39	2	.20	2551.00	.00	.02
B × C	.09	4	.02	295.41	.00	.00
B × D	7.54	2	3.77	49,004.23	.00	.36
C × D	.50	8	.06	815.28	.00	.02
A × B × C	.01	4	.00	21.49	.00	.00
A × B × D	.09	2	.05	603.77	.00	.01
A × C × D	.03	8	.00	43.44	.00	.00
B × C × D	.23	8	.03	375.65	.00	.01
A × B × C × D	.01	8	.00	20.76	.00	.00
Error	2.17	28,207	.00			

Figure 5

OVERALL FINITE-SAMPLE PROPERTIES OF THE STANDARD ERROR ESTIMATES OF THE THREE APPROACHES UNDER CORRECT SPECIFICATION ACROSS DIFFERENT SAMPLE SIZES



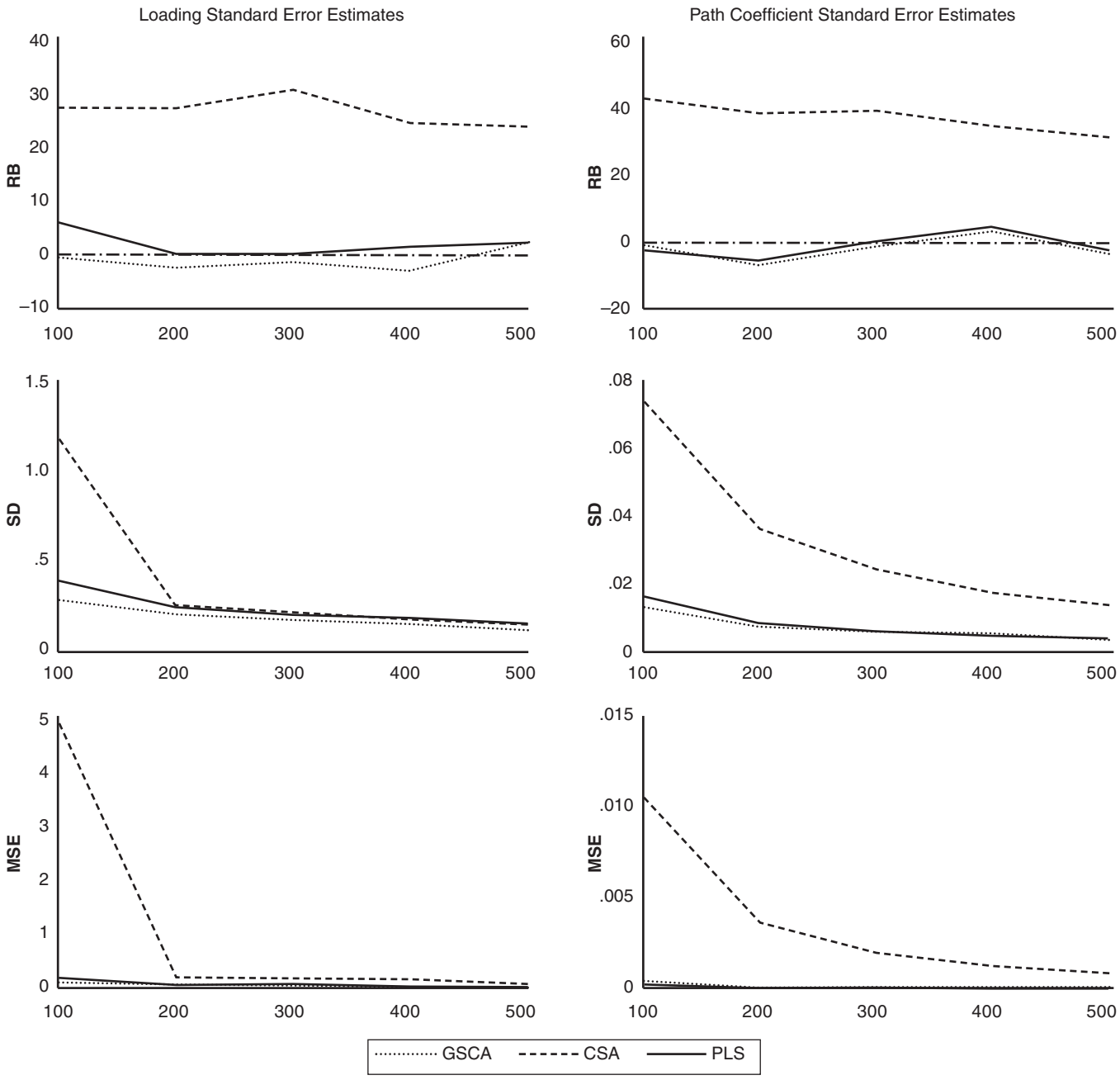
Notes: RB = relative bias, SD = standard deviation, and MSE = mean square error. A —·—·— line indicates no relative bias. GSCA = generalized structured component analysis, CSA = covariance structure analysis, and PLS = partial least squares.

