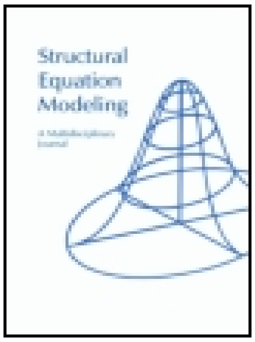

Structural Equation Modeling: A Multidisciplinary Journal

ISSN: 1070-5511 (Print) 1532-8007 (Online) Journal homepage: https://www.tandfonline.com/loi/hsem20

Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives

Li-tze Hu & Peter M. Bentler

STRUCTURAL EQUATION MODELING, 6(1), 1–55

Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives

Li-tze Hu
Department of Psychology
University of California, Santa Cruz

Peter M. Bentler
Department of Psychology
University of California, Los Angeles

This article examines the adequacy of the "rules of thumb" conventional cutoff criteria and several new alternatives for various fit indexes used to evaluate model fit in practice. Using a 2-index presentation strategy, which includes using the maximum likelihood (ML)-based standardized root mean squared residual (SRMR) and supplementing it with either Tucker–Lewis Index (TLI), Bollen's (1989) Fit Index (BL89), Relative Noncentrality Index (RNI), Comparative Fit Index (CFI), Gamma Hat, McDonald's Centrality Index (Mc), or root mean squared error of approximation (RMSEA), various combinations of cutoff values from selected ranges of cutoff criteria for the ML-based SRMR and a given supplemental fit index were used to calculate rejection rates for various types of true-population and misspecified models; that is, models with misspecified factor covariance(s) and models with misspecified factor loading(s). The results suggest that, for the ML method, a cutoff value close to .95 for TLI, BL89, CFI, RNI, and Gamma Hat; a cutoff value close to .90 for Mc; a cutoff value close to .08 for SRMR; and a cutoff value close to .06 for RMSEA are needed before we can conclude that there is a relatively good fit between the hypothesized model and the observed data. Furthermore, the 2-index presentation strategy is required to reject reasonable proportions of various types of true-population and misspecified models. Finally, using the proposed cutoff criteria, the ML-based TLI, Mc, and RMSEA tend to overreject true-population models at small sample size and thus are less preferable when sample size is small.

Requests for reprints should be sent to Li-tze Hu, Department of Psychology, University of California, Santa Cruz, CA 95064.

Structural equation modeling (SEM) has become a standard tool in many scientific disciplines for investigating the plausibility of theoretical models that might explain the interrelations among a set of variables. A structural equation model represents a series of hypotheses about how the variables in the analysis are generated and related. The application of the SEM technique thus starts with the specification of a model to be estimated. Consequently, the assessment of goodness of fit and the estimation of parameters of the hypothesized model(s) are the primary goals. The two most popular ways of evaluating model fit are those that involve the χ^2 goodness-of-fit statistics and fit indexes.

The χ^2 goodness-of-fit statistic assesses the magnitude of discrepancy between the sample and fitted covariance matrices, and it is the product of the sample size minus one and the minimum fitting function (denoted as $T = (N - 1)F_{\text{min}}$). The T statistic (called χ^2 by other researchers) has an asymptotic (large sample) χ^2 distribution under an assumed distribution and the hypothesized model for the population covariance matrix. The T statistics can be derived from various estimation methods that vary in the degrees of sensitivity to the distributional assumptions, and the one derived from maximum likelihood (ML) under the multivariate normal assumption is the most widely used summary statistic for assessing model fit (Gierl & Mulvenon, 1995).

Another popular way of evaluating model fit is the so-called fit indexes that have been offered to supplement the χ^2 test. A fit index can be used to quantify the degree of fit along a continuum. Fit indexes can be classified into absolute and incremental fit indexes (Bollen, 1989; Gerbing & Anderson, 1993; Hu & Bentler, 1995; Marsh, Balla, & McDonald, 1988; Tanaka, 1993). An absolute fit index assesses how well an a priori model reproduces the sample data. No reference model is used to assess the amount of increment in model fit, but an implicit or explicit comparison may be made to a saturated model that exactly reproduces the sample covariance matrix. Examples of absolute fit indexes include the Goodness-of-Fit Index (GFI) and the Adjusted Goodness-of-Fit Index (AGFI; Bentler, 1983; Jöreskog & Sörbom, 1984; Tanaka & Huba, 1985), Steiger's (1989) Gamma Hat, a rescaled version of Akaike's information criterion (CAK; Cudeck & Browne, 1983), a cross-validation index (CK: Browne & Cudeck, 1989), McDonald's (1989) Centrality Index (Mc), Hoelter's (1983) Critical N (CN), a standardized version of Jöreskog and Sörbom's (1981) root mean squared residual (SRMR; Bentler, 1995), and the root mean square error of approximation (RMSEA; Steiger & Lind, 1980). In contrast, an incremental fit index measures the proportionate improvement in fit by comparing a target model with a more restricted, nested baseline model. A null model in which all the observed variables are uncorrelated is the most typically used baseline model (Bentler & Bonett, 1980), although other baseline models have been suggested (e.g., Sobel & Bohrnstedt, 1985). Examples of incremental fit indexes include the Normed Fit Index (NFI; Bentler & Bonett, 1980), a fit index by Bollen (BL86; 1986), the Tucker–Lewis Index (TLI; 1973), an index developed by Bollen (BL89; 1989), Bentler's (1989, 1990) and McDonald and Marsh's (1990) Relative Noncentrality Index (RNI), and Bentler's Comparative Fit Index (CFI). See Table 1 for some of the formulas.

As noted by Bentler and Bonett (1980), fit indexes were designed to avoid some of the problems of sample size and distributional misspecification associated with the conventional overall test of fit (the χ^2 statistic) in the evaluation of a model. However, this promising claim that fit indexes would more unambiguously point to model adequacy as compared to the χ^2 test has little empirical support. Thus, two pressing issues that are relevant to proper applications of fit indexes for model evalu-

TABLE 1
Formulas and Descriptions for Incremental and Absolute Fit Indexes

Formula	*Description*
Incremental fit indexes	
TLI (or NNFI) $= [(T_B/df_B) - (T_T/df_T)]/[(T_B/df_B) - 1]$	Nonnormed (can fall outside the 0–1 range). Compensates for the effect of model complexity.
BL89 (or IFI) $= (T_B - T_T)/(T_B - df_T)$	Nonnormed. Compensates for the effect of model complexity.
RNI $= [(T_B - df_B) - (T_T - df_T)]/(T_B - df_B)$	Nonnormed. Noncentrality-based.
CFI $= 1 - \max[(T_T - df_T), 0]/\max[(T_T - df_T), (T_B - df_B), 0]$	Normed (has a 0–1 range). Noncentrality-based.
Absolute Fit Indexes	
Gamma Hat $= p/\{p + 2[(T_T - df_T)/(N - 1)]\}$	Has a known distribution. Noncentrality-based.
Mc $= \exp\{-1/2[(T_T - df_T)/(N - 1)]\}$	Noncentrality-based. Typically has the 0–1 range (but it may exceed 1).
$\text{SRMR} = \sqrt{\left\{2\sum_{i=1}^{p}\sum_{j=1}^{i}\left[\left(s_{ij} - \hat{\sigma}_{ij}\right)/\left(s_{ii}s_{jj}\right)\right]^2\right\}/p(p+1)}$	Standardized root mean squared residual.
$\text{RMSEA} = \sqrt{\hat{F}_0/df_T}$, where $\hat{F}_0 = \max[(T_T - df_T)/(N - 1), 0]$	Has a known distribution. Compensates for the effect of model complexity. Noncentrality-based.

Note. T_T = T statistic for the target model; df_T = df for the target model; T_B = T statistic for the baseline model; df_B = df for the baseline model; p = number of observed variables; s_{ij} = observed covariances; $\hat{\sigma}_{ij}$ = reproduced covariances; s_{ii} and s_{jj} are the observed standard deviations; TLI = Tucker–Lewis Index; NNFI = Nonnormed Fit Index; BL89 = Bollen's Fit Index (1989); IFI = Incremental Fit Index; RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; Mc = McDonald's Centrality Index; SRMR = standardized root mean squared residual; RMSEA = root mean squared error of approximation.

ation have become the primary concern of many researchers. The first pressing issue is determination of adequacy of fit indexes under various data and model conditions often encountered in practice. These conditions include sensitivity of fit index to model misspecification, small sample bias, estimation method effect, effects of violation of normality and independence, and bias of fit indexes resulting from model complexity. The second pressing issue is the selection of the "rules of thumb" conventional cutoff criteria for given fit indexes used to evaluate model fit.

Although the first issue has been addressed by many researchers (e.g., Akaike, 1987; Ding, Velicer, & Harlow, 1995; Hu & Bentler, in press; James, Mulaik, & Brett, 1982; La Du & Tanaka, 1989; Marsh & Balla, 1994; Marsh, Balla, & Hau, 1996; Steiger & Lind, 1980; Sugawara & MacCallum, 1993; Tanaka, 1987), the second issue has rarely been studied empirically (e.g., Marsh & Hau, 1996). Consequently, researchers often question the adequacy of these conventional cutoff criteria due to the lack of empirical evidence and compelling rationale for these rules of thumb. For example, Marsh (1995) suggested that although researchers typically interpret values greater than .90 as acceptable for incremental fit indexes (e.g., RNI), no compelling rationale for this rule of thumb has been provided. Mulaik recently suggested raising the rule of thumb minimum standard for the CFI from .90 to .95 to reduce the number of severely misspecified models that are considered acceptable based on the .90 criterion (e.g., Carlson & Mulaik, 1993; cf. Rigdon, 1996). Using data simulated from a known population simplex model (i.e., a model in which the same latent construct is evaluated with the same three indicators on each of three occasions), Marsh and Hau (1996) evaluated the behavior of a wide variety of indexes of fit and decision rules based on these indexes in comparing parsimonious and nonparsimonious (with correlated uniqueness) simplex models. Their results revealed that decision rules such as RMSEA < .05, NFI (Relative Fit Index [RFI], Nonnormed Fit Index [NNFI], Incremental Fit Index [IFI], RNI, CFI, or GFI) > .90, and parsimony indexes > .80 may be useful in some solutions but they often lead to inappropriate decisions in other solutions (e.g., decision rules for the acceptability of the parsimonious model often lead to inappropriate decisions), and should be considered only as rules of thumb. In addition, decision rules based on the comparison of the parsimonious and nonparsimonious models were more likely to result in the appropriate acceptance of the nonparsimonious model.

This discussion undoubtedly points to the need for identifying adequate rule of thumb cutoff criteria for fit indexes used to evaluate goodness of fit of hypothesized models. In this study, we evaluate the adequacy of the rules of thumb conventional cutoff criteria and other alternative criteria for various fit indexes. Although other decision rules (e.g., the selection of either the largest or smallest values for fit indexes incorporating parsimony or estimation penalties) have been proposed for fit indexes used to compare the fit of competing (i.e., nested) models (e.g., Marsh & Hau, 1996), our study only evaluates cutoff criteria under a priori models.

DEALING WITH A PRESSING ISSUE IN ASSESSING FIT BY FIT INDEXES

Hu and Bentler (in press) evaluated the sensitivity of various types of incremental fit indexes and absolute fit indexes derived from ML, generalized least squares (GLS), and asymptotically distribution-free (ADF) estimators to underparameterized model misspecification. They also examined adequacy of these indexes when (a) distributional, (b) assumed independence, and (c) asymptotic sample size requirements were violated. Their results include the following. First, most of the ML-based fit indexes outperform those obtained from GLS and ADF, and should be preferred indicators for evaluating model fit. Second, NFI, BL86, CAK, CK, CN, GFI, and AGFI performed poorly and are not recommended for evaluating model fit. Third, the ML-based SRMR is the most sensitive index to models with misspecified factor covariance(s) or latent structure(s), and the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, and RMSEA are the most sensitive indexes to models with misspecified factor loadings. Fourth, on the basis of a correlation matrix among the ML-based fit indexes obtained to determine which fit indexes might behave similarly along three major dimensions (sample size, distribution, and model misspecification), two major clusters of correlated fit indexes were identified. NFI, BL86, GFI, AGFI, CAK, and CK were clustered with high correlations. Another cluster of high intercorrelations included TLI, BL89, RNI, CFI, Mc, and RMSEA. SRMR performed least similarly to the other ML-based fit indexes. A series of analyses of variance using sample size, distribution, and model misspecification as independent variables lend further support to the behavioral pattern of these indexes identified from the correlation matrix. The findings suggested that there was variation of performance among the recommended fit indexes, and thus a two-index presentation strategy that includes using the ML-based SRMR, and supplementing it with the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, or RMSEA was proposed to distinguish good models from poor ones that include models with misspecified factor covariance(s), factor loading(s), or both.

Given that a researcher does use recommended fit indexes (Hu & Bentler, in press) to evaluate a model, what rule of thumb cutoff values should be considered? An adequate cutoff criterion for a given fit index should result in minimum Type I error rate (i.e., the probability of rejecting the null hypothesis when it is true) and Type II error rate (i.e., the probability of accepting the null hypothesis when it is false). To address this pressing issue, our study evaluates the adequacy of rules of thumb conventional cutoff criteria (e.g., Bentler, 1989; Bentler & Bonett, 1980) and other alternative criteria for the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, RMSEA, and SRMR.

First, considering any model with a fit index above .9 as acceptable (e.g., Bentler, 1989; Bentler & Bonett, 1980) and any one with an index below this value as unacceptable, we evaluate the rejection rates for simple (i.e., models with misspecified factor covariance(s)) and complex (i.e., models with misspecified factor loading(s)) true-population/misspecified models for the ML-based TLI, BL89, RNI, CFI, Gamma Hat, and Mc. A cutoff value of .05 was used for SRMR and RMSEA. Steiger (1989), Browne and Mels (1990), and Browne and Cudeck (1993) recommended that values of RMSEA less than .05 be considered as indicative of close fit. Browne and Cudeck also suggested that values in the range of .05 to .08 indicate fair fit, and that values greater than .10 indicate poor fit. MacCallum, Browne, and Sugawara (1996) considered values in the range of .08 to .10 to indicate mediocre fit. These preliminary analyses will allow us to determine Type I error and Type II error rates under rules of thumb conventional cutoff criteria for these ML-based fit indexes. Second, based on the preliminary analyses and the two-index presentation strategy proposed by Hu and Bentler (in press), various combinations of cutoff values from selected ranges of cutoff values for the ML-based SRMR and a given supplemental fit index (i.e., the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, or RMSEA) were used to calculate rejection rates for simple and complex true-population/misspecified models. For example, rejection rates for different types of models were calculated by the combinational rule of SRMR > .08 and RMSEA > .05, SRMR > .08 and RMSEA > .06, SRMR > .08 and CFI < .95, or SRMR > .08 and CFI < .96. First, we compare the performance of the rules of thumb conventional and several new alternative cutoff values for the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, SRMR, and RMSEA. The adequacy of our proposed combinational rules is then evaluated by comparing (a) Type I and Type II error rates for simple and complex true-population models and misspecified models (I and II) and (b) the sums and average values of sums of Type I and Type II error rates for simple and complex true-population models and misspecified models (I).

