Summer 1998

The Influence of Model Features on Goodness-of-Fit Indices: Choosing Indices to Evaluate Your Model

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THE INFLUENCE OF MODEL FEATURES ON GOODNESS-OF-FIT INDICES:

CHOOSING INDICES TO EVALUATE YOUR MODEL

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M.S., August 1994, Old Dominion University

A Dissertation submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirement for the Degree of

DOCTOR OF PHILOSOPHY

INDUSTRIAL/ORGANIZATIONAL PSYCHOLOGY

OLD DOMINION UNIVERSITY

August 1998

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ABSTRACT

THE INFLUENCE OF MODEL FEATURES ON GOODNESS-OF-FIT INDICES: CHOOSING INDICES TO EVALUATE YOUR MODEL

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Two studies were conducted to examine the performance of eight goodness-of-fit indices (i.e., the chi-square statistic, Comparative fit index, Critical N, Goodness-of-fit index, Normed fit index, Nonnormed fit index, Root mean square error of approximation, and Relative noncentrality index) used in structural equation applications. Study 1 consisted of (a) an empirical review in four journals (1986 - 1996) to determine the "typical" application; (b) a "recreation" of the goodness-of-fit indices from the published research; (c) a multiple regression analysis of the "recreated" indices to determine if values were predicted based on model and sample features; and (d) the development of a representative sample for model selection in Study 2. Study 1 identified 366 articles, and recreated indices for 187 of those articles. The regression analysis demonstrated that several indices were predicted by sample size and the hypothesized model's degrees of freedom. Study 2 consisted of (a) three Monte Carlo simulations differing in model complexity which assessed the performance of the indices under conditions of sample size, number of indicators, and model misspecifications; and (b) an evaluation of recommended and alternative cutoff values for the indices. In Study 2, simulated results replicated effects for sample size and number of indicators and extended findings to single indicator models. In agreement with prior research, indices were successful at detecting omitted misspecifications, but unsuccessful at detecting inclusion misspecifications. Most indices favored simple over complex models. Previously recommended values of indices were often inappropriate, but alternative values were suggested to reduce the frequency of accepted models with omission errors. When evaluating model fit with indices, researchers should consider the effects of sample and model features to avoid drawing erroneous conclusions.

I dedicate this dissertation to my children, Lauren and Adam, who inspire me in all that I do.

ACKNOWLEDGEMENTS

The completion of this dissertation would not have been possible without the assistance, encouragement, and support of many individuals. First, I would like to thank my dissertation committee: Terry Dickinson, Glynn Coates, Michelle Kelley, and Jacobina Skinner. Terry worked with me on my master's thesis and doctoral dissertation. Terry has had significant impact on my research abilities, critical thinking skills, and ability to spot APA errors. In addition, he provided moral support and encouragement during my graduate experience. For this and more, I am very grateful. Glynn Coates helped me when I had questions about statistics and students and kept me in line with his wit and humor. I have had the pleasure to work with Michelle Kelley on many projects, including my undergraduate honor's thesis. I have enjoyed these collaborative efforts and look forward to maintaining our friendship and research interests for a very long time. I also want to thank Jacobina Skinner for agreeing to serve on my dissertation committee. Jacobina has been a source of emotional strength for me over the last year in addition to listening to me on a regular basis about dissertation ideas. There are several other people at Old Dominion University who I would also like to acknowledge.

Mary Boswell, Jenny Caja, Peggy Kinard, and Jacqueline Winston in the main Psychology office were always encouraging, supportive, and willing to help in any way. I also want to thank Valerian Derlega, Ray Kirby, Robin Lewis, Pete Mikulka, and Janis Sanchez for taking an active interest in my graduate career and providing me with research and teaching experiences. Several students in the program have been good friends to my children and me, and I count myself very lucky to know them. Among them are Ratchaneewan (Lek) Wanichtanom, Greg Loviscky, Johanna Merritt, Tonya Miller, Arlene Pace, David Sawin, and Jeff Sinn. I also need to thank the United States Air Force for providing the financial support that allowed me to focus exclusively on this project for the last two years. Several individuals at Brooks Air Force Base assisted me with different aspects of the dissertation process and deserve mention. In particular, Malcolm Ree assisted with editing and was a good listener. Other people who helped me at Brooks Air Force Base included Bill Alley, Eric Heggestad, Ginger Goff, Bruce Gould, Larry Looper, and Mike Halliburton. The technical staff for LISREL support at Scientific Software was also key in getting several glitches worked out with programs and the simulations. I also express my love and deepest gratitude to my family and friends who have been there for me over the last ten years. This quest to get a Ph.D has not always been easy. However, I have always known that my family and friends believed in me and that I had their complete and total support. Special thanks go to my parents, Arthur and Ines Berndt for providing emotional, moral, and financial support along the way. My sisters, Lisa and Heidi, my brother, Eric, and Lisa's husband, Walter, also have been a source of strength. I am especially blessed to have Lisa as my sister and friend. Her support has meant more to me than she will ever know. I also want to thank my new friends in San Antonio for reminding me how enriching it is to meet new people and grow. Thanks go to Scott Bage, Nancy and Lester Murphy, and Carol and Rich Sexton. Last but certainly not least, I thank my children, Lauren and Adam, for accepting my mom/student status and helping me to remember what this quest is really about.