structured component analysis. The major findings of this study are twofold.

First, only the model specification factor led to differences in parameter recovery among the approaches. Whether or not the model is correctly specified was the only meaningful factor in differentiating the performance of the three approaches in parameter recovery. Specifically, when the model was correctly specified, in general, covariance structure analysis recovered loadings and path coefficients better than generalized structured component analysis and partial least squares. Conversely, when the model was misspecified, generalized structured component analysis resulted in more accurate estimates of these parameters. However, generalized structured component analysis appeared to estimate standard errors more precisely under both levels of model specification. The relatively poor performance of covariance structure analysis under misspecification has been previously reported in the literature (e.g., Bollen et al.

Figure 6

OVERALL FINITE-SAMPLE PROPERTIES OF THE STANDARD ERROR ESTIMATES OF THE THREE APPROACHES UNDER MISSPECIFICATION ACROSS DIFFERENT SAMPLE SIZES



Notes RB = relative bias, SD = standard deviation, and MSE = mean square error. A —·—·— line indicates no relative bias. GSCA = generalized structured component analysis, CSA = covariance structure analysis, and PLS = partial least squares.

2007; Hoogland and Boomsma 1998). What is novel in this study is the superior performance of generalized structured component analysis over covariance structure analysis under misspecification.

Similarly, the overall finite-sample properties of the three approaches were distinct between the two levels of model specification. In particular, covariance structure analysis and generalized structured component analysis tended to result in parameter estimates with relatively small mean square errors (i.e., close to their parameters) when the model was correctly specified. Conversely, generalized structured component analysis and partial least squares tended to yield parameter estimates with relatively small mean square errors when the model was misspecified. In addition, generalized structured component analysis produced standard error estimates with the smallest mean square errors regardless of model specification. This suggests that the bootstrap method adopted by generalized

structured component analysis performed well in the estimation of standard errors of the parameter estimates.

Bias in parameter estimates and standard errors under the three approaches also appeared to differ between the two levels of model specification. For example, when the model was correctly specified, in general, covariance structure analysis resulted in unbiased parameter estimates, whereas the other two approaches tended to provide biased parameter estimates. Conversely, when the model was misspecified, all three approaches tended to yield biased parameter estimates. Bias represents an important piece of information regarding the finite-sample behavior of a parameter estimate (i.e., how close the mean of an estimate is to the parameter). Nonetheless, as Equation 8 implies, bias per se may not be of serious concern unless it increases mean square error in combination with variance, thereby making an estimate far from its true value on average (e.g., Hastie, Tibshirani, and Friedman 2001).

In addition, the violation of normality, to the extent that it is frequently faced in practice, did not seem to greatly affect parameter recovery among the three approaches. This is consistent with Hulland, Ryan, and Rayner (2005), who compare the recovery of path coefficients between covariance structure analysis and partial least squares with simulated data.