METHOD

Study Design

Two types of models (called simple and complex here) are used to generate measured variables under various conditions on the common factors and unique variates (cf. Hu & Bentler, in press). Simple and complex models are both confirmatory factor-analytic models based on 15 observed variables with three common factors. The factor-loading matrix (transposed) L′ for the simple model has the following structure:

$$\begin{bmatrix} .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .00 & .00 & .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .70 & .70 & .75 & .80 & .80 \end{bmatrix}$$

The structure of the factor-loading matrix (transposed) L′ for the complex model is the following:

$$\begin{bmatrix} .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 \\ .00 & .00 & .00 & .70 & .00 & .70 & .70 & .75 & .80 & .80 & .00 & .00 & .00 & .00 & .00 \\ .70 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .70 & .00 & .70 & .70 & .75 & .80 & .80 \end{bmatrix}$$

For both simple and complex true-population models, variances of the factors are 1.0, and the covariances among the three factors are 0.30 (between Factors 2 and 3), 0.40 (between Factors 1 and 3), and 0.50 (between Factors 1 and 2). The unique variances are taken as values that would yield unit-variance measured variables under normality for the simple true-population model. For the complex true-population model, the unique variances are taken as values that would yield unit-variance for most measured variables (except for the first, fourth, and ninth observed variables in the model) under normality. The unique variances for the first, fourth, and ninth observed variables are .51, .36, and .36, respectively. In estimation, the factor loading of the last indicator of each factor is fixed for identification at 0.80, and the remaining nonzero parameters are free to be estimated.

Two hundred replications (samples) of a given sample size are drawn from a known population model in each of the seven conditions as defined by Hu, Bentler, and Kano (1992; also Hu & Bentler, in press). The first was a nominal condition involving normality, the next three involved nonnormal variables that were independently distributed when uncorrelated, and the final three conditions involved nonnormal variables that, although uncorrelated, remained dependent.[1] Conditions are as follows:

---

[1]The theoretical basis for the generation of the seven conditions used in this study includes the following. Estimation methods such as maximum likelihood (ML) and generalized least squares (GLS) in covariance structure analysis are traditionally developed under the multivariate normality assumptions (e.g., Bollen, 1989; Browne, 1974; Jöreskog, 1969). A violation of the multivariate normality assumption can seriously invalidate normal-theory test statistics. The recent development of a theory for the asymptotic robustness of normal-theory methods offers hope for the appropriate use of normal-theory methods even under violation of the normality assumption (e.g., Amemiya & Anderson, 1990; Anderson & Amemiya, 1988; Browne, 1987; Browne & Shapiro, 1988; Mooijaart & Bentler, 1991; Satorra & Bentler, 1990, 1991). The purpose of this line of research is to determine under what conditions normal-theory-based methods such as ML or GLS can still correctly describe and evaluate a model with nonnormally distributed variables. The conditions are very technical, but require the strong condition that the latent variables (common factors, unique factors, or error) that are typically considered as simply uncorrelated must actually be mutually independent, and common factors, when correlated, must have freely estimated variance/covariance parameters. Normally distributed variables that are uncorrelated are also independent, but this is not true of nonnormal variables. For a more technical review of each method, readers are encourage to consult Hu et al. (1992), Bentler and Dudgeon (1996), or, especially, the original sources.

1. The factors and errors and hence measured variables are multivariate normally distributed.
2. Nonnormal factors and errors, when uncorrelated, are independent, but asymptotic robustness theory does not hold because the covariances of common factors are not free parameters.
3. Nonnormal factors and errors that are independent but not multivariate normally distributed.
4. The errors and hence the measured variables are not multivariate normally distributed.
5. An elliptical distribution in which factors and errors are uncorrelated but dependent on each other.
6. The errors and hence the measured variables are not multivariate normally distributed and both factors and errors are uncorrelated but dependent on each other.
7. Nonnormal factors and errors that are uncorrelated but dependent on each other.

These seven conditions are created through various distributional specifications on the common and (unique) error factors. In Condition 1, both common and error factors are normally distributed, with no excess kurtosis. The true kurtoses for the nonnormal common factors in Conditions 2 and 3 are –1.0, 2.0, and 5.0. The true kurtoses of the unique variates for Conditions 2 through 4, in which the errors are nonnormal, are –1.0, 0.5, 2.5, 4.5, 6.5, –1.0, 1.0, 3.0, 5.0, 7.0, –0.5, 1.5, 3.5, 5.5, and 7.5. In Conditions 5 through 7, the factors and error variates are divided by a random variable $z = \left[\chi^2(5)\right]^{1/2} / \sqrt{3}$ that is distributed independently of the original common and unique factors. As a consequence of this division, the factors and errors are uncorrelated but dependent on each other. Because of the dependence, asymptotic robustness of normal-theory statistics is not to be expected under Conditions 5 through 7. Using modified simulation procedures in EQS (Bentler & Wu, 1995a) and SAS programs[2] (SAS, 1993), the various fit indexes based on ML method are computed in each sample.

Model Specification and Procedure

For each type of model (i.e., simple or complex), one true-population model and two misspecified models are used to examine the adequacy of rules of thumb conventional and several new alternative cutoff values for fit indexes used for model evaluation.

[2]BL89, Relative Noncentrality Index, Gamma Hat, McDonald's Centrality Index, and root mean squared error of approximation were computed by SAS programs.

True-population model. For the true-population model, the adequacy of conventional cutoff criteria for the ML-based fit indexes are examined. A sample of size *N* was drawn from the population and the model was estimated in that sample. The results were saved, and the process was repeated for 200 replications. This process was repeated for sample sizes *N* = 150, 250, 500, 1,000, 2,500, and 5,000. In all, there were 7 × 6 × 200 (Conditions × Sample Sizes × Replications) = 8,400 samples. The fit indexes based on ML method were calculated for each of these samples. This procedure was conducted for simple and complex models separately.

Misspecified models. Although both underparameterized and overparameterized models have been considered as incorrectly specified models, our study only examines the adequacy of conventional cutoff criteria for fit indexes derived from underparameterized models, because overparameterized models have zero population noncentrality (e.g., MacCallum et al., 1996; Satorra & Saris, 1985). For a simple model, the covariances among the three factors in the correctly specified population model (true-population model) are nonzeros. The covariance between Factors 1 and 2 was fixed to zero for the first misspecified model (simple misspecified model 1). The covariances between Factors 1 and 2 and between Factors 1 and 3 were fixed to zeros for the second misspecified model (simple misspecified model 2). For a complex model, three observed variables loaded on two factors in the true-population model: (a) the first observed variable loaded on Factors 1 and 3, (b) the fourth observed variable loaded on Factors 1 and 2, and (c) the ninth observed variable loaded on Factors 2 and 3. In the first misspecified model (complex misspecified model 1), the first observed variable only loaded on Factor 1, whereas the rest of the model specification remained the same as the complex true-population model. In the second misspecified model (complex misspecified model 2), the first and fourth observed variables only loaded on one single factor (both on Factor 1).

Using the design parameters specified in either the simple or complex true-population model, a sample of size *N* was drawn from the population and each of the misspecified models was estimated in that sample. The results were saved, and the process was repeated for 200 replications. This process was repeated for six sample sizes. For each misspecified model, there were 7 (conditions) × 6 (sample sizes) × 200 (replications) = 8,400 samples. The fit indexes based on the ML method were calculated for each of these samples.

RESULTS

Preliminary Comparison Between Conventional and Alternative Cutoff Values for the ML-Based Fit Indexes

The tendency for committing Type I error of the ML-based fit indexes was evaluated based on the overrejection rates obtained for the simple and complex true-population models under various conditions. The tendency for committing Type II error was evaluated based on the underrejection rates obtained for various simple and complex misspecified models. Note that our purpose here is to evaluate adequacy of the rules of thumb conventional cutoff values discussed earlier. These are arbitrary in nature for various fit indexes (e.g., Bentler & Bonett, 1980; Browne & Cudeck, 1993; MacCallum et al., 1996; Steiger, 1989).

For preliminary analyses, the original six sample sizes (N = 150, 250, 500, 1,000, 2,500, and 5,000) across Conditions 1 through 7 were further classified into three categories: $N \leq 250$, $N = 500$, and $1{,}000 \leq N$. Using various cutoff values, rejection rates for each of the recommended ML-based fit indexes under each type of the simple or complex true-population and misspecified models were calculated across seven distributional conditions and tabulated for the three sample sizes. Tables 2 and 3 display the rejection rates based on the ML-based TLI, BL89, RNI, CFI, Gamma Hat, SRMR, and RMSEA under the selected cutoff criteria for simple and complex true-population models and misspecified models (I and II).

With a cutoff value of .90 and across three sample size categories, BL89, RNI, and CFI only rejected 0.1% to 54.4% of all types of misspecified models, whereas TLI rejected about 0.1% to 27.6% of all types of misspecified models, except the complex misspecified models (II) (81.8%–97.5% were rejected by TLI). Substantial Type II error rates were observed with a cutoff value of .90, and thus a cutoff value greater than .90 is required to reject adequate proportions of misspecified models. Using a cutoff value of .93 or .94, TLI, BL89, RNI, and CFI rejected less than 50% of simple misspecified models (I and II) and complex misspecified models (I) in most conditions. More than 95% of the complex misspecified models (II) were rejected by these cutoff values. With a cutoff value of .95 and $N \leq 500$, only about 29.8% to 71.5% of simple misspecified models (I and II) were rejected, and about 67.4% to 92.6% of complex misspecified models (I) and 99.9% to 100% of the complex misspecified models (II) were rejected. With a cutoff value of .95 and $N \geq 1{,}000$, only 4.6% to 57.6% of simple misspecified models (I and II) were rejected, and about 56.7% to 99.4% of complex misspecified models (I) and 100% of complex misspecified models (II) were rejected. With a cutoff value of .96, they rejected less than 50% (except TLI) of simple misspecified models (I) in most conditions, 76.3% to 99% of simple misspecified models (II), 88.5% to 99.6% of complex misspecified models (I), and 100% of complex misspecified models (II). With a cutoff value of .90, Gamma Hat rejected 0.1% to 12% of simple misspecified models (I and II), 0.1% to 14.4% of complex misspecified models (I), and 24.6% to 57.9% of complex misspecified models (II). With a cutoff value of .93 or .94, Gamma Hat rejected 0.1% to 40.6% of simple misspecified models (I and II), 4.1% to 60.5% of complex misspecified models (I), and 96.3% to 100% of complex misspecified models (II). With a cutoff value of .95, Gamma Hat rejected 2.4% to 51% of simple misspecified models (I and II) and 78.6% to 100% of complex misspecified models (I and II). With a cutoff value of .96, Gamma Hat rejected 8.7% to 68.4% of simple misspecified models (I and II) and 91.5% to 100% of complex misspecified models (I and II). Note that, with a cutoff value of .95, there was a slight tendency for TLI, BL89, RNI, CFI, and Gamma Hat to overreject true-population models at small sample sizes ($N \le 250$). This tendency became more serious with a cutoff value of .96 or higher.

With a cutoff value of .90, Mc rejected more than 73.7% of simple misspecified models (I) and 91.6% to 100% of simple misspecified models (II) and complex misspecified models (I and II). However, with a cutoff value of .90, Mc substantially overrejected both types of true-population models at $N \le 250$ and slightly overrejected these true-population models at $N = 500$. With cutoff values of .93, .94, .95, and .96, Mc rejected 91.7% to 100% of all types of misspecified models, but substantial overrejection rates were also observed for simple and complex true-population models when $N \le 500$.

With a cutoff value of .045 or .05 and $N \le 250$, SRMR rejected 40.5% to 67.8% of simple and complex true-population models, and 99% to 100% of simple and complex misspecified models. When $N \ge 500$, SRMR rejected 0.1% to 5.4% of both types of true-population models, and 99% to 100% of simple and complex misspecified models. With a cutoff value of .06 or .07 and $N \le 250$, SRMR tended to overreject both types of true-population models. SRMR rejected 100% of simple misspecified models (I and II) at all sample sizes, and it rejected 21.6% to 93% of complex misspecified models (I) and 96.6% to 100% of complex misspecified models (II). With a cutoff value less than .08, SRMR tended to overreject true-population models at small sample sizes, and thus is less preferable. With a cutoff value of .08, SRMR rejected 0% to 6.8% of both types of true-population models across three sample size categories. It rejected 99.9% to 100% of simple misspecified models (I and II) and 0.9% to 66.5% of complex misspecified models (I and II). With a cutoff value of .090, SRMR rejected 0% to 3.1% of true-population models, 99.4% to 100% of simple misspecified models (I and II), and 0% to 38% of complex misspecified models (I and II). Substantial underrejection rates for complex misspecified models (I and II) were observed with a cutoff value greater than .06.

With a cutoff value of .045, .050, or .055 and $N \le 250$, RMSEA rejected 33.4% to 42% of both types of true-population models. RMSEA rejected 20% to 100% of simple misspecified models (I and II), and 96.8% to 100% of complex misspecified models (I and II). With a cutoff value of .06 and $N \le 250$, RMSEA rejected about 28% of both simple and complex true-population models, 52.6% to 65.5% of simple misspecified models (I and II), and 91.6% to 100% of complex misspecified models (I and II). With a cutoff value of .07 or .08, RMSEA substantially underrejected simple misspecified models (I and II) and complex misspecified models (I). With a cutoff value of .09 or greater, RMSEA substantially underrejected all types of misspecified models. Also note that RMSEA substantially overrejected both types of true-population models at small sample sizes

TABLE 2
Rejection Rates (%) for The ML-Based TLI, BL89, RNI, CFI, Gamma Hat, and Mc Under Various Cutoff Values

	.90			*.93*			*.94*			*.95*			*.96*		
Cutoff Value	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000
TLI															
Simple	8.0[a]	0.7	0.0	17.5	2.8	0.1	23.1	3.7	0.1	28.9	6.5	0.1	36.3	11.4	0.6
	19.4[b]	3.4	0.1	39.1	19.4	1.5	46.1	29.5	4.5	56.9	92.6	11.7	70.7	63.6	47.6
	25.5[c]	6.6	0.2	47.1	31.8	5.8	57.8	43.7	16.9	71.5	67.1	57.6	87.1	91.9	99.0
Complex	5.2	0.2	0.0	11.9	1.4	0.0	15.8	2.6	0.0	21.9	3.5	0.1	29.8	6.3	0.1
	27.6	6.6	0.2	57.8	44.8	15.2	73.5	90.9	64.0	87.6	92.6	99.4	95.6	99.4	99.6
	81.8	89.1	97.5	99.3	100.0	100.0	99.8	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
BL89															
Simple	4.8	0.2	0.0	11.7	1.4	0.1	16.8	2.6	0.1	22.5	3.6	0.1	29.7	6.7	0.1
	11.7	1.2	0.1	29.0	8.5	0.3	37.7	17.4	1.3	46.6	29.8	4.6	60.0	47.3	16.2
	16.5	2.0	0.1	37.8	17.1	1.3	46.4	30.5	5.3	59.0	45.4	19.2	76.3	76.4	83.3
Complex	2.4	0.2	0.0	6.7	0.6	0.0	9.9	1.1	0.0	14.3	2.5	0.1	21.4	3.5	0.1
	14.0	1.1	0.1	37.1	13.1	1.8	52.3	37.6	9.0	91.3	67.4	56.3	88.5	94.0	99.6
	52.9	41.9	19.2	95.3	98.9	100.0	98.8	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0