TABLE OF CONTENTS

Page

Page

Page

Page

LIST OF TABLES

TABLE

Page

LIST OF TABLES CONCLUDED

LIST OF FIGURES

FIGURE

Page

LIST OF FIGURES CONTINUED

FIGURE

Page

LIST OF FIGURES CONTINUED

FIGURE

Page

LIST OF FIGURES CONCLUDED

FIGURE

Page

LIST OF FIGURES CONCLUDED

FIGURE

Page

CHAPTER I

INTRODUCTION

The use of structural equation modeling procedures in psychological research has grown markedly in recent years as evidenced by the increasing number and diversity of applications (e.g., Bagozzi, 1977; Cudeck, 1989; Marsh, 1994; Tremblay & Gardner, 1996; Widaman, 1985). These procedures help researchers to account for structural or theoretical relationships among variables. Further, these procedures offer researchers the ability to account for errors in the measurement of the variables.

One reason for the rising use of structural equation procedures is the ability to investigate a large number of variables and relationships within a single model. For example, models have examined the determinants of adolescent substance abuse (Windle, Barnes, & Welte, 1989), and perceived social support (Vinokur, Schul, & Caplan, 1987). In particular, structural equation procedures allow researchers to examine highly abstract variables (e.g., intelligence, job satisfaction, power, motivation) that are central to many theories in the social sciences.

Note. This dissertation uses the following style manual: American Psychological Association (1994). Publication manual of the American Psychological Association (4th ed.). Washington, DC: Author.

Not surprisingly, there has been an increase in the number of universities offering courses on structural equation modeling (Hoyle, 1995); an increase in the number of journals publishing articles using structural equation modeling (Tremblay & Gardner, 1996); and, an increase in the number of statistical software programs including procedures to estimate structural equation models.[1] Furthermore, a wide choice of technical manuals, special journal issues, and texts are available that offer instruction and guidelines in the use of structural equation modeling procedures.

What is Structural Equation Modeling?

Structural equation modeling (SEM) is a statistical approach to testing hypotheses about relations among observed and latent variables. Latent variables are abstract concepts (or hypothetical variables) that are not directly measured. Observed variables are directly measured and serve as indicators for the latent variables.

The hypothesized model is the statistical statement about the expected relations among the variables. Depending on the expected relations, the hypothesized model can assume different forms and be tested using a variety of

[1] Waller (1993) provides an excellent description and critique of seven popular software programs using structural equation modeling procedures.

analytic approaches. For example, the hypothesized model might be a multivariate or univariate regression, a confirmatory factor analysis (i.e., a measurement model), or a structural equation analysis. Within each possibility, the number of latent variables examined could range from one (e.g., a one factor confirmatory factor analysis) to an unlimited number (e.g., a complex structural equation analysis).

The basic structural modeling approach involves the formal statement (i.e., specification) of a model and its corresponding parameters. The model parameters are constants that indicate the nature of the relations between two variables and can be fixed or freed depending on the researcher's a priori hypotheses. A fixed parameter is set to a particular value (typically 0.00 or 1.00) and is not estimated from the observed data. In contrast, a freed parameter is estimated from the observed data and is typically believed to have a non-zero value.

The estimation method chosen by the researcher obtains the model parameter estimates. The estimation method minimizes a fit function iteratively until the elements in **S** (the sample variance-covariance matrix) and $\Sigma(\theta)$ (the model implied variance-covariance matrix) correspond to one another as closely as possible. Researchers most often use maximum likelihood estimators of the model's parameters, because these estimators have many desirable properties (Bollen, 1989a). Maximum likelihood estimators are asymptotic, consistent, and efficient. Additionally, the distribution of an estimator approximates a normal distribution as sample size increases.

A structural equation model specifies measurement models and the structural relationships among the latent variables. The measurement models specify how the theoretical or latent variables are measured in terms of the observed variables (i.e., the indicators) with no specification of structural relations among the latent variables. Importantly, the measurement model reflects the extent to which the observed variables define the latent variables in terms of reliability and validity (Schumacker & Lomax, 1996). Two structural coefficient matrices specify the structural relationships: (a) beta matrix; and (b) gamma matrix. The beta matrix specifies the causal relationships among the dependent latent variables, whereas the gamma matrix specifies the causal relationships from the independent to the dependent latent variables.

The hypothesized model is evaluated by examining individual parameter estimates (e.g., lambda values, standard errors, and structural coefficients) and overall indices of model adequacy, known as goodness-of-fit indices. In assessing the measurement model(s), individual parameter estimates are examined to determine whether they are plausible and fall within expected ranges (Cuttance, 1987). Estimated correlations are expected to fall within a 0.00 to 1.00 range and estimated variances of latent constructs, standard errors and residual terms should be positive.

Standard errors demonstrate how accurately the values of the free parameters have been estimated. When the standard errors are small, then the researcher can assume that the parameters have been estimated accurately. Large standard errors suggest that the parameter cannot be estimated from the data reasonably. For each free parameter in the model, a t-value is produced by dividing the parameter estimate by its respective standard error. When the t-value is either below -1.96 or above 1.96, it is significantly different from zero, and it suggests that the inclusion of the estimated freed parameter improves the fit of the model.

Next, the measurement model is assessed by examining the estimates of lambda parameters (i.e., the weights for the latent variables in a measurement equation) and associated squared multiple correlations. The estimates of the lambda values are analogous to the factor loadings or weights in factor analysis. These weights display the relative strengths of the indicators in reflecting their latent variables.