Second, the performance of partial least squares was relatively poor in parameter recovery compared with the other two approaches. Partial least squares showed relatively inferior performance in parameter recovery compared with the other two approaches. In particular, this tendency was prominent when the model was correctly specified. This may hinge on the correct model in this study being composed of cross-loadings. Partial least squares performed similarly to generalized structured component analysis when the model was misspecified to exclude cross-loadings. This implies that the performance of partial least squares may be affected by how the model is specified, not by whether the model is correct. This result is somewhat unexpected because partial least squares has been regarded and presented as a model-free or soft-modeling approach that requires minimal demands on prior assumptions for structural equation modeling (Wold 1982). It is unclear which technical mechanism underlying partial least squares is related to our finding. Further research might investigate this issue more fully.

Recommendations

At the risk of generalizing from the results of our simulation study, we venture to provide some recommendations for the marketing/applied researcher. First, we recommend the adoption of generalized structured component analysis as a sensible alternative to partial least squares. As we demonstrated, generalized structured component analysis performed better than or as well as partial least squares in parameter recovery. In addition, generalized structured component analysis maintains all the advantages of partial least squares as a component-based structural equation modeling methodology. However, it also offers additional benefits, such as overall measures of model fit (Hwang and Takane 2004).

Second, if correct model specification is ensured, we recommend the use of covariance structure analysis. This approach resulted in more accurate parameter estimates than generalized structured component analysis under correct model specification.

Finally, if correct model specification cannot be ensured, researchers should use generalized structured component analysis because it outperformed covariance structure analysis in the recovery of parameters under misspecification.

Note that we offer these recommendations on the basis of the capability of parameter recovery among the three approaches in this simulation study. In practice, however, the data analytic flexibility of the three approaches may also be important to the researcher. Although generalized structured component analysis has been rapidly extended and refined to enhance its generality and versatility (e.g., Hwang 2009b; Hwang, DeSarbo, and Takane 2007; Hwang and Takane 2010; Hwang, Takane, and Malhotra 2007; Takane, Hunter, and Hwang 2004), covariance structure analysis still seems more versatile because it has been extended by many researchers over several decades. For example, since the seminal work of Kenny and Judd (1984), many researchers have elaborated covariance structure analysis to accommodate nonlinear latent variables, such as quadratic and interaction terms of latent variables (e.g., Klein and Muthén 2007; Marsh, Wen, and Hau 2004; Schumacker and Marcoulides 1998; Wall and Amemiya 2001). As in partial least squares, generalized structured component analysis may readily address a two-way interaction of latent variables by adopting the so-called product-indicator procedure (Chin, Marcolin, and Newsted 1996), in which new product terms of observed variables taken to underlie two latent variables are computed in advance and then used as the indicators for the two-way interaction. Nonetheless, no formal study has yet been carried out to deal with such nonlinear latent variables in generalized structured component analysis. In addition, the product-indicator procedure is mainly limited to examine a two-way interaction of latent variables because it is difficult to decide which and how many observed variables should be selected to form product indicators for higher-way latent interactions. Thus, covariance structure analysis may remain more flexible in accounting for nonlinear latent variables.

Limitations and Contributions

As do other simulation studies, this study has limitations. First, we generated simulated data on the basis of covariance structure analysis. This data generation procedure may have had an unfavorable effect on the performance of partial least squares and generalized structured component analysis. We adopted the procedure because it was rather difficult to arrive at an impartial way of generating synthetic data for all three different approaches. Nevertheless, the same procedure has been used in other studies that compared the performance of covariance structure analysis with that of partial least squares (e.g., Hulland, Ryan, and Rayner 2005). In any case, it appears necessary in future studies to investigate whether a particular data generation procedure may influence the relative performance of the different approaches.