RNI (or CFI)															
Simple	5.0	0.2	0.0	12.2	1.4	0.1	16.5	2.6	0.1	25.0	3.6	0.1	30.1	6.9	0.2
	12.3	1.2	0.1	29.5	8.6	0.3	38.4	17.5	1.3	47.2	30.1	4.7	60.7	47.7	16.5
	17.3	2.0	0.1	38.4	17.8	1.4	47.1	31.0	5.4	59.8	45.7	19.4	77.2	77.2	83.7
Complex	2.5	0.2	0.0	7.0	0.6	0.0	10.1	1.1	0.0	14.6	2.5	0.1	21.9	3.5	0.1
	14.9	1.2	0.1	38.1	13.4	1.8	53.2	37.9	9.1	72.2	68.2	56.7	89.1	94.2	99.6
	54.4	42.8	19.7	95.8	99.1	100.0	99.1	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0
Gamma Hat															
Simple	3.9	0.2	0.0	10.1	0.8	0.0	15.1	1.4	0.1	21.3	3.4	0.1	28.1	5.4	0.1
	8.9	0.4	0.1	25.1	5.3	0.1	33.9	11.1	0.4	42.0	24.5	2.4	54.2	37.7	8.7
	12.0	0.6	0.0	32.5	10.4	0.3	40.6	21.3	2.2	51.0	35.3	8.6	68.4	59.1	36.3
Complex	3.3	0.2	0.0	9.1	0.6	0.0	13.9	1.2	0.1	18.8	3.2	0.1	26.9	5.1	0.1
	14.4	2.1	0.1	45.9	30.4	4.1	60.5	47.9	18.0	78.6	78.9	82.5	91.5	97.6	99.9
	57.9	48.9	24.6	96.3	99.6	99.0	99.4	100.0	99.5	99.9	100.0	100.0	100.0	100.0	100.0
Mc															
Simple	38.9	15.3	1.0	45.0	30.9	3.6	47.0	35.6	5.1	49.9	61.3	7.4	53.8	40.9	11.3
	76.1	73.7	75.1	91.7	92.0	99.8	95.1	99.1	99.9	96.9	99.9	100.0	98.1	100.0	100.0
	91.6	96.9	99.6	97.6	99.9	100.0	98.3	100.0	100.0	98.9	100.0	100.0	99.3	100.0	100.0
Complex	38.1	14.7	0.6	44.6	29.9	3.1	46.8	34.6	4.8	49.4	38.0	7.1	53.0	40.5	10.4
	98.6	99.9	100.0	99.9	100.0	100.0	99.9	100.0	100.0	99.9	100.0	100.0	100.0	100.0	100.0
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Note. TLI = Tucker–Lewis Index; BL89 = Bollen's Fit Index (1989); RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; Mc = McDonald's Centrality Index.

TABLE 3
Rejection Rates (%) for ML-Based SRMR and RMSEA Under Various Cutoff Values

	.045			.050			.055			.060			.070		
Cutoff Value	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000	*N* ≤ 250	*N* = 500	*N* ≥ 1,000
SRMR															
Simple	67.8[a]	11.7	0.3	52.5	5.2	0.1	38.4	3.4	0.1	28.0	2.1	0.1	20.0	1.3	0.1
	100.0[b]	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
	100.0[c]	100.0	100.0	100.0	100.0	100.0	99.6	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Complex	54.9	8.6	0.4	40.5	5.4	0.2	28.4	3.2	0.1	20.6	2.2	0.1	14.6	1.1	0.1
	100.0	100.0	100.0	99.5	99.0	99.5	98.0	93.6	88.8	93.0	76.4	46.6	80.5	52.8	21.6
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.9	99.8	100.0	98.5	96.6	98.5
RMSEA															
Simple	42.0	23.6	1.7	38.5	14.0	0.8	34.2	8.4	0.2	28.0	5.4	0.1	18.8	2.6	0.1
	84.1	87.4	97.1	73.6	68.1	61.2	62.4	49.7	20.0	52.6	36.4	8.2	37.8	17.7	1.0
	95.2	99.3	100.0	88.9	93.6	99.3	77.5	77.5	83.9	65.5	54.0	30.6	44.7	28.3	4.7
Complex	41.8	23.4	1.8	38.1	14.8	0.6	33.4	7.3	0.1	28.3	5.4	0.1	17.7	2.6	0.1
	99.5	100.0	100.0	98.5	99.9	100.0	96.8	99.5	100.0	91.6	97.7	99.8	72.8	67.3	58.0
	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	99.7	100.0	99.7

Cutoff Value	.080 N ≤ 250	.080 N = 500	.080 N ≥ 1,000	.090 N ≤ 250	.090 N = 500	.090 N ≥ 1,000	.100 N ≤ 250	.100 N = 500	.100 N ≥ 1,000	.110 N ≤ 250	.110 N = 500	.110 N ≥ 1,000	.120 N ≤ 250	.120 N = 500	.120 N ≥ 1,000
SRMR															
Simple	6.8	0.3	0.0	3.1	0.2	0.0	1.3	0.2	0.0	0.5	0.2	0.0	0.3	0.2	0.0
	99.9	100.0	100.0	99.4	100.0	100.0	98.4	99.4	100.0	94.6	97.0	99.6	88.1	90.4	97.3
	100.0	100.0	100.0	100.0	100.0	100.0	99.9	100.0	100.0	99.4	100.0	100.0	98.4	99.9	100.0
Complex	5.6	0.4	0.0	2.9	0.2	0.0	1.6	0.2	0.0	0.8	0.2	0.0	0.3	0.2	0.0
	36.5	10.6	0.9	19.6	2.9	0.2	9.6	0.7	0.1	3.9	0.4	0.0	1.6	0.3	0.0
	66.5	35.4	16.5	38.0	14.4	6.8	20.5	5.3	0.7	9.7	1.9	0.1	4.8	0.5	0.0
RMSEA															
Simple	10.4	0.8	0.0	6.1	0.2	0.0	3.3	0.2	0.0	1.5	0.2	0.0	0.7	0.2	0.0
	25.1	5.3	0.1	14.3	1.1	0.1	7.4	0.4	0.0	3.7	0.2	0.0	1.5	0.2	0.0
	32.0	10.0	0.3	19.3	2.6	0.1	9.9	0.4	0.0	5.0	0.2	0.0	2.2	0.2	0.0
Complex	10.3	0.9	0.0	6.2	0.2	0.0	3.3	0.2	0.0	1.4	0.2	0.0	0.5	0.1	0.0
	47.9	33.1	5.6	30.2	7.2	0.3	18.4	1.9	0.1	9.1	0.4	0.1	3.7	0.2	0.0
	96.6	99.8	99.0	82.6	87.3	94.8	51.2	37.6	12.2	28.8	11.4	0.5	15.4	2.0	0.1

Note. SRMR = standardized root mean squared residual; RMSEA = root mean squared error of approximation.
[a]True-population model. [b]Misspecified model I. [c]Misspecified model II.

($N \leq 250$) for any chosen cutoff value (including a cutoff value of .06) that can reject a reasonable proportion of misspecified models.

The findings from preliminary analyses mirrored those of Hu and Bentler (in press) that the ML-based SRMR is the most sensitive index to models with misspecified factor covariances or latent structures, and the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, and RMSEA are the most sensitive indexes to models with misspecified factor loadings. These findings suggested that combinational rules using various combinations of cutoff values from selected ranges of cutoff values for the ML-based SRMR and a supplemental fit index (the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, or RMSEA) might perform superior to a single-index presentation strategy.

Comparisons Between the Single-Index and the Two-Index Presentation Strategies

Hu and Bentler (1997) found that a designated cutoff value may not work equally well with various types of fit indexes, sample sizes, estimators, or distributions. Our preliminary analyses also revealed that sample size and violation of (asymptotic) robustness theory influences the selection of cutoff values for the ML-based TLI, BL89, RNI, CFI, Gamma Hat, Mc, SRMR, and RMSEA. Subsequent analyses were thus performed after reclassifying the seven conditions into a robustness condition (includes Conditions 1, 3, and 4) and a nonrobustness condition (includes Conditions 2, 5, 6, and 7). Under the nonrobustness condition, the asymptotic robustness theory broke down either as a result of a fixed factor covariance matrix Φ or dependence among latent variates. Cutoff values of .06, .07, .08, .09, .10, and .11 for the ML-based SRMR and cutoff values of .90, .91, .92, .93, .94, .95, and .96 for the ML-based TLI, BL89, RNI, CFI, Mc, or Gamma Hat (note that cutoff values of .05, .06, .07, and .08 were used for RMSEA) were used to form various combinational rules for model evaluation. The rejection rates for simple and complex true-population models and misspecified models (I and II) were calculated separately for robustness and nonrobustness conditions at sample sizes of 150, 250, 500, 1,000, 2,500, and 5,000.

Using cutoff values of .90, .91, .92, .93, .94, .95, and .96 for TLI, BL89, RNI, CFI, or Gamma Hat in combination with SRMR < .06 (.07, .08, .09, .10, or .11), reasonable proportions (about 94%–100%) of simple misspecified models (I and II) were rejected. These results suggested that these combinational rules were extremely sensitive in detecting models with misspecified factor covariance(s). Although reasonable proportions (0%–4.2%) of simple and complex true-population models were rejected under the robustness condition across all sample sizes, overrejection rates of simple and complex true-population models were observed under the nonrobustness condition for these combinational rules at small sample sizes (i.e., at $N \leq 250$ in most conditions and at $N \leq 500$ in some conditions).

Using cutoff values of .90, .91, .92, .93, and .94 for TLI, BL89, RNI, CFI, or Gamma Hat in combination with SRMR < .06 (or any of the other selected cutoff values) at all six sample sizes, substantial underrejection rates for the complex misspecified models (I) were obtained (less than 50% of misspecified models were rejected in most conditions) under both robustness and nonrobustness conditions. Using these combinational rules, the rejection rates for complex misspecified models (II) were also unacceptably high in some conditions. These results showed that these combinational rules resulted in substantial Type II error rates (i.e., underrejection rates) for complex misspecified models (I; and, in some cases, for complex misspecified models, II), and thus are less preferable for model evaluation.

Only with a cutoff value of .95 or .96 for TLI (BL89, RNI, CFI, or Gamma Hat) in combination with any of the selected cutoff values for SRMR, reasonable proportions of rejection rates for simple and complex misspecified models (I and II) were obtained in most conditions. Different cutoff values for Mc (.90 and .91) and RMSEA (.05 and .06) are required to form appropriate combinational rules with SRMR and they are discussed separately later. The rejection rates and the sum of Type I and Type II error rates for simple and complex true-population models and misspecified models (I) based on these combination rules were calculated and tabulated (see Appendix Tables 1–12).

Inspection of Appendix Tables 1 to 12 revealed that the magnitudes of sum of Type I and Type II error rates under sample sizes of 150, 250, and 500 are substantially different from those under sample sizes of 1,000, 2,500, and 5,000. Thus, average values of sums of Type I and Type II error rates for simple and complex true-population models and misspecified models (I) were calculated across two sets of sample sizes for each combinational rule. The first set includes sample sizes of 150, 250, and 500, and the second set includes sample sizes of 1,000, 2,500, and 5,000. A similar procedure was also conducted for the single-index presentation strategy, which used only a cutoff criterion from a single fit index. Tables 4 and 5 show average values of sums of Type I and Type II error rates for simple and complex true-population models and misspecified models (I) across two sets of sample sizes derived from the single-index and two-index presentation strategies.

Under the robustness condition, the average values (59.0% and 82.4%) of sums of Type I and Type II error rates across sample sizes of 150, 250, and 500 derived from a single-index presentation strategy with a cutoff value of .95 for TLI were substantially greater than those (average sums of error rates ranged from 0.8%–28.2%) derived from combinational rules (based on the two-index presentation strategy) with TLI < .95 and SRMR > .06 (.07, .08, .09, .10, or .11). This pattern was observed for both simple and complex models (see columns 1 to 7 and rows 1 to 4 in Table 4). Under the nonrobustness condition, the average (59.4%)

TABLE 4
Average Value of Sums of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Across Sample Sizes of 150, 250, and 500 Derived From the ML-Based Fit Indexes

	SRMR						
Cutoff Value	*N/A*[a]	*.06*	*.07*	*.08*	*.09*	*.10*	*.11*
TLI = 95							
Simple	82.4 (59.4)	0.8 (48.7)	0.4 (43.9)	0.4 (40.6)	0.6 (39.0)	1.3 (38.2)	4.2 (38.5)
Complex	59.0 (32.3)	9.9 (38.7)	17.2 (35.3)	28.2 (33.7)	18.6 (33.1)	18.6 (33.0)	18.6 (32.7)
TLI = .96							
Simple	59.0 (60.2)	1.4 (52.6)	1.1 (54.7)	1.1 (51.5)	1.3 (49.9)	1.9 (48.9)	4.5 (49.0)
Complex	5.8 (39.6)	3.3 (49.0)	5.4 (45.5)	5.8 (42.9)	5.8 (41.4)	5.8 (40.8)	5.8 (40.1)
BL89 = .95							
Simple	93.1 (61.8)	0.6 (41.5)	0.1 (35.2)	0.1 (34.0)	0.2 (30.1)	1.0 (29.6)	3.9 (30.5)
Complex	53.1 (30.9)	18.2 (32.9)	47.2 (28.8)	52.5 (23.9)	53.1 (30.0)	53.1 (30.0)	54.7 (30.7)
BL89 = .96							
Simple	79.2 (56.5)	0.8 (49.6)	0.5 (44.8)	0.5 (41.6)	0.7 (40.0)	1.4 (39.2)	4.1 (39.5)
Complex	18.5 (30.0)	9.7 (38.2)	17.0 (34.6)	18.4 (32.4)	18.5 (31.4)	18.5 (30.9)	18.5 (30.5)
RNI (or CFI) = .95							
Simple	92.7 (61.8)	0.9 (41.9)	0.1 (35.8)	0.1 (32.4)	0.2 (30.1)	1.0 (12.2)	3.9 (31.1)
Complex	51.8 (30.6)	16.4 (33.0)	46.3 (29.0)	51.3 (29.3)	53.1 (30.0)	51.8 (30.5)	51.8 (30.4)
RNI (or CFI) = .96							
Simple	78.3 (56.8)	0.8 (50.1)	0.5 (45.4)	0.5 (42.2)	0.7 (40.6)	1.4 (25.5)	4.1 (40.0)
Complex	17.5 (30.4)	9.4 (38.7)	16.2 (35.2)	17.4 (32.9)	17.5 (31.9)	17.5 (31.4)	17.5 (30.9)