Typically, the strongest indicator for a latent variable has its weight fixed to 1.00 to establish a scale for the latent variable. Each observed indicator also has a corresponding squared multiple correlation which describes the proportion of variance that is accounted for by its assignment to a latent variable. A small squared multiple correlation suggests the indicator is a weak or unreliable measure of the latent variable. In contrast, a large squared multiple correlation (e.g., .60 or greater) suggests the indicator is a strong and reliable measure of the latent variable.

Another way to evaluate reliability in the measurement model is to calculate the composite reliability for each latent variable. Composite reliability is calculated by creating a ratio of the sum of the squared lambda values to the sum of the squared lambda values and their respective measurement errors (Werts, Rock, Linn, & Jöreskog, 1977). Similar to Cronbach's alpha (Cronbach, 1951), composite reliability can demonstrate whether a latent variable is efficiently measured.

In assessing the structural model, the researcher first reviews structural coefficients in the beta and gamma matrices. Structural coefficients are expected to be significant and in the hypothesized directions. A squared multiple correlation for each structural equation reflects on the adequacy of the structural relationships. A large squared multiple correlation suggests a large proportion of variance in the latent dependent variable can be explained by hypothesized structural relationships in the model.

Finally, the researcher assesses the adequacy of the hypothesized structural model by comparing the sample variance-covariance matrix to the model implied variance-covariance matrix (i.e., the matrix generated by equations containing parameter estimates). A model is assumed to "fit" the observed data to the extent that the model implied variance-covariance matrix is consistent with the sample variance-covariance matrix.

Researchers draw conclusions about the "fit" of the hypothesized model by examining goodness-of-fit indices. Generally, these indices fall into one of two types: Indices based on a chi-square statistic for goodness-of-fit of the model, and indices that supplement the chi-square statistic. Most indices reflect goodness-of-fit as the degree of closeness between the observed (or sample) variance-covariance matrix and the hypothesized (or model implied) variance-covariance matrix.

An advantage of fit indices is that they can evaluate the entire model and reveal problems with the model that might not be noted by examining individual parameter estimates (e.g., lambda values, structural coefficients, and standard errors). However, there are issues regarding guidelines for the selection and interpretation of fit indices (Tanaka, 1993). Many of the interpretation problems arise from the fact that these indices have unknown sampling distributions and thus, do not have significance tests associated with them (Brannick, 1995).

Research Purpose

The purpose of the current research is to evaluate the performance of eight goodness-of-fit indices under conditions that more closely approximate the "typical" modeling application in psychological research. Prior research has examined the performance of many goodness-of-fit indices, however, often only for a confirmatory factor analysis model.

The present research is designed to supplement the current knowledge regarding goodness-of-fit indices by utilizing structural models. The findings could then be used to develop guidelines for selecting and interpreting goodness-of-fit measures when evaluating structural models.

The following sections of this chapter describe (a) issues regarding the selection and interpretation of the goodness-of-fit indices, (b) the development and computation of several goodness-of-fit indices, and (c) existing research on the performance of the fit indices.

Issues Regarding Goodness-of-Fit Indices

Cutoff Values

One issue surrounds the recommended cutoff value at which a researcher would decide a model was acceptable. For many goodness-of-fit indices, values range between 0.00 and 1.00. A value of 0.00 suggests that the hypothesized model does not fit the observed data at all, whereas a value of 1.00 suggests a very close fit. A widely accepted cutoff value for acceptable model fit has been .90 or greater (e.g., Bentler & Bonett, 1980; Jöreskog & Sörbom, 1993a; Mulaik, James, Van Alstine, Bennett, Lind, & Stillwell, 1989).

However, several researchers have expressed skepticism regarding the appropriateness of cutoff values. For example, Brannick (1995) questioned whether a goodness-of-fit value of .80 was able to indicate moderate rather than poor fit within a specific set of data. Marsh, Balla, and MacDonald (1988) noted that no absolute values of acceptable fit appear to be justified.

A recent study by Hu and Bentler (1995) examined the appropriateness of the .90 cutoff value under varying conditions of sample size, estimation method, correct and incorrect model specifications, and violations of normality and independence. They rated any model with a fit index above .90 as acceptable, and they evaluated the rejection rates for several indices.

Hu and Bentler (1995) found that almost all of the fit indices under one or more of the conditions overrejected models using the .90 cutoff. Interestingly, for some indices, the .90 cutoff value was too low and all models (correct and incorrect) were accepted under varying conditions of sample size and independence. Hu and Bentler concluded that the .90 cutoff as a guideline for accepting models is inadequate and often totally inappropriate.

Sample Size

A question posed by many researchers is "How large should the sample be to yield trust in structural equation modeling results, but not so large as to statistically reject models that have trivial levels of misfit?" (Raycov & Widaman, 1995, p. 290). Several articles have examined this question and have produced a variety of guidelines (Anderson & Gerbing, 1984; Bentler & Chou, 1986; Boomsma, 1982; Ding, Velicer, & Harlow, 1995; Raycov & Widaman, 1995; Tanaka, 1987).

Ding et al. (1995) proposed that a sample size of 50 is "very poor", 100 is "fair", 200 is "good", and 500 is "excellent". Bentler and Chou (1986) recommended an adequate sample size could be based on a sample to parameter ratio of 5 to 1 for normally or elliptically distributed data, and a ratio of 10 to 1 for nonnormal data. In contrast, Tanaka (1987) recommended a ratio of 4 to 1 for multivariate normal data. Boomsma (1982) proposed a minimum sample size of 200 for testing structural equation models, while Tanaka (1987) stated that a sample size of 100 was adequate in most applications.