Second, as we stated previously, this study analyzed only converged samples without improper solutions for covariance structure analysis. Nonconvergence or improper solutions are likely to lead to outliers or suboptimal estimates

for covariance structure analysis. Thus, the purposeful exclusion of such solutions may render covariance structure analysis solutions biased by enhancing the differences between the distributions of the sample and population covariance matrices (Hoogland and Boomsma 1998). Conversely, we carried out no such manipulation for generalized structured component analysis and partial least squares, because they did not involve any convergence problems. This may have led to results that were more favorable for covariance structure analysis.

Finally, the simulation study took into account diverse experimental conditions that are frequently considered in simulations based on structural equation modeling. Nonetheless, as with all simulation studies, the range of conditions in this study may still be limited in scope. Thus, it may be necessary to consider a greater variety of experimental levels/conditions (e.g., a wider range of skewness and kurtosis and different models) for more thorough investigations of the relative performance of the three approaches.

Notwithstanding these limitations, this research makes several contributions. We present the technical underpinnings of generalized structured component analysis to marketing researchers. Moreover, we compare generalized structured component analysis with the two traditional approaches to structural equation modeling to highlight similarities and differences and to assess its relative performance with respect to the traditional approaches using simulated data. Overall, the results of the Monte Carlo analysis provide rather clear guidelines with respect to the conditions under which generalized structured component analysis is preferable to the two traditional approaches. We hope that this study provides a greater understanding of the three currently available approaches to structural equation modeling and leads marketing researchers to adopt generalized structured component analysis in many situations, particularly those in which the researchers have little confidence that their models are correctly specified.

REFERENCES

Anderson, James C. and David W. Gerbing (1988), "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach," *Psychological Bulletin*, 103 (3), 411–23.

Arbuckle, James (1994), "AMOS: Analysis of Moment Structures," *Psychometrika*, 59 (1), 135–37.

Bagozzi, Richard P. (1980), *Causal Models in Marketing*. New York: John Wiley & Sons.

Baumgartner, Hans and Christian Homburg (1996), "Applications of Structural Equation Modeling in Marketing and Consumer Research," *International Journal of Research in Marketing*, 13 (2), 139–61.

Bentler, Peter M. (1995), *EQS Structural Equations Program Manual*. Encino, CA: Multivariate Software.

Bollen, Kenneth A. (1989), *Structural Equations with Latent Variables*. New York: John Wiley & Sons.

———, James B. Kirby, Patrick J. Curran, Pamela Paxton, and Feinian Chen (2007), "Latent Variable Models Under Misspecification. Two-Stage Least Squares (2SLS) and Maximum Likelihood (ML) Estimators," *Sociological Methods and Research*, 36 (August), 48–86.

Browne, Michael W. (1982), "Covariance Structures," in *Topics in Applied Multivariate Analysis*, Douglas M. Hawkins, ed. Cambridge, UK: Cambridge University Press, 72–41.

——— (1984), "Asymptotically Distribution Free Methods for the Analysis of Covariance Structures," *British Journal of Mathematical and Statistical Psychology*, 37 (1), 62–83.

Chin, Wynne W. (1998), "Issues and Opinion on Structural Equation Modeling," *Management Information Systems Quarterly*, 22 (1), 7–16.

——— (2001), *PLS-Graph User's Guide Version 3.0*. Houston: Soft Modeling Inc.

———, Barbara L. Marcolin, and Peter R. Newsted (1996), "A Partial Least Squares Latent Variable Approach for Measuring Interaction Effects: Results from a Monte Carlo Simulation Study and Voice Mail Emotion/Adoption Study," in *Proceedings of the Seventeenth International Conference on Information Systems*, Janice I. DeGross, Sirkka Jarvenpaa, and Ananth Srinivasan, eds. Cleveland: Association for Information Systems, 21–41.

Cohen, Jacob (1988), *Statistical Power Analysis for the Behavioral Sciences*, 2d ed. Hillsdale, NJ: Lawrence Erlbaum Associates.

De Leeuw, Jan, Forrest W. Young, and Yoshio Takane (1976), "Additive Structure in Qualitative Data: An Alternating Least Squares Method with Optimal Scaling Features," *Psychometrika*, 41 (4), 471–503.