Gamma Hat=.95							
Simple	96.1 (66.6)	0.5 (40.5)	0.0 (33.9)	0.0 (30.5)	0.0 (29.0)	0.9 (28.4)	3.8 (28.8)
Complex	38.8 (31.9)	15.7 (24.4)	34.9 (32.6)	38.5 (27.8)	38.8 (49.8)	38.8 (32.3)	38.8 (32.1)
Gamma Hat=.96							
Simple	86.9 (60.5)	0.7 (47.3)	0.3 (42.4)	0.3 (39.1)	0.5 (37.5)	1.2 (43.9)	4.2 (37.6)
Complex	12.4 (36.4)	6.4 (45.2)	11.3 (41.8)	12.3 (39.3)	5.6 (38.0)	12.4 (37.6)	12.4 (37.0)
Mc=.90							
Simple	48.8 (60.9)	1.7 (63.5)	1.4 (59.7)	1.4 (56.6)	1.6 (55.0)	2.3 (54.1)	4.8 (54.1)
Complex	3.3 (52.3)	2.6 (62.1)	3.3 (58.9)	3.3 (56.1)	3.3 (54.5)	3.3 (53.2)	3.3 (53.0)
Mc=.91							
Simple	36.3 (63.2)	2.2 (68.7)	2.0 (65.0)	2.0 (62.0)	2.2 (60.5)	2.8 (59.4)	5.2 (59.4)
Complex	2.9 (56.3)	4.3 (66.2)	2.9 (62.9)	2.9 (60.2)	2.9 (58.5)	2.9 (57.8)	2.9 (47.8)
RMSEA=.05							
Simple	53.1 (62.7)	1.6 (62.5)	1.3 (58.6)	1.3 (55.5)	1.5 (53.9)	2.2 (52.9)	4.9 (52.9)
Complex	3.4 (52.3)	2.7 (62.2)	3.4 (58.9)	3.4 (56.1)	3.4 (54.5)	3.4 (53.9)	3.4 (53.1)
RMSEA=.06							
Simple	87.7 (62.5)	0.7 (47.2)	0.3 (42.4)	0.3 (39.0)	0.5 (37.5)	1.2 (36.8)	4.2 (37.5)
Complex	11.2 (35.4)	6.1 (46.9)	10.2 (43.6)	11.2 (41.4)	11.2 (40.3)	11.2 (40.0)	11.2 (39.5)

Note. Two entries are shown under each condition. Values outside parentheses are the average values of sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the average values of sums of error rates derived from the nonrobustness condition. SRMR = standardized root mean squared residual; TLI = Tucker–Lewis Index; BL89 = Bollen's Fit Index (1989); RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; Mc = McDonald's Centrality Index; RMSEA = root mean squared error of approximation.

[a]A single-index presentation strategy that does not include SRMR as a supplemental fit index.

TABLE 5
Average Value of Sums of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Across Sample Sizes of 1,000, 2,500, and 5,000 Derived From the ML-Based Fit Indexes

	SRMR						
Cutoff Value	*N/A*[a]	*.06*	*.07*	*.08*	*.09*	*.10*	*.11*
TLI = .95							
Simple	66.7 (79.9)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.8)
Complex	0.9 (0.4)	0.9 (0.4)	0.9 (0.4)	0.9 (0.4)	0.9 (0.4)	0.9 (0.4)	0.9 (0.4)
TLI = .96							
Simple	86.3 (27.9)	0.0 (1.0)	0.0 (1.0)	0.0 (1.0)	0.0 (1.0)	0.0 (1.0)	0.1 (1.5)
Complex	0.0 (0.3)	0.0 (0.4)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)
BL89 = .95							
Simple	100.0 (92.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)
Complex	65.7 (27.2)	59.8 (18.1)	69.0 (24.5)	69.0 (27.0)	69.0 (27.2)	69.0 (27.2)	69.0 (27.2)
BL89 = .96							
Simple	99.3 (72.4)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.1 (0.6)
Complex	0.9 (0.2)	0.9 (0.3)	0.9 (0.2)	0.9 (0.2)	0.9 (0.2)	0.9 (0.2)	0.0 (0.1)
RNI (or CFI) = .95							
Simple	100.0 (91.9)	0.0 (0.0)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.1 (0.8)
Complex	65.4 (26.9)	59.6 (17.9)	65.4 (20.9)	65.4 (26.7)	65.7 (27.2)	65.4 (26.9)	65.4 (26.9)
RNI (or CFI) = .96							
Simple	99.2 (72.0)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.0 (0.3)	0.1 (0.8)
Complex	0.9 (0.2)	0.9 (0.3)	0.9 (0.2)	0.9 (0.2)	0.9 (0.2)	0.9 (0.2)	0.9 (0.2)

Gamma Hat = .95							
Simple	100.0 (95.9)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.0 (0.1)	0.1 (0.8)
Complex	29.2 (8.8)	27.9 (3.3)	29.2 (8.2)	29.2 (8.6)	29.2 (8.6)	29.2 (8.6)	29.2 (8.6)
Gamma Hat = .96							
Simple	100.0 (85.0)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.1 (0.7)
Complex	0.2 (0.2)	0.2 (0.3)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)	0.2 (0.2)
Mc = .90							
Simple	50.1 (7.6)	0.0 (1.7)	0.0 (1.7)	0.0 (1.7)	0.0 (1.7)	0.0 (1.7)	0.1 (2.3)
Complex	0.0 (1.1)	0.0 (1.2)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)
Mc = .91							
Simple	12.2 (3.6)	0.0 (2.2)	0.0 (2.2)	0.0 (2.2)	0.0 (2.2)	0.0 (2.2)	0.0 (2.7)
Complex	0.0 (2.1)	0.0 (2.2)	0.0 (2.1)	0.0 (2.1)	0.0 (2.1)	0.0 (2.1)	0.0 (2.1)
RMSEA = .05							
Simple	69.3 (17.4)	0.0 (1.4)	0.0 (1.4)	0.0 (1.4)	0.0 (1.4)	0.0 (1.4)	0.1 (2.0)
Complex	0.0 (1.1)	0.0 (1.3)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)	0.0 (1.1)
RMSEA = .06							
Simple	66.7 (85.8)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)	0.0 (0.2)
Complex	0.2 (0.3)	0.2 (0.4)	0.2 (0.3)	0.2 (0.3)	0.2 (0.3)	0.2 (0.3)	0.2 (0.3)

Note. Two entries are shown under each condition. Values outside parentheses are the average values of sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the average values of sums of error rates derived from the nonrobustness condition. SRMR = standardized root mean squared residual; TLI = Tucker–Lewis Index; BL89 = Bollen's Fit Index (1989); RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; Mc = McDonald's Centrality Index; RMSEA = root mean squared error of approximation.

[a]A single-index presentation strategy that does not include SRMR as a supplemental fit index.

sums of error rates of simple models across sample sizes of 150, 250, and 500 derived from a single-index presentation strategy with a cutoff value of .95 for TLI was also greater than those derived from combinational rules with TLI < .95 and SRMR > .06 (.07, .08, .09, .10, or .11). This pattern was not observed for complex models because the single-index and two-index presentation strategies behaved similarly for complex models under the nonrobustness condition.

Under the robustness condition, the average (59.0%) sums of error rates for simple and complex models derived from the single-index presentation strategy with a cutoff value of .96 for TLI were substantially greater than those derived from combinational rules with TLI < .96 and SRMR > .06 (.07, .08, .09, .10, or .11). Under the nonrobustness condition, the average values of sums of error rates for simple and complex models derived from single-index and two-index presentation strategies were similar (see Table 4).

The patterns of results derived from the single-index and two-index presentation strategies based on BL89, RNI, CFI, and Gamma Hat were similar to that derived from the two presentation strategies based on TLI.

Under the robustness condition, the average (48.8% for Mc < .90 or 36.3% for Mc < .91) sums of error rates across sample sizes of 150, 250, and 500 for simple true-population models and misspecified models (I) derived from single-index presentation strategy with Mc < .90 (or .91) was substantially greater than those derived from the two-index presentation strategy with Mc < .90 (or .91) and SRMR > .06 (.07, .08, .09, .10, or .11). The single-index and two-index presentation strategies based on Mc performed similarly for complex models under the robustness condition and for both simple and complex models under the nonrobustness condition.

Under the robustness condition, the average value (53.1% for RMSEA > .05 or 87.7% for RMSEA > .06) of sums of error rates across sample sizes of 150, 250, and 500 for simple true-population models and misspecified models (I) derived from single-index presentation strategy with RMSEA > .05 (or .06) was substantially greater than those derived from two-index presentation strategy with RMSEA > .05 (or .06) and SRMR > .06 (.07, .08, .09, .10, or .11). The single-index and two-index presentation strategies based on RMSEA performed similarly for complex models under the robustness condition and for both simple and complex models under the nonrobustness condition.

Under the robustness condition, the average values of sums of error rates for simple and complex true-population and misspecified models (I) across sample sizes of 1,000, 2,500, and 5,000 derived from the single-index presentation strategy based on TLI, BL89, RNI, CFI, Gamma Hat, or RMSEA were substantially greater than those derived from the two-index presentation strategies based on TLI, BL89, RNI, CFI, Gamma Hat, or RMSEA in combination with SRMR (see Table 5). The single-index and two-index presentation strategies based on these fit indexes performed similarly for both simple and complex models under the nonrobustness condition. Under the robustness condition, the average values of sums of error rates for simple true-population models and misspecified models (I) across sample sizes of 1,000, 2,500, and 5,000 derived from the single-index presentation strategy based on Mc were much greater than those derived from the two-index presentation strategy based on Mc in combination with SRMR (see Table 5). The single-index and two-index presentation strategies based on Mc performed similarly for complex models under the robustness condition and for simple and complex models under the nonrobustness condition.

In general, it can be concluded that combinational rules based on the two-index presentation strategy committed less sums of Type I and Type II error rates than the single-index presentation strategy, and thus are preferred criteria for model evaluation.

Detailed Evaluation of the Proposed Combinational Rules

TLI and SRMR. With combinational rules of TLI < .95 (or .96) and SRMR > .06 (or any of the other selected cutoff values), reasonable proportions of rejection rates for simple and complex misspecified models (I and II) were obtained in most conditions. Appendix Tables 1 and 2 display rejection rates and the sum of Type I and Type II error rates for simple and complex true-population models and misspecified models (I) based on combinational rules with TLI < .95 (or .96) and SRMR > .06 (.07, .08, .09, .10, or .11). Although the rejection rates for simple and complex true-population models were acceptable under the robustness conditions (0%–4.2%), the rejection rates for simple and complex true-population models under the nonrobustness condition when $N \leq 250$ were substantial (27.4%–89.1%). Inspection of Appendix Tables 1 and 2 revealed that with combinational rules of TLI < .96 and SRMR > .06 (or any of the other selected cutoff values) resulted in the least sum of Type I and Type II error rates under the robustness condition across six sample sizes. Under the nonrobustness condition, combinational rules of TLI < .95 and SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates when $N \leq 500$; however, combinational rules of TLI < .96 and SRMR > .06 (or any of the other selected cutoff values) resulted in the least sum of Type I and Type II error rates when $N \geq 1{,}000$. In general (especially, under the nonrobustness condition), combinational rules of TLI < .95 and SRMR > .09 (or .10) are preferable when $N \leq 500$, and combinational rules of TLI < .96 and SRMR > .06 (.07, .08, .09, .10, or .11) are preferable when ≥ 1,000.

BL89 and SRMR. With combinational rules of BL89 < .95 and SRMR > .06 (or any of the other selected cutoff values), substantial underrejection rates for complex misspecified models (I) in most conditions were obtained (see Appendix Table 3). The sum of Type I and Type II error rates for the complex true-population models and misspecified models (I) was unacceptably high in every condition.

Type I error rates (i.e., overrejection rates) for simple and complex true-population models were relatively high when $N \leq 250$ under the nonrobustness condition but were acceptable under the robustness condition across all sample sizes. With combinational rules of BL89 < .96 and SRMR > .06 (or any of the other selected cutoff values), reasonable proportions of misspecified models (I and II) were rejected in most conditions except when $N \leq 500$ (a slight underrejection rate under the robustness condition were observed; see Appendix Table 4). Although Type I error rates were acceptable under the robustness condition, substantial overrejection rates for simple and complex true-population models (Type I error rates) at $N \leq 250$ were observed under the nonrobustness condition. Inspection of Appendix Tables 3 and 4 revealed that combinational rules with BL89 < .96 and SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates, and thus are most preferable. Note that there is a trade-off between Type I and Type II error rates for any recommended combinational rule when $N \leq 250$ under the nonrobustness condition. A given combinational rule may be more appropriate depending on which type of error rate is less desirable in one's areas of research. For example, combinational rules with BL89 < .95 and SRMR > .09 (or .10) may be more appropriate when $N \leq$ 250 if committing Type I error is less desirable.

RNI (or CFI) and SRMR. With combinational rules of RNI (or CFI) < .95 and SRMR > .06 (or any of the other selected cutoff values), substantial underrejection rates for complex misspecified models (I) in most conditions were obtained (see Appendix Table 5). Type I error rates for simple and complex true-population models were relatively high when $N \leq 250$ under the nonrobustness condition but were acceptable under the robustness condition across six sample sizes. With combinational rules of RNI (or CFI) < .96 and SRMR > .06 (or any of the other selected cutoff values), reasonable proportions of misspecified models (I and II) were rejected in most conditions except when $N \leq 500$ (a slight underrejection rate for misspecified models [I] was observed under the robustness condition; see Appendix Table 6). Type I error rates were acceptable under the robustness condition, but substantial overrejection rates for simple and complex true-population models (Type I error rates) at $N \leq 250$ were observed under the nonrobustness condition.

Inspection of Appendix Tables 5 and 6 revealed that combinational rules with RNI (or CFI) < .96 and SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates and thus are most preferable. Note that there is a trade-off between Type I and Type II error rates for any recommended combinational rule when $N \leq 250$ under the nonrobustness condition. A given combinational rule may be more appropriate depending on which type of error rate is less desirable in one's area(s) of research. For example, combinational rules with RNI (or CFI) < .95 and

SRMR > .09 (or .10) may be more appropriate when $N \leq 250$ if committing Type I error is less desirable.

Gamma Hat and SRMR. With combinational rules of Gamma Hat < .95 and SRMR > .06 (or any of the other selected cutoff values), substantial underrejection rates under the robustness condition and small underrejection rates under the nonrobustness condition for Complex misspecified models (I) were obtained (see Appendix Table 7). Type I error rates for simple and complex true-population models were relatively high when $N \leq 250$ under the nonrobustness condition but were acceptable under the robustness condition across six sample sizes. With combinational rules of Gamma Hat < .96 and SRMR > .06 (or any of the other selected cutoff values), reasonable proportions of misspecified models (I and II) were rejected in most conditions except when $N \leq 250$ (a slight underrejection rate for misspecified models [I] was observed under the robustness condition; see Appendix Table 8). Type I error rates for simple and complex true-population models were acceptable under the robustness condition, but substantial Type I error rates at $N \leq 250$ were obtained under the nonrobustness condition.

Inspection of Appendix Tables 7 and 8 reveals that combinational rules with Gamma Hat < .96 and SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates and are most preferable for model evaluation. Note that there is a trade-off between Type I and Type II error rates for any recommended combinational rule when $N \leq 250$ under the nonrobustness condition. A given combinational rule may be more appropriate depending on which type of error rate is less desirable in one's areas of research. For example, combinational rules with Gamma Hat < .95 and SRMR > .09 (or .10) may be more appropriate when $N \leq 250$ if committing Type I error is less desirable.