Many goodness-of-fit indices are affected by sample size. Anderson and Gerbing (1984) demonstrated that several goodness-of-fit indices have significantly lower obtained values when the sample size is 200 or less. Recently, however, studies have demonstrated that a large sample size (e.g., 500 or greater) also could be related to inaccurate evaluations of model fit (Browne & Cudeck, 1993). Hu and Bentler (1995) noted that the Critical N (Hoelter, 1983; discussed shortly) accepted all models when the sample size is 500 or greater. In contrast, Browne and Cudeck (1993) demonstrated that the Expected Cross-

Validation Index (Cudeck & Browne, 1983; not investigated in the present research) consistently rejected the correct model when the sample size is 5000 or greater.

Monte Carlo studies examining the behavior of goodness-of-fit indices have shown that sample size is often a component in interaction effects (e.g., Anderson & Gerbing, 1984; Browne & Cudeck, 1993; Ding et al., 1995; Hu, Bentler, & Kano, 1992). That is, the combination of sample size with other conditions, such as the number of latent variables or the number of indicators per latent variable, results in variability in goodness-of-fit values.

Indicators per Latent Variable

Another important question is how the number of indicators used per latent variable affects the values of the fit indices. Optimally, latent variables should be measured by multiple observed variables (i.e., indicators) rather than a single variable. Drasgow and Kanfer (1985) recommended using at least three indicators per latent variable, whereas Bullock, Harlow, and Mulaik (1994) stated that a minimum of four indicators is a necessary condition for identifying each latent variable.

Cliff (1983) cautioned researchers that an insufficient number of indicators per latent variable raises issues related to the nominalistic fallacy. This fallacy can occur when the latent variable is given a "name", and the meaning of the latent variable must be inferred from the content of its indicators (i.e., measured variables). The nominalistic fallacy can lead to an invalidity problem because the indicators may be partially measuring something different from what the researcher believes is being measured. Of course, the invalidity problem is particularly salient when models are considered in which one or only a few indicators are interpreted as defining a latent variable. Although these indicators may be used to define the latent variable in question, the researcher can never be entirely certain what exactly is measured because latent variables are "latent" by definition (Mulaik, 1987).

In practice, a wide range of indicators per latent variable (from one to six) are used in structural modeling applications. The use of single indicators is more common than might be expected. James and James (1989) noted that structural equation models often have at least one latent variable that is measured with a single indicator.

In some situations, this choice is due to the latent variable in question. For example, job experience might be measured with a single measured variable such as the number of years in a position. Another reason for using single indicators is to increase the utility of a small sample by meeting requirements such as the 5 to 1 or 10 to 1 sample to parameter ratio.

A number of studies have examined the impact of indicators per latent variable on goodness-of-fit indices (Anderson & Gerbing, 1984; Ding et al., 1995; Gerbing & Anderson, 1993). Their findings suggest that as the number of indicators per latent variable increases the fit indices are adversely affected (i.e., their values suggest a poorer fit). This conclusion is interesting because studies examining the stability and strength of factors in principal components analysis have demonstrated that as the number of indicators per factor increases, factors are more easily identified and tend to be more stable (Fava & Velicer, 1993; Guadagnoli & Velicer, 1988; Zwick & Velicer, 1986). Thus, in principal components analysis a larger ratio of indicators per factor (or latent variable) yields positive results, whereas the opposite effect is found for the goodness-of-fit indices in structural modeling applications.

Model Misspecifications

Another question with the goodness-of-fit indices is how they behave when there are model misspecifications. Misspecifications can occur for two reasons: Parameters have been included in the model that are not correct; or, parameters have been omitted that are needed. When specification errors exist for an hypothesized model, goodness-of-fit indices should show that the model is unacceptable.

Several Monte Carlo studies have been conducted to assess the effects of model misspecifications on goodness-of-fit indices (e.g., Bandalos, 1993; Bentler, 1990; La Du & Tanaka, 1989; Marsh et al., 1988; Mulaik et al., 1989; Williams & Holahan, 1994). Marsh et al. (1988) analyzed correct and misspecified models to evaluate the ability of goodness-of-fit indices to detect misfit. Confirmatory factor analysis models with three latent variables were utilized to examine the performance of 29 fit indices for sample sizes ranging from 25 to 32,000. In two conditions, the models were true (i.e., they had no specification errors). In the remaining two conditions, measurement paths (i.e., lambda weights or factor loadings) were omitted to create specification errors.

Overall, the fit indices yielded greater average values under the true conditions than the misspecified conditions. However, these average values often did not suggest acceptable fit for true models (e.g., .90 or greater) until the sample size was 200 or greater.

Moreover, several indices displayed significantly greater variability for true conditions at smaller sample sizes than at larger sample sizes.

Similarly, Bentler (1990) found that the fit indices produced greater average values under true conditions than misspecified conditions. However, Bentler created a specification error by omitting a structural path rather than a measurement path. In agreement with Marsh et al. (1988), Bentler found that standard errors for the fit indices were larger at a sample size of 50. One index produced values ranging from .57 to 1.36. Thus, in some samples, the researcher would conclude that the model was incorrect, whereas in other samples that the model was correct.