Efron, Bradley (1982), *The Jackknife, the Bootstrap and Other Resampling Plans*. Philadelphia: SIAM.

Fleishman, Allen I. (1978), "A Method for Simulating Non-Normal Distributions," *Psychometrika*, 43 (4), 521–32.

Fornell, Claes and Fred Bookstein (1982), "Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory," *Journal of Marketing Research*, 19 (November), 440–52.

Fu, Jen-Ruei (2006), *VisualPLS 1.04*, (accessed April 12, 2010), [available at http://fs.mis.kuas.edu.tw/~fred/vpls/].

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2001), *The Elements of Statistical Learning; Data Mining, Inference, and Prediction*. New York: Sringer-Verlag.

Hoogland, Jeffrey J. and Anne Boomsma (1998), "Robustness Studies in Covariance Structure Modeling. An Overview and A Meta-Analysis," *Sociological Methods and Research*, 26 (February), 329–67.

Hulland, John, Michael J. Ryan, and Robert Rayner (2005), "Covariance Structure Analysis Versus Partial Least Squares: A Comparison of Path Coefficient Estimation Accuracy Using Simulations," working paper, Joseph M. Katz Graduate School of Business, University of Pittsburgh.

Hwang, Heungsun (2009a), *GeSCA*, (accessed April 12, 2010), [available at http://www.sem-gesca.org].

——— (2009b), "Regularized Generalized Structured Component Analysis," *Psychometrika*, 74 (3), 57–30.

———, Wayne S. DeSarbo, and Yoshio Takane (2007), "Fuzzy Clusterwise Generalized Structured Component Analysis," *Psychometrika*, 72 (2), 181–98.

——— and Yoshio Takane (2004), "Generalized Structured Component Analysis," *Psychometrika*, 69 (1), 81–99.

——— and ——— (2010), "Nonlinear Generalized Structured Component Analysis," *Behaviormetrika*, 37 (1), 1–14.

———, ———, and Naresh K. Malhotra (2007), "Multilevel Generalized Structured Component Analysis," *Behaviormetrika*, 34 (2), 95–109.

Jöreskog, Karl G. (1973), "A General Method for Estimating a Linear Structural Equation System," in *Structural Equation Models in the Social Sciences*, Arthur S. Goldberger and Otis D. Duncan, eds. New York: Academic Press, 85–112.

——— and Dag Sörbom (1993), *LISREL 8: Structural Equation Modeling with the SIMPLIS Command Language*. Hillsdale, NJ: Lawrence Erlbaum Associates.

——— and Herman Wold (1982), "The ML and PLS Techniques for Modeling with Latent Variables: Historical and Comparative Aspects," in *Systems Under Indirect Observation: Causality, Structure, Prediction I*, Herman Wold and Karl G. Jöreskog, eds. Amsterdam: North-Holland, 263–70.

Kaplan, David (2000), *Structural Equation Modeling: Foundations and Extensions*. Newbury Park, CA: Sage Publications.

Kenny, David A. and Charles M. Judd (1984), "Estimating the Non-Linear and Interactive Effects of Latent Variables," *Psychological Bulletin*, 96 (July), 201–210.

Klein, Andreas and Bengt Muthén (2007), "Quasi-Maximum Likelihood Estimation of Structural Equation Models with Multiple Interaction and Quadratic Effects," *Multivariate Behavioral Research*, 42 (4), 647–73.

Lei, Pui-Wa (2009), "Evaluating Estimation Methods for Ordinal Data in Structural Equation Modeling," *Quality and Quantity*, 43 (3), 495–507.

Lohmöller, Jan-Bernd (1984), *LVPLS Program Manual*. Cologne, Germany: Zentralarchiv für Empirische Sozialforschung, Universität zu Köln.

——— (1989), *Latent Variable Path Modeling with Partial Least Squares*. New York: Springer-Verlag.