Mc and SRMR. With combinational rules of Mc < .90 (or any of the other selected cutoff values) and SRMR > .06 (or any of the other selected cutoff values), reasonable proportions (about 95%–100%) of simple and complex misspecified models (I and II) were rejected. These results indicated that these combinational rules were extremely sensitive to simple and complex misspecified models.

Under the robustness condition, slight overrejection rates for simple and complex true-population models (Type I error rates) were observed for combinational rules with Mc < .93 (.94 or .95) and SRMR > .06 (.07, .08, .09, .10, or .11) at $N =$ 150, and were also observed for combinational rules with Mc < .96 and SRMR > .06 (or any of the other selected cutoff values) when $N \leq 250$. Under the nonrobustness condition, substantial Type I error rates for simple and complex true-population models were observed for combinational rules with Mc < .93 (.94, .95, or .96) and SRMR > .06 (or any of the other selected cutoff values) when $N \leq$

1,000. Substantial Type I error rates for simple and complex true-population models were also observed under the nonrobustness condition for combinational rules with Mc < .90 (.91 or .92) and SRMR > .06 (or any of the selected cutoff values) when $N \leq 500$.

These results suggested that using any of the selected combinational rules will yield acceptable Type II error rates. However, when using combinational rules with Mc < .90 and SRMR > .09 (or .10), the sum of Type I and Type II error rates seemed to be minimum, and thus are preferable combinational rules (see Appendix Tables 9 and 10). Note that when $N \leq 250$, the combinational rules with Mc tended to yield relatively large Type I error rates under both robustness and nonrobustness conditions and thus is less preferable at small sample sizes.

RMSEA and SRMR. With combinational rules of RMSEA > .05 (.06, .07, or .08) and SRMR > .06 (.07, .08, .09, .10, or .11), reasonable proportions (94%–100%) of simple misspecified models (I and II) were rejected. These results suggested that these combinational rules were extremely sensitive in detecting models with misspecified factor covariance(s). Although reasonable proportions (0%–4.7%) of simple and complex true-population models were rejected under the robustness condition across all sample sizes, overrejection rates of simple and complex true-population models (Type I error rates) were obtained under the nonrobustness condition for RMSEA > .06 (.07 or .08) in combination with any of the selected cutoff values for SRMR when $N \leq 250$ and for RMSEA > .05 in combination with any of the selected cutoff values for SRMR when $N \leq 500$.

With combinational rules of RMSEA > .07 (or .08) and any of the selected cutoff values for SRMR, substantial underrejection rates (Type II error rates) of complex misspecified models (I) were observed. (In most conditions, less than 50% of complex misspecified models [I] under the robustness condition and less than 80% of complex misspecified models [I] under the nonrobustness condition were rejected.) More than 90% of complex misspecified models (II) were rejected under both robustness and nonrobustness conditions. With combinational rules of RMSEA > .05 (or .06), acceptable proportions of rejection rates for simple and complex misspecified models (I and II) were obtained. These results indicated that combination rules with RMSEA > .05 (or .06) and some of the selected cutoff values for SRMR might be preferable. Appendix Tables 11 and 12 display rejection rates and the sum of Type I and Type II error rates for simple and complex true-population models and misspecified models (I) based on combinational rules with RMSEA > .05 (or .06) and SRMR > .06 (.07, .08, .09, .10, or .11). With combinational rules of RMSEA > .05 and SRMR > .06 (or any of the other selected cutoff values), Type II error rates for simple and complex misspecified models were acceptable (i.e., reasonable proportions of misspecified models were rejected) under both robustness and nonrobustness conditions. Type I error rates for simple and complex true-population models were acceptable under the robustness condition, but were substantial when $N \leq 500$ under the nonrobustness condition. With combinational rules of RMSEA > .06 and SRMR > .06 (or any of the other selected cutoff values), Type II error rates for simple and complex misspecified models were acceptable under both robustness and nonrobustness conditions. Type I error rates for simple and complex true-population models were acceptable under the robustness condition, but were relatively high when $N \leq 250$ under the nonrobustness condition. Inspection of Appendix Tables 11 and 12 reveals that using combinational rules of RMSEA > .06 and SRMR > .09 (or .10) resulted in the least sums of Type I and Type II error rates, and thus are more preferable for model evaluation.

CONCLUSION AND RECOMMENDATION

Our preliminary analyses suggest that, for all the recommended fit indexes, except Mc (a cutoff value of .90 is recommended for the ML-based Mc), a cutoff criterion greater (or, for some fit indexes, smaller) than the conventional rule of thumb is required for model evaluation or selection. Although it is difficult to designate a specific cutoff value for each fit index because it does not work equally well with various conditions, a cutoff value close to .95 for the ML-based TLI, BL89, CFI, RNI, and Gamma Hat; a cutoff value close to .90 for Mc; a cutoff value close to .08 for SRMR; and a cutoff value close to .06 for RMSEA seem to result in lower Type II error rates (with acceptable costs of Type-I error rates).

The analyses also suggested that some of our combinational rules, based on Hu and Bentler's (1997) two-index presentation strategy, were able to retain relatively acceptable proportions of simple and complex true-population models and reject reasonable proportions of various types of misspecified models in most conditions. Specifically, our analyses revealed that substantial underrejection rates (i.e., Type II error rates) for simple and complex misspecified models (I; and, in some conditions, for simple and complex misspecified models [II]) were obtained when using combinational rules with TLI (BL89, RNI, CFI, or Gamma Hat) < .90 (.91, .92, .93, or .94) and SRMR > .06 (.07, .08, .09, .10, or .11). These combinational rules are not recommended for model evaluation. We recommend that practitioners use a cutoff value close to .95 for TLI (BL89, RNI, CFI, or Gamma Hat) in combination with a cutoff value close to .09 for SRMR to evaluate model fit. In general, a cutoff value of .96 for TLI, BL89, RNI, CFI, or Gamma Hat in combination with SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates. Combinational rules with RMSEA > .05 (or .06) and SRMR > .06 (.07, .08, .09, .10, or .11) resulted in acceptable Type II error rates for simple and complex misspecified models under both robustness and nonrobustness conditions. A combinational rule with RMSEA > .06 and SRMR > .09 (or .10) resulted in the least sum of Type I and Type II error rates. It should be noted that, when $N \leq 250$ and under the nonrobustness condition, there is a trade-off between Type I and Type II error rates for any combinational rule recommended for TLI, BL89, RNI, CFI, or Gamma Hat. Unfortunately, because the data generating process is unknown for real data, one cannot generally know whether the robustness condition is satisfied, and thus a given combinational rule may be more appropriate depending on which type of error rate is less desirable when sample size is small. That is, a trade-off between Type I and Type II error rates was observed for all recommended combinational rules when sample size is small, and thus practitioners should choose a combinational rule that will minimize the least desirable error rate in their areas of research. In addition, when $N \leq 250$, the recommended combinational rules based on BL89, RNI, CFI, or Gamma Hat in combination with SRMR are more preferable because combinational rules based on RMSEA (or TLI) and SRMR tended to reject more simple and complex true-population models under the nonrobustness condition. Furthermore, using combinational rules with Mc < .90 and SRMR > .09 (or .10) yielded minimum sum of Type I and Type II error rates. Combinational rules with Mc < .90 (.91, .92, .93, .94, .95, or .96) and SRMR < .06 (.07, .08, .09, .10, or .11) resulted in acceptable proportions of simple and complex misspecified models (I and II) under both robustness and nonrobustness conditions. However, when $N \leq 250$, any chosen combinational rules with Mc tended to yield relatively large Type I error rates under both robustness and nonrobustness conditions, and thus are less preferable at small sample sizes.

Finally, regardless of whether one's data satisfied the robustness condition, if a combinational rule indicates that the model fit observed data well, then one can have more confidence about the goodness of fit of the model. However, when sample size is small ($N \leq 250$), most of the combinational rules have a slight tendency to overreject true-population models under nonrobustness condition. Thus, we recommend that the Satorra–Bentler scaling-corrected (SCALED) test statistic be used in conjunction with the proposed combinational rules because it works well under various conditions, including even the nonrobustness condition (e.g., Curran, West, & Finch, 1996; Hu et al., 1992). Note that, relatively speaking, combinational rules with the ML-based TLI, Mc, and RMSEA are less preferable when sample size is small (e.g., $N \leq 250$).

ACKNOWLEDGMENTS

This research was supported by a grant from the Division of Social Sciences and by a Faculty Research Grant from the University of California, Santa Cruz, and by U.S. Public Health Service (USPHS) Grants DA00017 and DA01070.

The computer assistance of Shinn-Tzong Wu is gratefully acknowledged.

REFERENCES

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52,* 317–332.

Amemiya, Y., & Anderson, T. W. (1990). Asymptotic chi-square tests for a large class of factor analysis models. *The Annals of Statistics, 18,* 1453–1463.

Anderson, T. W., & Amemiya, Y. (1988). The asymptotic normal distribution of estimators in factor analysis under general conditions. *The Annals of Statistics, 16,* 759–771.

Bentler, P. M. (1983). Some contributions to efficient statistics for structural models: Specification and estimation of moment structures. *Psychometrika, 48,* 493–571.

Bentler, P. M. (1989). *EQS structural equations program manual.* Los Angeles: BMDP Statistical Software.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107,* 238–246.

Bentler, P. M. (1995). *EQS structural equations program manual.* Encino, CA: Multivariate Software.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88,* 588–606.

Bentler, P. M., & Dudgeon, P. (1996). Covariance structure analysis: Statistical practice, theory, and directions. *Annual Review of Psychology, 47,* 541–570.

Bentler, P. M., & Wu, E. J. C. (1995). *EQS for Windows user's guide.* Encino, CA: Multivariate Software.

Bollen, K. A. (1986). Sample size and Bentler and Bonett's nonnormed fit index. *Psychometrika, 51,* 375–377.

Bollen, K. A. (1989). A new incremental fit index for general structural equation models. *Sociological Methods & Research, 17,* 303–316.

Browne, M. W. (1974). Generalized least squares estimators in the analysis of covariance structures. *South African Statistical Journal, 8,* 1–24.

Browne, M. W. (1987). Robustness of statistical inference in factor analysis and related models. *Biometrika, 74,* 375–384.

Browne, M. W., & Cudeck, R. (1989). Single sample cross-validation indexes for covariance structures. *Multivariate Behavioral Research, 24,* 445–455.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162). Newbury Park, CA: Sage.

Browne, M. W., & Mels, G. (1990). *RAMONA user's guide.* Unpublished report, Department of Psychology, The Ohio State University, Columbus.

Browne, M. W., & Shapiro, A. (1988). Robustness of normal theory methods in the analysis of linear latent variate models. *British Journal of Mathematical and Statistical Psychology, 41,* 193–208.

Carlson, M., & Mulaik, S. (1993). Trait ratings from descriptions of behavior as mediated by components of meaning. *Multivariate Behavioral Research, 28,* 111–159.

Cudeck, R., & Browne, M. W. (1983). Cross-validation of covariance structures. *Multivariate Behavioral Research, 18,* 147–167.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. *Psychological Methods, 1,* 16–29.

Ding, L., Velicer, W. F., & Harlow, L. L. (1995). Effects of estimation methods, number of indicators per factor, and improper solutions on structural equation modeling fit indices. *Structural Equation Modeling, 2,* 119–144.

Gerbing, D. W., & Anderson, J. C. (1993). Monte Carlo evaluations of goodness-of-fit indices for structural equation models. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 40–65). Newbury Park, CA: Sage.

Gierl, M. J., & Mulvenon, S. (1995, April). *Evaluation of the application of fit indices to structural equation models in educational research: A review of literature from 1990 through 1994.* Paper presented at the annual meeting of American Educational Research Association, San Francisco.

Hoelter, J. W. (1983). The analysis of covariance structures: Goodness-of-fit indices. *Sociological Methods and Research, 11*, 325–344.

Hu, L., & Bentler, P. M. (1995). Evaluating model fit. In R. Hoyle (Ed.), *Structural equation modeling: Issues, concepts, and applications* (pp. 76–99). Newbury Park, CA: Sage.

Hu, L., & Bentler, P. M. (1997). *Selecting cutoff criteria for fit indexes for model evaluation: Conventional versus new alternatives* (Tech. Rep.). Santa Cruz: University of California.

Hu, L., & Bentler, P. M. (in press). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods.*

Hu, L., Bentler, P. M., & Kano, Y. (1992). Can test statistics in covariance structure analysis be trusted? *Psychological Bulletin, 112*, 351–362.

James, L. R., Mulaik, S. A., & Brett, J. M. (1982). *Causal analysis: Assumptions, Models, and data.* Beverly Hills: Sage.

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika, 34*, 183–202.

Jöreskog, K. G., & Sörbom, D. (1981). *LISREL V: Analysis of linear structural relationships by the method of maximum likelihood.* Chicago: National Educational Resources.

Jöreskog, K. G., & Sörbom, D. (1984). *LISREL VI user's guide* (3rd ed.). Mooresville, IL: Scientific Software.

La Du, T. J., & Tanaka, S. J. (1989). The influence of sample size, estimation method, and model specification on goodness-of-fit assessments in structural equation models. *Journal of Applied Psychology, 74*, 625–636.

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*, 130–149.

Marsh, H. W. (1995). Δ2 and χ^2I2 fit indices for structural equation models: A brief note of clarification. *Structural Equation Modeling, 2*, 246–254.

Marsh, H. W., & Balla, J. R. (1994). Goodness of fit in confirmatory factor analysis: The effect of sample size and model parsimony. *Quality & Quantity, 28*, 185–217.

Marsh, H. W., Balla, J. R., & Hau, K.-T. (1996). An evaluation of incremental fit indices: A clarification of mathematical and empirical properties. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling: Issues and techniques* (pp. 315–353). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Marsh, H. W., Balla, J. R., & McDonald, R. P. (1988). Goodness-of-fit indices in confirmatory factor analysis: Effects of sample size. *Psychological Bulletin, 103*, 391–411.

Marsh, H. W., & Hau, K. T. (1996). Assessing goodness of fit: Is parsimony always desirable? *The Journal of Experimental Education, 64*, 364–390.

McDonald, R. P. (1989). An index of goodness-of-fit based on noncentrality. *Journal of Classification, 6*, 97–103.

McDonald, R. P., & Marsh, H. W. (1990). Choosing a multivariate model: Noncentrality and goodness of fit. *Psychological Bulletin, 107*, 247–255.

Mooijaart, A., & Bentler, P. M. (1991). Robustness of normal theory statistics in structural equation models. *Statistica Neerlandica, 45*, 159–171.

Rigdon, E. E. (1996). CFI versus RMSEA: A comparison of two fit indexes for structural equation modeling. *Structural Equation Modeling, 3*, 369–379.

SAS Institute Inc. (1993). SAS/STAT user's guide. Cary, NC: Author.

Satorra, A., & Bentler, P. M. (1990). Model conditions for asymptotic robustness in the analysis of linear relations. *Computational Statistics & Data Analysis, 10*, 235–249.