Another important finding from Marsh et al. (1988) and Bentler (1990) was that at sample sizes between 400 to 1600, there was very little difference in the fit indices as a function of model specification. In other words, although the correct model had greater average values for fit indices (e.g., .96 to 1.10), the misspecified model also had average values that suggested an acceptable fit (e.g., .88 to .98).

La Du and Tanaka (1989) argued that model misspecifications were influenced more strongly by estimation method and type of misspecification than by sample size. Results indicated that indices are adversely affected more often when maximum likelihood compared to generalized least squares is the estimation method. They also noted that adding a model path (i.e., structural coefficient) that did not exist in the correct model has less of an impact on the values of the fit indices than deleting a path from that correct model. Unfortunately, La Du and Tanaka only examined two goodness-of-fit indices in their investigation.

The number of indicators per latent variable may be another critical component in the effects of model misspecifications on the goodness-of-fit values. One possibility is that as the number of indicators per latent variable increases, the effects of model misspecification also may increase. For example, in a model with several indicators per latent variable, when a true nonzero path is restricted (i.e., the path is omitted), the effects of the misspecification could ripple throughout the model implied matrix because of the many connections between the indicators and the latent variables. In contrast, when a path is omitted and the model has fewer indicators per latent variable, the overall effects on the model implied matrix and the effects of the misspecification should be less.

Another possibility is that as the number of indicators per latent variable increases, the effects of model misspecification may decrease. That is, as the number of indicators increases, the latent variables should be more reliable than when there are fewer indicators per latent variable. Thus, when a true nonzero path is restricted, the effects of the misspecification could be more easily absorbed because of the additional indicators per latent variable. In contrast, when a path is omitted and the model has fewer indicators per latent variable, the overall effects on the model implied matrix may be greater because of the weakened reliability of the latent variables.

Model Complexity

A complex model has a greater number of latent variables and estimated parameters. Several researchers have noted that the fit of a more complex model tends to be better than that of simpler models (e.g., Akaike, 1987; Jöreskog & Sörbom, 1981; Mulaik et al., 1989).

As the number of parameters to be estimated increases, the model approaches a saturated model. In a saturated model, the number of parameters to be estimated is equal to the number of independent elements in the sample variance-covariance matrix. Because a saturated model has zero degrees of freedom, many fit indices produce values approaching unity.

When the fit indices suggest a complex model has an acceptable model fit, there can be speculation as to whether this results from: (a) overparameterization by the complex model, or (b) correct specification by that complex model. This speculation has led some researchers to develop fit indices that attempt to adjust for overparameterization resulting from model complexity (e.g., Akaike, 1987; Browne & Cudeck, 1989; James, Mulaik, & Brett, 1982; Jöreskog & Sörbom, 1981; Mulaik et al., 1989).

Mulaik et al. (1989) discussed the rationale for preferring parsimonious models over complex models. As early as the 14th century, scientists have advocated the virtues of parsimonious theories over complex theories. Philosopher and theologian, William of Occam, is credited with the development of the parsimony principle, known today as Occam's razor. Not all philosophers embraced this principle, however. For example, Kant (1781/1900) warned that the parsimony principle cannot be applied to theories unilaterally. In particular, Kant noted that the parsimony principle is in direct opposition to the diversity principle, which states that the varieties of things should not be overly diminished if individuality and distinctness of experience are to be understood.

The parsimony principle, however, continues to be an important criterion in selecting among competing models and theories. Mulaik et al. (1989) noted that parsimony was a guiding principle in Thurstone's development of simple structure in factor analysis. In addition, George Herbert Mead's position that one abandons a hypothesis for another when that other hypothesis is simpler, also appears to be driven by the parsimony principle.

Of course, the primary benefit from endorsing the parsimony principle is that simpler theories and models are more testable than complex theories and models. However, just because a model is simpler than another does not mean that it is the correct model. Most researchers believe that model parsimony should be examined, but some researchers (e.g., Cudeck & Henly, 1991; Marsh & Balla, 1994) suggest that index adjustments for complexity may not be appropriate.

Recently, Marsh and Balla (1994) investigated whether indices intended to adjust for model complexity actually overpenalize complex models in assessment of model fit. They conducted a Monte Carlo study in which several goodness-of-fit indices were examined under varying conditions of sample size and model complexity for confirmatory factor analysis models. They found that several indices favored simpler models over complex models even when the complex model is correct.

The Ideal Goodness-of-Fit Index

According to Marsh et al. (1988) an ideal index of overall model fit should possess several characteristics. First, it should be relatively independent of sample size. Second, it should vary along an externally meaningful, well defined, absolute continuum such that values can be easily interpreted. Third, it should be replicable. That is, the index should give an indication of which model can be most successfully cross-validated when tested with new data. Finally, an ideal index of overall model fit should provide an accurate and consistent measure of differences in goodness of fit for competing models.

To date, a single goodness-of-fit index that meets all of the preceding criteria has yet to be found. Indices also can differ in several respects such as assumptions of underlying distributions, use of null versus informed null models, and evaluation of various model features (e.g., parsimony of the model, degree of error reflected). These differences, and the fact that researchers tend to report a variety of fit indices, make it difficult to compare competing models.

Marsh, Balla, and Hau (1996) proposed that it is unlikely that a single index can be used across levels of sample size and model complexity. They suggested that researchers examine at least two indices and remember that fit indices should only be one component in the evaluation of model fit. Brannick (1995) also recommended that researchers examine multiple indices; he further argued that more attention should be given to the elements of the measurement model(s) before considering overall model fit.