Marsh, Herbert W., Zhonglin Wen, and Kit-Tai Hau (2004), "Structural Equation Models of Latent Interactions: Evaluation of Alternative Estimation Strategies and Indicator Construction," *Psychological Methods*, 9 (3), 275–300.

Mason, Charlotte H. and William D. Perreault Jr. (1991), "Collinearity, Power, and Interpretation of Multiple Regression Analysis," *Journal of Marketing Research*, 28 (August), 268–80.

McArdle, John J. and Roderick P. McDonald (1984), "Some Algebraic Properties of the Reticular Action Model for Moment Structures," *British Journal of Mathematical and Statistical Psychology*, 37 (2), 234–51.

Mood, Alexander M., Franklin A. Graybill, and Duane C. Boes (1974), *Introduction to the Theory of Statistics*. New York: McGraw-Hill.

Muthén, Bengt O. and Linda K. Muthén (1994), *Mplus User's Guide*. Los Angeles: Muthén and Muthén.

Paxton, Pamela, Patrick J. Curran, Kenneth K. Bollen, James B. Kirby, and Feinian Chen (2001), "Monte Carlo Experiments: Design and Implementation," *Structural Equation Modeling*, 8 (2), 287–312.

Ringle, Christian M., Sven Wende, and Alexander Will (2005), *SmartPLS*. Hamburg: University of Hamburg.

Schumacker, Randall E. and George A. Marcoulides (1998), *Interaction and Nonlinear Effects in Structural Equation Modeling*. Mahwah, NJ: Lawrence Erlbaum Associates.

Sharma, Subhash, Srinivas Durvasula, and William R. Dillon (1989), "Some Results on the Behavior of Alternate Covariance Structure Estimation Procedures in the Presence of Non-Normal Data," *Journal of Marketing Research*, 26 (May), 214–21.

Srinivasan, V. and Charlotte H. Mason (1986), "Nonlinear Least Squares Estimation of New Product Diffusion Models," *Marketing Science*, 5 (Spring), 169–78.

Steenkamp, Jan-Benedict E.M. and Hans Baumgartner (2000), "On the Use of Structural Equation Models in Marketing Modeling," *International Journal of Research in Marketing*, 17 (2–3), 195–202.

Takane, Yoshio, Michael A. Hunter, and Heungsun Hwang (2004), "An Improved Method for Generalized Structured Component Analysis," paper presented at the International Meeting of the Psychometric Society, Pacific Grove, California (June 14–17).

Tenenhaus, Michel (2008), "Component-Based Structural Equation Modelling," *Total Quality Management & Business Excellence*, 19 (7–8), 871–86.

———, Vincenzo Esposito Vinzi, Yves-Marie Chateline, and Carlo Lauro (2005), "PLS Path Modeling," *Computational Statistics and Data Analysis*, 48 (1), 159–205.

Velicer, Wayne F. and Douglas N. Jackson (1990), "Component Analysis Versus Common Factor Analysis: Some Issues in Selecting Appropriate Procedure," *Multivariate Behavioral Research*, 25 (1), 1–28.

Wall, Melanie M. and Yasuo Amemiya (2001), "Generalized Appended Product Indicator Procedure for Nonlinear Structural Equation Analysis," *Journal of Educational and Behavioral Statistics*, 26 (1), 1–29.

Wold, Herman (1965), "A Fixed-Point Theorem with Econometric Background, I-II," *Arkiv for Matematik*, 6, 209–240.

——— (1975), "Path Models with Latent Variables: The NIPALS Approach," in *Quantitative Sociology: International Perspectives on Mathematical Statistical Model Building*, H.M. Blalock, A. Aganbegian, F.M. Borodkin, R. Boudon, and V. Cappecchi, eds. New York: Academic Press, 307–357.

——— (1982), "Soft Modeling: The Basic Design and Some Extensions," in *Systems Under Indirect Observation: Causality, Structure, Prediction II*, Herman Wold and Karl G. Jöreskog, eds. Amsterdam: North-Holland, 589–91.