Satorra, A., & Bentler, P. M. (1991). Goodness-of-fit test under IV estimation: Asymptotic robustness of a NT test statistic. In R. Gutierrez & M. J. Valderrama (Eds.), Applied stochastic models and data analysis (pp. 555–567). Singapore: World Scientific.

Satorra, A., & Saris, W. E. (1985). Power of the likelihood ratio test in covariance structure analysis. *Psychometrika, 50,* 83–90.

Sobel, M. E., & Bohrnstedt, G. W. (1985). Use of null models in evaluating the fit of covariance structure models. In N. B. Tuma (Ed.), *Sociological methodology* (pp. 152–178). San Francisco: Jossey-Bass.

Steiger, J. H. (1989). *EzPATH: A supplementary module for SYSTAT and SYGRAPH.* Evanston, IL: SYSTAT.

Steiger, J. H., & Lind, J. C. (1980, May). *Statistically based tests for the number of common factors.* Paper presented at the annual meeting of the Psychometric Society, Iowa City, IA.

Sugawara H. M., & MacCallum, R. C. (1993). Effect of estimation method on incremental fit indexes for covariance structure models. *Applied Psychological Measurement, 17,* 365–377.

Tanaka, J. S. (1987). How big is big enough?: Sample size and goodness of fit in structural equation models with latent variables. *Child Development, 58,* 134–146.

Tanaka, J. S. (1993). Multifaceted conceptions of fit in structure equation models. In K. A. Bollen & J. S. Long (Eds.), *Testing structural equation models* (pp. 136–162). Newbury Park, CA: Sage.

Tanaka, J. S., & Huba, G. J. (1985). A fit index for covariance structural models under arbitrary GLS estimation. *British Journal of Mathematical and Statistical Psychology, 42,* 233–239.

Tucker, L. R, & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika, 38,* 1–10.

APPENDIX TABLE 1

Rejection Rates (%) and The Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With TLI < .95 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
TLI = .95 and SRMR = .06						
Simple	2.3[a] (*83.0*)	0.0 (*50.8*)	0.0 (*12.4*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.3[c] (83.0)	*0.0* (50.8)	*0.0* (12.4)	*0.0* (*0.6*)	*0.0* (*0.0*)	*0.0* (*0.0*)
Complex	0.2 (*70.3*)	0.0 (*37.5*)	0.0 (*8.3*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.7 (100.0)	*88.3* (100.0)	*87.5* (99.9)	97.2 (99.9)	100.0 (99.8)	100.0 (100.0)
	5.5 (70.3)	11.7 (37.5)	12.5 (8.4)	2.8 (0.9)	0.0 (0.2)	0.0 (0.0)
TLI = .95 and SRMR = .07						
Simple	1.3 (*73.9*)	0.0 (*45.9*)	0.0 (*11.8*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.3 (73.9)	0.0 (45.9)	0.0 (11.8)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*64.6*)	0.0 (*33.1*)	0.0 (6.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	79.5 (100.0)	*82.0* (99.4)	*87.2* (98.9)	97.2 (99.3)	100.0 (99.8)	100.0 (100.0)
	20.7 (64.6)	18.0 (33.7)	12.8 (7.7)	2.8 (*1.1*)	*0.0* (*0.2*)	*0.0* (*0.0*)
TLI = .95 and SRMR = .08						
Simple	1.3 (*67.8*)	0.0 (*42.6*)	0.0 (*11.5*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.3 (67.8)	0.0 (42.6)	0.0 (11.5)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*58.6*)	0.0 (*30.1*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	75.3 (99.3)	*82.0* (*97.3*)	87.2 (97.4)	97.2 (99.3)	100.0 (99.8)	100.0 (100.0)
	24.9 (59.3)	18.0 (32.8)	12.8 (9.0)	2.8 (1.1)	0.0 (0.2)	0.0 (0.0)

TLI = .95 and SRMR = .09						
Simple	1.3 (*63.8*)	0.0 (*41.6*)	0.0 (*11.4*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.8 (64.0)	0.0 (41.6)	0.0 (11.4)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*54.8*)	0.0 (*28.6*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	75.2 (97.1)	*82.0* (96.1)	*87.2* (96.9)	97.2 (99.3)	100.0 (99.8)	100.0 (100.0)
	25.0 (57.7)	18.0 (32.5)	12.8 (9.2)	2.8 (1.1)	0.0 (0.2)	0.0 (0.0)
TLI = .95 and SRMR = .10						
Simple	1.3 (*61.4*)	0.0 (*40.9*)	0.0 (*11.4*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.5)	99.0 (100.0)	100.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.0 (61.9)	1.0 (40.9)	0.0 (11.8)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*53.0*)	0.0 (*28.0*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	75.2 (95.8)	*82.0* (95.4)	*87.2* (96.8)	97.2 (99.3)	100.0 (99.8)	100.0 (100.0)
	25.0 (57.2)	18.0 (32.6)	12.8 (9.3)	2.8 (1.1)	0.0 (0.2)	0.0 (0.0)
TLI = .95 and SRMR = .11						
Simple	1.3 (*60.1*)	0.0 (*40.9*)	0.0 (*11.4*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	94.5 (98.9)	95.8 (99.4)	98.5 (98.6)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	6.8 (61.2)	4.2 (41.5)	1.5 (12.8)	0.0 (2.1)	0.0 (0.4)	0.0 (0.0)
Complex	0.2 (*51.3*)	0.0 (*27.4*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	75.2 (95.0)	*82.0* (94.8)	*87.2* (96.8)	97.2 (99.3)	100.0 (99.8)	100.0 (100.0)
	25.0 (56.3)	18.0 (32.6)	12.8 (9.3)	2.8 (1.1)	0.0 (0.2)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. TLI = Tucker–Lewis Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 2

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With TLI < .96 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
TLI = .96 and SRMR = .06						
Simple	4.2[a] (*89.1*)	0.0 (*65.8*)	0.0 (*20.8*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.2[c] (89.1)	0.0 (65.8)	0.0 (20.8)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
Complex	1.2 (*80.1*)	0.0 (*53.8*)	0.0 (*12.9*)	0.0 (1.1)	0.0 (0.0)	0.0 (0.0)
	96.0 (100.0)	95.3 (100.0)	99.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.2 (80.1)	4.7 (53.8)	0.0 (13.0)	0.0 (1.1)	0.0 (0.0)	0.0 (0.0)
TLI = .96 and SRMR = .07						
Simple	3.3 (*82.9*)	0.0 (*60.9*)	0.0 (*20.3*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.3 (82.9)	0.0 (60.9)	0.0 (20.3)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
Complex	1.2 (*75.0*)	0.0 (*49.4*)	0.0 (*11.5*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	90.7 (100.0)	95.2 (*99.6*)	99.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	10.5 (75.0)	4.8 (49.8)	1.0 (11.6)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
TLI = .96 and SRMR = .08						
Simple	3.3 (*77.0*)	0.0 (*57.6*)	0.0 (*20.0*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.3 (77.0)	0.0 (57.6)	0.0 (20.0)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
Complex	1.2 (*69.3*)	0.0 (*46.4*)	0.0 (*11.3*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	89.5 (99.5)	95.2 (99.1)	99.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	11.7 (69.8)	4.8 (47.3)	1.0 (11.7)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)

TLI = .96 and SRMR = .09						
Simple	3.3 (*73.1*)	0.0 (*56.6*)	0.0 (*19.9*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.8 (73.3)	0.0 (56.6)	0.0 (19.9)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
Complex	1.2 (*65.4*)	0.0 (*44.9*)	0.0 (*11.0*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	89.5 (98.5)	95.2 (98.9)	99.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	11.7 (66.9)	4.8 (46.0)	1.0 (11.4)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
TLI = .96 and SRMR = .10						
Simple	3.3 (*70.8*)	0.0 (*55.9*)	0.0 (*19.9*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	98.5 (99.8)	99.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.8 (71.0)	1.0 (55.9)	0.0 (19.9)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
Complex	1.2 (*63.6*)	0.0 (*44.3*)	0.0 (*11.0*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	89.5 (98.1)	95.2 (98.9)	99.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	11.7 (65.5)	4.8 (45.4)	1.0 (11.4)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
TLI = .96 and SRMR = .11						
Simple	3.3 (*69.5*)	0.0 (*55.9*)	0.0 (*19.9*)	0.0 (2.6)	0.0 (0.4)	0.0 (0.0)
	95.3 (99.3)	95.8 (99.6)	98.8 (99.5)	99.7 (98.8)	100.0 (99.6)	100.0 (100.0)
	8.0 (70.2)	4.2 (56.3)	1.2 (20.4)	0.3 (3.8)	0.0 (0.8)	0.0 (0.0)
Complex	1.2 (*61.9*)	0.0 (*43.6*)	1.0 (*11.0*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	89.5 (98.0)	95.2 (98.6)	99.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	11.7 (63.9)	4.8 (45.0)	1.0 (11.4)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. TLI = Tucker–Lewis Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 3

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With BL89 < .95 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
BL89 = .95 and SRMR = .06						
Simple	1.7[a] (*78.1*)	0.0 (*38.8*)	0.0 (*7.6*)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.7[c] (78.1)	0.0 (38.9)	0.0 (7.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*60.6*)	0.0 (*26.3*)	0.0 (6.6)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.0 (99.6)	*83.8* (98.6)	*67.5* (96.5)	*54.7* (*91.9*)	*36.5* (*80.9*)	*29.3* (*73.8*)
	6.0 (61.0)	16.2 (27.7)	32.5 (10.1)	45.3 (8.9)	63.5 (19.1)	70.7 (26.2)
BL89 = .95 and SRMR = .07						
Simple	0.2 (*65.3*)	0.0 (*33.4*)	0.0 (6.8)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.2 (65.3)	0.0 (33.4)	0.0 (6.8)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*50.4*)	0.0 (*21.8*)	0.0 (5.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	64.8 (99.3)	*50.3* (97.4)	*43.3* (94.0)	*41.7* (*87.4*)	*33.0* (*72.8*)	*28.2* (*66.8*)
	35.2 (51.1)	49.7 (24.4)	56.7 (11.0)	58.3 (13.0)	77.0 (27.2)	71.8 (33.2)
BL89 = .95 and SRMR = .08						
Simple	0.2 (*58.6*)	0.0 (*30.1*)	0.0 (6.5)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.2 (65.3)	0.0 (30.2)	0.0 (6.5)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*43.8*)	0.0 (*18.8*)	0.0 (4.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	51.5 (97.9)	*47.8* (93.0)	*43.2* (*88.3*)	*41.7* (*82.9*)	*33.0* (*70.9*)	*28.2* (*65.5*)
	48.5 (45.9)	52.2 (25.8)	56.8 (0.0)	58.3 (17.5)	77.0 (29.1)	71.8 (34.5)

BL89 = .95 and SRMR = .09						
Simple	0.2 (*54.6*)	0.0 (*30.1*)	0.0 (6.5)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.7 (54.8)	0.0 (29.2)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*39.9*)	0.0 (*17.3*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	49.8 (94.3)	*47.8 (90.8)*	*43.2 (86.5)*	*41.7 (82.4)*	*33.0 (70.9)*	*28.2 (65.5)*
	50.2 (45.6)	52.2 (26.5)	56.8 (17.9)	58.3 (18.0)	77.0 (29.2)	71.8 (34.5)
BL89 = .95 and SRMR = .10						
Simple	0.2 (*52.5*)	0.0 (*28.4*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.9 (52.9)	1.1 (28.9)	0.0 (7.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*38.1*)	0.0 (*16.6*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	49.8 (94.3)	*47.8 (89.1)*	*43.2 (85.9)*	*41.7 (82.4)*	*33.0 (70.8)*	*28.2 (65.5)*
	50.2 (45.6)	52.2 (27.5)	56.8 (18.5)	58.3 (18.0)	77.0 (29.2)	71.8 (34.5)
BL89 = .95 and SRMR = .11						
Simple	0.2 (*51.0*)	0.0 (*28.4*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	94.3 (98.8)	95.7 (98.1)	98.5 (97.3)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	5.9 (52.2)	4.3 (30.3)	1.5 (9.1)	0.3 (0.0)	0.0 (0.4)	0.0 (0.0)
Complex	0.0 (*36.4*)	0.0 (*16.0*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	49.8 (90.8)	*47.8 (88.4)*	*43.2 (85.6)*	*41.7 (82.4)*	*33.0 (70.8)*	*28.2 (65.5)*
	50.2 (45.6)	57.2 (27.6)	56.8 (18.8)	58.3 (18.0)	77.0 (29.2)	71.8 (34.5)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. BL89 = Bollen's Fit Index (1989); SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 4
Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With BL89 < .96 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
BL89 = .96 and SRMR = .06						
Simple	2.5[a] (*83.8*)	0.0 (*52.3*)	0.0 (*12.6*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.5[c] (83.8)	0.0 (52.3)	0.0 (12.6)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*69.5*)	0.0 (*36.6*)	0.0 (*8.3*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.7 (100.0)	*88.5* (100.0)	*88.0* (99.9)	97.3 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.5 (69.5)	*11.5 (36.6)*	12.0 (8.4)	2.7 (0.8)	0.0 (0.0)	0.0 (0.0)
BL89 = .96 and SRMR = .07						
Simple	1.5 (*74.8*)	0.0 (*47.4*)	0.0 (*12.1*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (0.0)
	1.5 (74.8)	0.0 (47.4)	0.0 (12.1)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*63.8*)	0.0 (*32.3*)	0.0 (6.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	79.0 (100.0)	*82.5* (99.4)	*87.7* (99.4)	97.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	21.2 (63.8)	17.5 (32.9)	12.3 (7.2)	2.7 (0.6)	0.0 (0.0)	0.0 (0.0)
BL89 = .96 and SRMR = .08						
Simple	1.5 (*68.8*)	0.0 (*44.1*)	0.0 (*11.9*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5 (68.8)	0.0 (44.1)	0.0 (11.9)	0.0 (0.8)	0.0 (0.0)	0.0 (0.00)
Complex	0.2 (*57.8*)	0.0 (*29.3*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	74.7 (99.3)	*82.5* (98.0)	*87.7* (99.0)	97.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	25.3 (58.5)	17.5 (31.3)	12.3 (7.4)	2.7 (0.6)	0.0 (0.0)	0.0 (0.0)