Development and Computation of Goodness-of-Fit Indices

Several goodness-of-fit indices have been developed to assess the global fit of models. Although the intent of every index is the same (i.e., to provide information about the overall model fit), the procedures and assumptions defining the various indices differ. For the purpose of the current research, eight goodness-of-fit indices were chosen for further examination (see Appendix A to view formulas for all goodness-of-fit indices examined in the present research).

The chi-square test was chosen because it is routinely reported, and because it is a component in the formulas of all of the remaining indices chosen in the present research. The remaining indices of interest in the present research are: The root mean square error of approximation (RMSEA; Steiger, 1990); the goodness of fit index (GFI; Jöreskog & Sörbom, 1981); the critical N (CN; Hoelter, 1983); the normed fit index (NFI; Bentler & Bonett, 1980); the nonnormed fit, or Tucker-Lewis index (NNFI or TLI; Bentler & Bonett, 1980; Tucker & Lewis, 1973); the comparative fit index (CFI; Bentler, 1990); and the relative noncentrality index (RNI; McDonald & Marsh, 1990).

These indices were included in the present research for a variety of reasons. The GFI and NFI were selected because they have been used extensively in the past, although they have fallen somewhat out of favor recently with many researchers. The CFI and NNFI were chosen because they were developed as improvements to the chi-square test statistic and the NFI. However, the CFI differs from the NNFI in that the NNFI is designed to reward model parsimony, whereas the CFI is designed to reduce the heavy reliance on sample size that has been noted with the NFI. The RNI is very similar to the CFI, however, it was developed based on an alternative distribution and is not normed. The remaining two indices, the CN and RMSEA were chosen because they evaluate different aspects of the model than do the remaining indices. That is, the CN examines the sample size at which the chi-square test statistic would reject the hypothesized model, and the RMSEA reflects the extent of discrepancy per degree of freedom in the model.

The following sections will discuss the development and computation of the selected indices in the present research. First, the central and non-central chi-square distribution will be outlined because this information is needed to understand the chi-square test statistic. Following the chi-square test statistic, the remaining goodness-of-fit indices will be discussed.

Central and Non-Central Chi-Square Distribution

The most commonly assumed distribution for calculation of goodness-of-fit indices is the central chi-square distribution. The central chi-square distribution is associated with several fit functions and is appropriate in the case of maximum likelihood (ML) and generalized least squares (GLS) estimation. Based on the assumptions of a central chi-square distribution, a null hypothesis test (i.e., the chi-square test statistic) can be constructed for ML and GLS estimates. The null hypothesis evaluates the likelihood that the model implied variance-covariance matrix could have generated the sample data.

When the null hypothesis is true, the chi-square test statistic is distributed as a central chi-square. The smaller the value of the chi-square test statistic, the better is the fit of the model. In fact, when the value of the chi-square test statistic is zero, the model implied variance-covariance matrix and the sample variance-covariance matrix have elements with identical values.

When the null hypothesis is untrue (i.e., the model is concluded to be misspecified), then the chi-square test statistic is distributed as a non-central chi-square. However, as the sample size increases even trivial misspecifications can lead to rejection of the hypothesized model. Browne and Cudeck (1989) recommend that researchers evaluate values from both the non-central and central chi-square distributions as a safeguard against rejection of a model due to trivial misspecifications. The values of the chi-square test statistic and the estimated non-centrality parameter are compared to meet this recommendation.

Chi-Square Goodness-of-Fit Index

An early approach to judging fit was based upon the chi-square test statistic (Tanaka, 1993). In this approach, researchers compare the value of the test statistic to a critical value in the central chi-square distribution to decide whether to "accept" or "reject" the null hypothesis. Thus, the fit of the model is evaluated by the overall magnitude of discrepancies between the sample matrix (**S**) and model implied variance-covariance matrix fitted from the sample data (i.e., $\Sigma(\theta)$).

The chi-square test statistic is defined from the maximum likelihood fit function (F_{ML}) as:

$$\chi^2 = (n-1)\ F_{ML} \tag{1}$$

The chi-square test statistic is distributed asymptotically as a central chi-square distribution, where **n** represents the sample size. The degrees of freedom for the statistic are (**c** - **p**), where **c** is the number of nonredundant variances and covariances of observed variables, and **p** is the total number of parameters estimated in the model. The chi-square test statistic can be used to evaluate model fit if: (a) The sample size is large, (b) distributional assumptions are met, and (c) if the model implied variance-covariance matrix (i.e., $\Sigma(\theta)$) holds in the population (Bollen, 1989a).

The fitting function for maximum likelihood estimation method is expressed as:

$$F_{ML} = \log|\Sigma(\theta)| + tr(S\Sigma^{-1}(\theta)) - \log|S| - (p + q) \tag{2}$$

In this equation, $\log|\Sigma(\theta)|$ is the log of the determinant of the model implied variance-covariance matrix, $tr(S\Sigma^{-1}(\theta))$ is the trace operator indicating the product of the sample variance-covariance matrix and the model implied variance-covariance matrix, **log|S|** is the log of the determinant of the sample variance-covariance matrix, **p** represents the number of indicators for the dependent latent variables, and **q** represents the number of indicators for the independent latent variables.

Initially, the chi-square statistic was popular with researchers because it was perceived to be free of the many subjective decisions associated with exploratory factor analysis (e.g., determining the appropriate rotation method, specifying the number of factors). However, several researchers noted that the chi-square statistic is adversely affected by increases in sample size (e.g., Bearden, Sharma, & Teel, 1982; Boomsma, 1982; Hu et al., 1992; Tanaka, 1987). That is, as the sample size increases, the null hypothesis is likely to be rejected because of trivial differences between the model implied and sample variance-covariance matrices.