BL89 = .96 and SRMR = .09						
Simple	1.5 (*64.9*)	0.0 (*43.1*)	0.0 (*11.8*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.0 (65.1)	0.0 (43.1)	0.0 (11.8)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*53.9*)	0.0 (*27.8*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	74.5 (97.5)	*82.5* (97.4)	*87.7* (98.8)	97.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	25.7 (56.4)	17.5 (30.4)	12.3 (7.3)	2.7 (0.6)	0.0 (0.0)	0.0 (0.0)
BL89 = .96 and SRMR = .10						
Simple	1.5 (*62.5*)	0.0 (*42.4*)	0.0 (*11.8*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.5)	99.0 (100.0)	100.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.2 (63.0)	1.0 (42.4)	0.0 (12.2)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*52.1*)	0.0 (*27.1*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	74.5 (96.6)	*82.5* (97.3)	*87.7* (98.8)	97.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	25.7 (55.5)	17.5 (29.8)	12.3 (7.3)	2.7 (0.6)	0.0 (0.0)	0.0 (0.0)
BL89 = .96 and SRMR = .11						
Simple	1.5 (*61.3*)	0.0 (*42.4*)	0.0 (*11.8*)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	94.8 (99.0)	95.8 (99.4)	98.5 (98.6)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	6.7 (62.3)	4.2 (43.0)	1.5 (13.2)	0.3 (1.5)	0.0 (0.4)	0.0 (0.0)
Complex	0.2 (50.4)	0.0 (*26.5*)	0.0 (6.1)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
	74.5 (95.9)	*82.5* (96.9)	*87.7* (98.8)	100.0 (99.8)	100.0 (100.0)	100.0 (100.0)
	25.7 (54.5)	17.5 (29.6)	12.3 (7.3)	0.0 (0.2)	0.0 (0.0)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. BL89 = Bollen's Fit Index (1989); SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 5
Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With RNI (or CFI) < .95 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
RNI (or CFI) = .95 and SRMR = .06						
Simple	1.7[a] (*78.5*)	0.0 (*39.6*)	0.0 (*7.6*)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.7[c] (78.5)	0.0 (39.6)	0.0 (7.6)	0.0 (0.0)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*61.1*)	0.0 (*26.6*)	0.0 (6.6)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.0 (99.6)	*83.8* (98.8)	*67.7* (96.9)	*55.0* (*92.1*)	*36.7* (*81.0*)	*29.5* (*74.1*)
	0.6 (61.5)	16.2 (27.8)	32.3 (9.7)	45.0 (8.7)	63.3 (19.0)	70.5 (25.9)
RNI (or CFI) = .95 and SRMR = .07						
Simple	0.2 (*66.3*)	0.0 (*34.3*)	0.0 (6.8)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.2 (66.3)	0.0 (34.3)	0.0 (6.8)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*51.0*)	0.0 (*22.1*)	0.0 (5.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	65.5 (99.3)	*51.3* (97.5)	*44.2* (94.4)	*42.3* (*87.8*)	*33.3* (*73.0*)	*28.3* (*67.0*)
	34.5 (51.7)	48.7 (24.6)	55.8 (10.6)	57.7 (12.6)	66.7 (27.0)	71.7 (23.0)
RNI (or CFI) = .95 and SRMR = .08						
Simple	0.2 (*59.6*)	0.0 (*31.0*)	0.0 (6.5)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.2 (59.6)	0.0 (31.0)	0.0 (6.5)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*44.4*)	0.0 (*19.1*)	0.0 (4.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	53.0 (97.9)	*49.3* (93.3)	*44.0* (*88.9*)	*42.3* (*83.3*)	*33.3* (*71.1*)	*28.3* (*65.9*)
	47.0 (46.5)	50.8 (25.8)	56.0 (15.7)	57.7 (17.1)	66.7 (28.9)	71.7 (34.1)

RNI (or CFI) = .95 and SRMR = .09						
Simple	0.2 (*54.6*)	0.0 (*29.1*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.7 (54.8)	0.0 (29.2)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*39.9*)	0.0 (*17.3*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	49.8 (94.3)	*47.8 (90.8)*	*43.2 (86.5)*	*41.7 (82.4)*	*33.0 (70.8)*	*28.2 (65.5)*
	50.2 (45.6)	52.2 (26.5)	56.8 (17.9)	58.3 (18.0)	67.0 (29.2)	71.8 (34.5)
RNI (or CFI) = .95 and SRMR = .10						
Simple	0.2 (*53.3*)	0.0 (*29.3*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.4)	99.0 (99.6)	100.0 (99.4)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.9 (0.0)	1.0 (29.7)	0.0 (7.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*38.8*)	0.0 (*17.0*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	51.5 (92.5)	*49.2 (89.5)*	*44.0 (86.6)*	*42.3 (82.8)*	*33.3 (71.0)*	*28.3 (65.9)*
	48.5 (46.3)	50.8 (27.5)	56.0 (17.8)	57.7 (17.6)	66.7 (29.0)	71.7 (34.1)
RNI (or CFI) = .95 and SRMR = .11						
Simple	0.2 (*52.0*)	0.0 (*29.3*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	94.3 (98.8)	95.7 (98.3)	98.5 (97.3)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	5.9 (53.2)	4.3 (31.0)	1.5 (9.1)	0.3 (1.9)	0.0 (0.4)	0.0 (0.0)
Complex	0.0 (*37.0*)	0.0 (*16.4*)	0.0 (4.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	51.5 (91.3)	*49.2 (88.8)*	*44.0 (86.4)*	*42.3 (82.8)*	*33.3 (71.0)*	*28.3 (65.9)*
	48.5 (45.7)	50.8 (27.6)	56.0 (17.8)	57.7 (17.6)	66.7 (29.0)	71.7 (34.1)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 6
Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With RNI (or CFI) < .96 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
RNI (or CFI) = .96 and SRMR = .06						
Simple	2.5[a] (*84.3*)	0.0 (*52.9*)	0.0 (*13.0*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.5[c] (84.3)	0.0 (52.9)	0.0 (13.0)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*70.3*)	0.0 (*37.5*)	0.0 (*8.3*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.7 (100.0)	*88.7* (*100.0*)	*88.5* (99.9)	97.3 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.5 (70.3)	11.3 (37.5)	11.5 (8.4)	2.7 (0.8)	0.0 (0.0)	0.0 (0.0)
RNI (or CFI) = .96 and SRMR = .07						
Simple	1.5 (*75.6*)	0.0 (*48.0*)	0.0 (*12.5*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5 (75.6)	0.0 (48.0)	0.0 (12.5)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*64.6*)	0.0 (*33.1*)	0.0 (6.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	80.3 (100.0)	*83.2* (99.4)	*88.2* (99.4)	97.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	19.9 (64.6)	16.8 (33.7)	11.8 (7.2)	2.7 (0.5)	0.0 (0.0)	0.0 (0.0)
RNI (or CFI) = .96 and SRMR = . 08						
Simple	1.5 (*69.6*)	0.0 (*44.8*)	0.0 (*12.3*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5 (69.6)	0.0 (44.8)	0.0 (12.3)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*58.6*)	0.0 (*30.1*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	76.5 (98.0)	*83.2* (99.4)	*88.2* (99.4)	97.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	23.7 (59.3)	16.8 (32.1)	11.8 (7.4)	2.7 (0.5)	0.0 (0.0)	0.0 (0.0)

RNI (or CFI) = .96 and SRMR = .09						
Simple	1.5 (*65.8*)	0.0 (*43.8*)	0.0 (*12.1*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.0 (66.0)	0.0 (43.8)	0.0 (12.1)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*54.8*)	0.0 (*28.6*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	76.3 (97.6)	*83.2* (97.4)	*88.2* (98.8)	97.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	23.9 (57.2)	16.8 (31.2)	11.8 (7.3)	2.7 (0.5)	0.0 (0.0)	0.0 (0.0)
RNI (or CFI) = .96 and SRMR = .10						
Simple	1.5 (*63.4*)	0.0 (*43.0*)	0.0 (*12.1*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.5)	99.0 (100.0)	100.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	3.2 (63.9)	1.0 (0.0)	0.0 (12.5)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*53.0*)	0.0 (*28.0*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	76.3 (96.9)	*83.2* (97.3)	*88.2* (98.8)	97.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	23.9 (56.1)	16.8 (30.7)	11.8 (7.3)	2.7 (0.5)	0.0 (0.0)	0.0 (0.0)
RNI (or CFI) = .96 and SRMR = .11						
Simple	1.5 (*62.1*)	0.0 (*43.0*)	0.0 (*12.1*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	94.8 (99.0)	95.8 (99.4)	98.5 (98.8)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	6.7 (63.1)	4.2 (43.6)	1.5 (13.3)	0.3 (2.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.2 (*51.3*)	0.0 (*27.4*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	76.3 (96.3)	*83.2* (96.9)	*88.2* (98.8)	97.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	23.9 (55.0)	16.8 (30.5)	11.8 (7.3)	2.7 (0.5)	0.0 (0.0)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. RNI = Relative Noncentrality Index; CFI = Comparative Fit Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 7

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With Gamma Hat < .95 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
Gamma Hat = .95 and SRMR = .06						
Simple	1.5[a] (*78.3*)	0.0 (*35.9*)	0.0 (*7.3*)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5[c] (78.3)	0.0 (35.9)	0.0 (7.3)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*67.3*)	0.0 (*32.0*)	0.0 (*7.8*)	0.0 (0.8)	0.0 (0.0)	0.0 (0.0)
	94.3 (99.9)	85.5 (100.0)	73.0 (99.3)	69.8 (96.6)	68.2 (94.3)	78.3 (100.0)
	5.7 (32.8)	14.5 (32.0)	27.0 (8.5)	30.2 (4.2)	31.8 (5.7)	21.7 (0.0)
Gamma Hat = .95 and SRMR = .07						
Simple	0.0 (*65.0*)	0.0 (*30.4*)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.0 (65.0)	0.0 (30.4)	0.0 (6.4)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*60.1*)	0.0 (*27.4*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	71.5 (99.9)	*63.0* (98.9)	*60.7* (97.1)	*65.8* (93.0)	*68.2* (*90.9*)	*78.3* (*91.9*)
	28.5 (60.2)	37.0 (28.5)	39.3 (9.0)	34.2 (7.4)	31.8 (9.1)	21.7 (8.1)
Gamma Hat = .95 and SRMR = .08						
Simple	0.0 (*58.0*)	0.0 (*27.1*)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (99.6)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.0 (58.0)	0.0 (27.5)	0.0 (6.1)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*53.8*)	0.0 (*24.4*)	0.0 (5.9)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	67.2 (98.9)	*61.2* (95.1)	*60.7* (93.5)	*65.8* (*91.9*)	*68.2* (*90.9*)	*78.3* (*91.9*)
	37.3 (54.1)	38.8 (29.3)	39.3 (0.0)	34.2 (8.5)	31.8 (9.1)	21.7 (8.1)

Gamma Hat = .95 and SRMR = .09						
Simple	0.0 (*53.9*)	0.0 (*26.1*)	0.0 (6.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.6)	100.0 (99.4)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	0.0 (54.3)	0.0 (26.7)	0.0 (6.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*49.9*)	0.0 (*76.0*)	0.0 (5.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	61.8 (96.0)	*61.2* (93.3)	*60.7* (*92.8*)	*65.8* (*91.1*)	*68.2* (*90.9*)	*78.3* (*91.9*)
	38.2 (53.9)	38.8 (82.7)	39.3 (12.8)	34.2 (8.5)	31.8 (9.1)	21.7 (8.1)
Gamma Hat = .95 and SRMR = .10						
Simple	0.0 (*51.4*)	0.0 (*25.4*)	0.0 (6.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.3)	99.0 (99.0)	100.0 (99.4)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.7 (52.1)	1.0 (26.4)	0.0 (6.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
Complex	0.0 (*48.1*)	0.0 (*22.3*)	0.0 (5.6)	0.0 (0.4)	0.0 (0.0)	0.0
	61.8 (94.5)	*61.2* (*92.1*)	*60.7* (*92.6*)	*65.8* (*91.1*)	*68.2* (*90.9*)	*78.3* (*91.9*)
	38.2 (53.6)	38.8 (30.2)	39.3 (13.0)	34.2 (8.5)	31.8 (9.1)	21.7 (8.1)
Gamma Hat = .95 and SRMR = .11						
Simple	0.0 (*50.1*)	0.0 (*25.4*)	0.0 (6.0)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	94.3 (98.5)	95.7 (97.3)	98.5 (96.9)	99.7 (98.4)	100.0 (*99.6*)	*100.0* (*100.0*)
	5.7 (51.6)	4.3 (28.1)	1.5 (6.6)	0.3 (2.0)	0.0 (0.4)	0.0 (0.0)
Complex	0.0 (*46.4*)	0.0 (*21.6*)	0.0 (5.6)	0.0 (0.4)	0.0 (0.0)	0.0 (0.0)
	61.8 (93.3)	*61.2* (*91.5*)	*60.7* (*92.5*)	*65.8* (*91.1*)	*68.2* (*90.9*)	*78.3* (*91.9*)
	38.2 (53.1)	38.8 (30.1)	39.3 (13.0)	34.2 (8.5)	31.8 (9.1)	21.7 (8.1)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 8

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With Gamma Hat < .96 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
Gamma Hat = .96 and SRMR = .06						
Simple	2.2[a] (*84.1*)	0.0 (*47.3*)	0.0 (*10.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (*100.0*)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.2[c] (84.1)	0.0 (47.3)	0.0 (10.4)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (78.3)	0.0 (*46.4*)	0.0 (*10.8*)	0.0 (0.9)	0.0 (0.0)	0.0 (0.0)
	95.0 (100.0)	*90.5* (100.0)	95.5 (99.9)	99.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	5.3 (78.3)	9.5 (46.4)	4.5 (10.9)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)
Gamma Hat = .96 and SRMR = .07						
Simple	1.0 (*75.1*)	0.0 (*42.4*)	0.0 (*9.8*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.0 (75.1)	0.0 (42.4)	0.0 (9.8)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (*73.0*)	0.0 (*42.0*)	0.0 (*9.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	83.2 (100.0)	*88.0* (99.4)	95.3 (99.6)	100.0 (99.8)	100.0 (100.0)	100.0 (100.0)
	17.1 (73.0)	12.0 (42.6)	4.7 (9.8)	0.0 (0.7)	0.0 (0.0)	0.0 (0.0)
Gamma Hat = .96 and SRMR = .08						
Simple	1.0 (*68.8*)	0.0 (*39.1*)	0.0 (*9.5*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.0 (68.8)	0.0 (39.1)	0.0 (9.5)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (*67.3*)	0.0 (*39.0*)	0.0 (*9.1*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	80.2 (99.3)	*87.8* (98.4)	95.3 (99.4)	99.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	20.1 (68.0)	12.2 (40.1)	4.7 (9.7)	0.7 (0.7)	0.0 (0.0)	0.0 (0.0)

Gamma Hat = .96 and SRMR = .09						
Simple	1.0 (*64.9*)	0.0 (*38.1*)	0.0 (*9.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5 (65.1)	0.0 (38.1)	0.0 (9.4)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (*63.4*)	0.0 (*37.5*)	0.0 (*8.9*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	80.0 (98.0)	*87.8* (98.4)	95.3 (99.4)	99.3 (*99.8*)	100.0 (100.0)	100.0 (100.0)
	20.3 (65.4)	12.2 (39.1)	4.7 (9.5)	0.7 (0.7)	0.0 (0.0)	0.0 (0.0)
Gamma Hat = .96 and SRMR = .10						
Simple	1.0 (*83.3*)	0.0 (*37.4*)	0.0 (*9.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.4)	99.0 (99.6)	100.0 (99.5)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.7 (83.9)	1.0 (37.8)	0.0 (9.9)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (*61.6*)	0.0 (*36.9*)	0.0 (*8.9*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	80.0 (97.0)	*87.8* (98.3)	95.3 (99.4)	99.3 (99.8)	100.0 (100.0)	100.0 (100.0)
	20.3 (64.6)	12.2 (38.6)	4.7 (9.5)	0.7 (0.7)	0.0 (0.0)	0.0 (0.0)
Gamma Hat = .96 and SRMR = .11						
Simple	1.0 (*61.3*)	0.0 (*37.4*)	0.0 (*9.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	94.3 (98.8)	95.7 (99.0)	98.5 (97.6)	99.7 (98.5)	100.0 (100.0)	100.0 (100.0)
	6.7 (62.5)	4.3 (38.4)	1.5 (11.8)	0.3 (2.0)	0.0 (0.0)	0.0 (0.0)
Complex	0.3 (*59.9*)	0.0 (*36.3*)	0.0 (*8.9*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	80.0 (96.6)	*87.8* (98.0)	95.3 (99.4)	99.3 (99.8)	100.0 (*100.0*)	100.0 (100.0)
	20.3 (63.3)	12.2 (38.3)	4.7 (9.5)	0.7 (0.7)	0.0 (0.0)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 9

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With Mc < .90 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
Mc = .90 and SRMR = .06						
Simple	5.0[a] (*90.9*)	0.0 (*72.1*)	0.0 (*27.6*)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.0[c] (90.9)	0.0 (72.1)	0.0 (27.6)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
Complex	4.5 (*88.8*)	0.0 (*69.9*)	0.0 (*27.6*)	0.0 (3.1)	0.0 (0.5)	0.0 (0.0)
	98.8 (100.0)	98.0 (100.0)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	10.0 (100.0)
	5.7 (88.8)	2.0 (69.9)	0.2 (27.7)	0.0 (3.1)	0.0 (0.5)	90.0 (0.0)
Mc = .90 and SRMR = .07						
Simple	4.3 (*84.6*)	0.0 (*67.3*)	0.0 (*27.1*)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.3 (84.6)	0.0 (67.3)	0.0 (27.1)	0.0 (4.5)	0.0 (0.6)	0.0 (*0.1*)
Complex	4.5 (*84.6*)	0.0 (*65.5*)	0.0 (*26.3*)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
	100.0 (100.0)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (84.6)	2.0 (65.6)	0.2 (26.4)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
Mc = .90 and SRMR = .08						
Simple	4.3 (*78.9*)	0.0 (*64.0*)	0.0 (26.9)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.3 (78.9)	0.0 (64.0)	0.0 (26.9)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
Complex	4.5 (*79.5*)	0.0 (*62.5*)	0.0 (*26.0*)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.9)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (79.6)	2.0 (62.6)	0.2 (26.1)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)

Mc = .90 and SRMR = .09						
Simple	4.3 (*75.1*)	0.0 (*63.0*)	0.0 (*26.8*)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.8 (75.3)	0.0 (63.0)	0.0 (26.8)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
Complex	4.5 (*75.9*)	0.0 (*61.0*)	0.0 (*25.8*)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.5)	98.0 (99.0)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (76.4)	2.0 (61.1)	0.2 (25.9)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
Mc = .90 and SRMR = .10						
Simple	4.3 (*72.8*)	0.0 (*62.3*)	0.0 (*26.8*)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	98.3 (99.6)	99.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	6.0 (73.2)	1.0 (62.3)	0.0 (26.8)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
Complex	4.5 (*74.1*)	0.0 (*60.4*)	0.0 (*25.8*)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.1)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (73.3)	2.0 (60.5)	0.2 (25.9)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
Mc = .90 and SRMR = .11						
Simple	4.3 (*71.5*)	0.0 (*62.3*)	0.0 (*26.8*)	0.0 (4.5)	0.0 (0.6)	0.0 (0.1)
	95.2 (99.3)	95.8 (99.6)	98.8 (99.5)	99.7 (99.8)	100.0 (99.6)	100.0 (100.0)
	9.1 (72.2)	4.2 (62.7)	1.2 (27.3)	0.3 (5.7)	0.0 (1.0)	0.0 (0.1)
Complex	4.5 (*72.4*)	0.0 (*59.8*)	0.0 (*25.8*)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.1)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (73.3)	2.0 (59.9)	0.2 (25.9)	0.0 (2.8)	0.0 (0.5)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. Mc = McDonald's Centrality Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 10

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With Mc < .91 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
Mc = .91 and SRMR = .06						
Simple	6.5[a] (*92.9*)	0.2 (*75.5*)	0.0 (*37.8*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	1.5 (100.0)
	6.5[c] (92.9)	0.2 (75.5)	0.0 (37.8)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
Complex	5.8 (*90.4*)	0.2 (*74.0*)	0.0 (*34.3*)	0.0 (5.9)	0.0 (0.6)	0.0 (0.1)
	93.8 (100.0)	99.3 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	12.0 (90.4)	0.9 (74.0)	0.0 (34.3)	0.0 (5.9)	0.0 (0.6)	0.0 (0.1)
Mc = .91 and SRMR = .07						
Simple	5.8 (*87.1*)	0.2 (*70.6*)	0.0 (*37.3*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.8 (87.1)	0.2 (70.6)	0.0 (37.3)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
Complex	5.8 (*86.3*)	0.2 (*69.6*)	0.0 (*32.9*)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	99.3 (100.0)	100.0 (100.00	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (86.3)	0.9 (69.6)	0.0 (32.9)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
Mc = .91 and SRMR = .08						
Simple	5.8 (*81.6*)	0.2 (*67.4*)	0.0 (*37.0*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.8 (81.6)	0.2 (67.4)	0.0 (37.0)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
Complex	5.8 (*81.3*)	0.2 (*66.6*)	0.0 (*32.6*)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
	98.0 (99.9)	99.3 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (81.4)	0.9 (66.6)	0.0 (32.6)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)

Mc = .91 and SRMR = .09						
Simple	5.8 (*78.0*)	0.2 (*66.4*)	0.0 (*36.9*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	6.3 (78.2)	0.2 (66.4)	0.0 (36.9)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
Complex	5.8 (*77.8*)	0.2 (*65.1*)	0.0 (*32.4*)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
	98.0 (99.8)	99.3 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (78.0)	0.9 (65.1)	0.0 (32.4)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
Mc = .91 and SRMR = .10						
Simple	5.8 (*75.6*)	0.2 (*65.6*)	0.0 (*36.9*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	98.5 (99.8)	99.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.3 (75.8)	1.2 (65.6)	0.0 (36.9)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
Complex	5.8 (*76.0*)	0.2 (*64.5*)	0.0 (*32.4*)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
	98.0 (99.5)	99.3 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (76.5)	0.9 (64.5)	0.0 (32.4)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
Mc = .91 and SRMR = .11						
Simple	5.8 (*74.4*)	0.2 (*65.6*)	0.0 (*36.9*)	0.0 (6.0)	0.0 (0.6)	0.0 (0.1)
	95.7 (99.4)	95.8 (99.6)	99.0 (99.8)	99.7 (99.1)	100.0 (99.6)	100.0 (100.0)
	10.1 (75.0)	4.4 (66.0)	1.0 (37.1)	0.3 (6.9)	0.0 (1.0)	0.0 (0.1)
Complex	5.8 (*74.3*)	0.2 (*63.9*)	0.0 (*32.4*)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)
	98.0 (99.5)	99.3 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	7.8 (74.8)	0.9 (36.1)	0.0 (32.4)	0.0 (5.5)	0.0 (0.6)	0.0 (0.1)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. Mc = McDonald's Centrality Index; SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 11

Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With RMSEA < .05 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
RMSEA = .05 and SRMR = .06						
Simple	4.7[a] (90.5)	0.0 (71.6)	0.0 (25.4)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.7[c] (90.5)	0.0 (71.6)	0.0 (25.4)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
Complex	4.7 (88.8)	0.0 (69.9)	0.0 (27.8)	0.0 (3.3)	0.0 (0.5)	0.0 (0.0)
	98.8 (100.0)	98.0 (100.0)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (0.0)
	5.9 (88.8)	2.0 (69.9)	0.2 (27.9)	0.0 (3.3)	0.0 (0.5)	0.0 (0.0)
RMSEA = .05 and SRMR = .07						
Simple	4.0 (84.1)	0.0 (66.8)	0.0 (24.9)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.0 (84.1)	0.0 (66.8)	0.0 (24.9)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
Complex	4.7 (84.5)	0.0 (65.5)	0.0 (26.4)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
	96.7 (100.0)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	8.0 (84.5)	2.0 (65.6)	0.2 (26.5)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
RMSEA = .05 and SRMR = .08						
Simple	4.0 (78.4)	0.0 (63.5)	0.0 (24.6)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.0 (78.4)	0.0 (63.5)	0.0 (24.6)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
Complex	4.7 (79.4)	0.0 (62.5)	0.0 (26.1)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.9)	98.0 (99.9)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	8.0 (79.5)	2.0 (62.6)	0.2 (26.2)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)

RMSEA = .05 and SRMR = .09						
Simple	4.0 (*74.5*)	0.0 (*62.5*)	0.0 (*24.5*)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	4.5 (74.7)	0.0 (62.5)	0.0 (24.5)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
Complex	4.7 (*75.8*)	0.0 (*61.0*)	0.0 (25.9)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.4)	98.0 (99.8)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	8.0 (76.4)	2.0 (61.2)	0.2 (26.0)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
RMSEA = .05 and SRMR = .10						
Simple	4.0 (*72.1*)	0.0 (*61.8*)	0.0 (*24.5*)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	98.3 (99.6)	99.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	5.7 (72.5)	1.0 (61.8)	0.0 (24.5)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
Complex	4.7 (*74.0*)	0.0 (*60.4*)	0.0 (*25.9*)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.0)	98.0 (99.8)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	8.0 (75.0)	2.0 (60.6)	0.2 (26.0)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
RMSEA = .05 and SRMR = .11						
Simple	4.0 (*70.9*)	0.0 (*61.8*)	0.0 (*24.5*)	0.0 (3.6)	0.0 (0.6)	0.0 (0.1)
	94.8 (99.3)	95.8 (99.6)	98.8 (99.5)	99.7 (98.8)	100.0 (99.6)	100.0 (100.0)
	9.2 (71.6)	4.2 (62.2)	1.2 (25.0)	0.3 (4.8)	0.0 (1.0)	0.0 (0.1)
Complex	4.7 (*72.3*)	0.0 (*59.8*)	0.0 (*25.9*)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)
	96.7 (99.0)	98.0 (99.8)	99.8 (99.9)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	8.0 (73.3)	2.0 (60.0)	0.2 (26.0)	0.0 (2.9)	0.0 (0.5)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. RMSEA = root mean squared error of approximation. SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.

APPENDIX TABLE 12
Rejection Rates (%) and the Sum of Type I and Type II Error Rates (%) for Simple and Complex True-Population Models and Misspecified Models (I) Based on Combinational Rules With RMSEA < .06 and SRMR > .06 (.07, .08, .09, .10, .11)

	N					
Cutoff Value	*150*	*250*	*500*	*1,000*	*2,500*	*5,000*
RMSEA = .06 and SRMR = .06						
Simple	2.2[a] (*84.1*)	0.0 (*47.1*)	0.0 (*10.4*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0[b] (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.2[c] (84.1)	0.0 (47.1)	0.0 (10.4)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.5 (*79.5*)	0.0 (*49.8*)	0.0 (*11.3*)	0.0 (1.0)	0.0 (0.0)	0.0 (0.0)
	95.3 (100.0)	*90.7* (100.0)	96.2 (99.9)	99.3 (99.9)	100.0 (100.0)	100.0 (100.0)
	5.2 (79.5)	9.3 (49.8)	3.8 (11.4)	0.7 (1.1)	0.0 (0.0)	0.0 (0.0)
RMSEA = .06 and SRMR = .07						
Simple	1.0 (*75.1*)	0.0 (*42.3*)	0.0 (*9.8*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.0 (75.1)	0.0 (42.3)	0.0 (9.8)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.5 (*74.4*)	0.0 (*45.4*)	0.0 (*9.9*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	84.5 (100.0)	89.3 (99.4)	96.0 (99.5)	99.3 (99.6)	100.0 (100.0)	100.0 (0.0)
	16.0 (74.4)	10.7 (46.0)	4.0 (10.4)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)
RMSEA = .06 and SRMR = .08						
Simple	1.0 (*68.6*)	0.0 (*39.0*)	0.0 (*9.5*)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.0 (68.6)	0.0 (39.0)	0.0 (9.5)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.5 (*68.6*)	0.0 (*42.4*)	0.0 (*9.6*)	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	81.7 (99.3)	*89.2* (98.1)	96.0 (99.1)	99.3 (99.6)	100.0 (100.0)	100.0 (100.0)
	18.8 (69.3)	10.8 (44.3)	4.0 (10.5)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)

RMSEA = .06 and SRMR = .09						
Simple	1.0 *(64.8)*	0.0 *(38.0)*	0.0 *(9.4)*	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	99.5 (99.8)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	1.5 (65.0)	0.0 (38.0)	0.0 (9.4)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.5 *(64.8)*	0.0 *(40.9)*	0.0 *(9.4)*	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	81.7 (97.8)	*89.2* (97.4)	96.0 (99.0)	99.3 (99.6)	100.0 (100.0)	100.0 (100.0)
	18.8 (67.0)	10.8 (43.5)	4.0 (10.4)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)
RMSEA = .06 and SRMR = .10						
Simple	1.0 *(62.3)*	0.0 *(37.3)*	0.0 *(9.4)*	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	98.3 (99.4)	99.0 (99.6)	100.0 (99.5)	100.0 (100.0)	100.0 (100.0)	100.0 (100.0)
	2.7 (62.9)	1.0 (37.7)	0.0 (9.9)	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
Complex	0.5 *(63.0)*	0.0 *(40.3)*	0.0 *(9.4)*	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	81.7 (96.8)	*89.2* (97.0)	96.0 (99.0)	99.3 (99.6)	100.0 (100.0)	100.0 (100.0)
	18.8 (66.2)	10.8 (43.3)	4.0 (10.4)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)
RMSEA = .06 and SRMR = .11						
Simple	1.0 *(61.0)*	0.0 *(37.3)*	0.0 *(9.4)*	0.0 (0.5)	0.0 (0.0)	0.0 (0.0)
	94.3 (98.8)	95.7 (98.9)	98.5 (97.6)	99.7 (98.5)	100.0 (99.6)	100.0 (100.0)
	6.7 (62.2)	4.3 (38.4)	1.5 (11.8)	0.3 (2.0)	0.0 (0.4)	0.0 (0.0)
Complex	0.5 *(61.3)*	0.0 *(39.6)*	0.0 *(9.4)*	0.0 (0.6)	0.0 (0.0)	0.0 (0.0)
	81.7 (96.3)	*89.2* (96.6)	96.0 (99.0)	99.3 (99.6)	100.0 (100.0)	100.0 (100.0)
	18.8 (65.0)	10.8 (43.0)	4.0 (10.4)	0.7 (1.0)	0.0 (0.0)	0.0 (0.0)

Note. Two entries are shown under each condition. Values outside parentheses are the sums of Type I and Type II error rates derived from the robustness condition, whereas values in parentheses are the sums of error rates derived from the nonrobustness condition. RMSEA = root mean squared error of approximation. SRMR = standardized root mean squared residual.

[a]True-population model. [b]Misspecified model I. [c]Sum of Type I and Type II error rates.