Although the chi-square statistic should not be used as the sole index of model fit, it is routinely reported in most articles. There are several reasons for this occurrence (Brannick, 1995). First, the chi-square value may provide information regarding overall model fit if the sample size is not too large. Second, the chi-square test statistic can often show significant differences among models within a given dataset. Third, by providing the chi-square test value, it is possible to compute other fit indices.

Estimated Non-Centrality Parameter

An index of the magnitude of the differences between the hypothesized model and sample data is the estimated non-centrality parameter (NCP) (McDonald & Marsh, 1990). The NCP and the 90 percent confidence interval for the NCP should be used in conjunction with the chi-square test statistic to evaluate the model (Browne & Cudeck, 1989). The larger the NCP value, the greater the discrepancy between S and $\Sigma(\theta)$ and between the central and non-central chi-square distribution. Therefore, the NCP is actually a "badness of fit" index. It is estimated as:

$$NCP = \chi^2 - df \qquad (3)$$

The 90 percent confidence interval of the NCP also can be used as a crude significance test. If the lower bound of the 90 percent confidence interval is zero, then it is probable that the hypothesized model fits the observed data.

Alternative Goodness-of-Fit Indices

Due to limitations of the chi-square test statistic (e.g., sample size and estimation method effects), a number of indices were developed and based on alternative strategies. Furthermore, because the chi-square statistic imposes a dichotomous decision strategy (i.e., reject or fail to reject), researchers cannot assess the degree of fit along a continuum of fit. As noted by Hu and Bentler (1995), alternative fit indexes should be designed to measure variance accounted for, and not solely to test a null hypothesis.

Chi-square to degrees-of-freedom ratio. Wheaton, Muthen, Alwin, and Summers (1977) recommended researchers compare the magnitude of an observed chi-square value divided by its degrees of freedom (i.e., χ^2/df) to the mean of the chi-square sampling distribution. Jöreskog and Sörbom (1981) noted that the mean of the sampling distribution should be equal to the degrees of freedom multiplied by two. Thus, a large value for χ^2/df (i.e., much greater than 2.0) would be indicative of a poor model fit, whereas a small value would indicate a good model fit.

However, there are no clear operational definitions of "large" and "small" values, and there has been considerable disagreement among researchers regarding acceptable ratios for "good" model fit. Wheaton et al. (1977) suggested that a ratio of 5:1 or less was an indication of an adequate fit, whereas Carmines and McIver (1981) recommended that a more stringent ratio of 2:1 was desirable.

Another problem with evaluating χ^2/df is that larger samples create larger chi-square values, thus leading to larger ratios. Thus, although the magnitude of the chi-square to degrees-of-freedom ratio can be used as a general indicator of badness of fit, the ratio fails to adjust for the effects of sample size.

Root mean square error of approximation. The root mean square error of approximation (RMSEA; Steiger, 1990) is based on the chi-square test statistic and is an adjustment to the chi-square to degrees-of-freedom ratio. The RMSEA attempts to control for two problems: (a) Sample size effects noted in the chi-square to degrees-of-freedom ratio, and (b) decreases in the value of the fit function as parameters are added to a model (Browne & Cudeck, 1993).

The RMSEA is designed to reflect the degree of discrepancy between the model implied and sample variance-covariance matrices expected in the population. A high degree of discrepancy reflects larger differences between the matrices, whereas a lower degree of discrepancy reflects smaller differences.

The RMSEA is computed as:

$$\sqrt{\frac{\chi^2_{\text{hypothesized}} - df_{\text{hypothesized}}}{(df_{\text{hypothesized}})(n-1)}} \qquad (4)$$

In this equation, **n** represents the sample size and **df** represents the hypothesized model's degrees of freedom.

Values from the RMSEA that are .05 or less indicate a close fit, whereas values up to .08 indicate reasonable discrepancies in the population. Browne and Cudeck (1989) also recommend reporting a 90 percent confidence interval for the RMSEA.

Goodness-of-fit index. Jöreskog and Sörbom (1981) proposed the goodness-of-fit (GFI) index to compare the hypothesized model to a model that has no estimated parameters (i.e., a simplified null model). The GFI usually ranges in value between 0 and 1, although it is possible for negative values to be computed. Larger values (i.e., .90 or greater) are assumed to indicate a better model fit.

The GFI is defined by the following equation:

$$\mathbf{GFI} = 1 - \frac{\mathrm{tr}[(\hat{\Sigma}^{-1}\mathbf{S} - \mathbf{I})^2]}{\mathrm{tr}[(\hat{\Sigma}^{-1}\mathbf{S})^2]} \tag{5}$$

The GFI formula is analogous to the formula for the coefficient of determination (i.e., 1 - [error variance/total variance]). Specifically, the numerator of the ratio is the trace of the estimated variance-covariance matrix for the hypothesized model, and the denominator is the trace of the sample variance-covariance matrix with no estimated parameters. In other words, the GFI evaluates the improvement in fit that occurs when the hypothesized model is compared to a model without any hypothesized relationships.

Critical N. The critical N statistic (CN) was proposed by Hoelter (1983) and is based on the chi-square test statistic. The CN indicates the sample size that would make the chi-square significant at a given alpha level, typically .05 or .01. The equation for the CN is:

$$\mathrm{CN} = \frac{\text{critical } \chi^2}{F_{ML}} + 1 \tag{6}$$

In this equation, the critical value of chi-square at .01 or .05 is divided by F_{ML} to reflect the sample size at which the model chi-square value would be significant at a given alpha level. The current version of LISREL (i.e., version 8.14) utilizes an alpha level equal to .01 for computation.

Hoelter (1983) cautioned researchers that no firm basis could be offered for an adequate fitting model, but he suggested a value of 200 for the CN as a reasonable starting point for suggesting that differences between the model and the data may be unimportant. In practice, the usefulness of the CN rests on the assumption that its obtained values are independent of sample sizes used for model estimation.

Relative Fit Indices

Relative fit indices are designed to measure how much better the hypothesized model fits as compared to a baseline model. The baseline model chosen is typically a null model, however, an informed null model also can be chosen. This comparison (i.e., from the hypothesized to the baseline model) reflects the extent to which there is any potential relationship among the variables as specified by the hypothesized model.

Relative fit indices that are frequently used include the normed fit index (NFI), the nonnormed fit index (NNFI), the comparative fit index (CFI), and the relative noncentrality index (RNI). Across all of these measures, values are expected to range between 0 and 1 with values of .90 or greater indicating acceptable model fit.

Baseline models. Bentler and Bonett's (1980) choice for the baseline model is a simplified null model (i.e., a model in which the covariances among all variables are assumed to be zero). Bentler and Bonett note that using the simplified null model creates a universally understood baseline in which comparisons can be made among the fit indices across research studies.

However, Sobel and Bohrnstedt (1984) argue that the simplified null model amounts to an assumption that does not correspond with actual research situations. That is, the simplified null model represents an extreme in the sense that it assumes there is no preceding knowledge about a given research situation. Sobel and Bohrnstedt's contention is that a null model should reflect the accumulated state of knowledge in the research area. Such an "informed" null model would be a restrictive model that demonstrates the current theory or empirical evidence in a given area. The more comprehensive model would demonstrate improvements or additions to the current theory.

Although use of an informed null model may appear superior to use of a simplified null model, there are several difficulties surrounding its use. One troublesome aspect is that current theory and empirical evidence are constantly changing, making it difficult to determine the "correct and current" informed null model. Furthermore, the definition of a current informed null model could vary significantly as a function of discipline and research approach.

Use of an informed null model also could lead to considerable confusion when evaluating the adequacy of models. That is, over a period of time, the relative improvement in fit should become considerably smaller than prior improvements in fit. Guidelines would need to be developed to determine how much of a change in fit would be considered a worthwhile improvement.

In general, most researchers have chosen to utilize the null model in computing goodness-of-fit indices. This practice will be followed in the present research.

Normed fit index. Bentler and Bonett (1980) developed the normed fit index (NFI). The NFI is defined as:

$$\mathrm{NFI} = \frac{\chi^2_{\mathrm{null}} - \chi^2_{\mathrm{hypothesized}}}{\chi^2_{\mathrm{null}}} \tag{7}$$

The NFI represents the proportion of total covariance among the observed variables explained by the hypothesized model when using the null model as a comparison model (Mulaik et al., 1989).

Not surprisingly, the NFI has limitations as a fit measure that are similar to the limitations of the chi-square test statistic. For example, the NFI is adversely affected by sample size effects. Tanaka (1987) also demonstrated that the index is affected by the choice of estimation method as well as the model chosen as the comparison model. Another limitation of the normed fit index is that it does not control for degrees of freedom. Specifically, the NFI value for the hypothesized model is reduced as parameters are added. Therefore, a very complex model with many estimated parameters may be rejected in favor of a model with fewer estimated parameters even though the complex model provides a better fit to its sample variance-covariance matrix.

Nonnormed fit index. In an attempt to correct some of the weaknesses associated with the NFI, Bentler and Bonett (1980) suggested using the NNFI, which is based on the Tucker-Lewis index (TLI) developed by Tucker and Lewis (1973). The NNFI is not normed (i.e., values can sometimes extend beyond the 0.00 to 1.00 range), and differs from the NFI in that its formula utilizes the degrees of freedom of the baseline and hypothesized model. Tucker and Lewis stated that the NNFI should be close to one to indicate an acceptable fit regardless of sample size.

Similar to the other parsimony-type indices, the NNFI favors more parsimonious models with increases in its value and penalizes more complex models with decreases in value. The NNFI is defined as:

$$\mathrm{NNFI} = \frac{\left(\frac{\chi^2_{\mathrm{null}}}{df_{\mathrm{null}}}\right) - \left(\frac{\chi^2_{\mathrm{hypothesized}}}{df_{\mathrm{hypothesized}}}\right)}{\left(\frac{\chi^2_{\mathrm{null}}}{df_{\mathrm{null}}}\right) - 1} \tag{8}$$

NNFI values greater than one may signify either an "overfit" of the model or an outstanding model fit, whereas values much lower than one may indicate a misspecified model.

Comparative fit index. The normed comparative fit index (CFI: Bentler, 1990) also was suggested as an improvement to the NFI. Similar to the NNFI, the CFI makes an adjustment for degrees of freedom. Additionally, it adjusts for sample size. The CFI is defined by the following equation:

$$\mathrm{CFI} = 1 - \frac{\text{maximum} \quad [[\chi^2_h - df_h], \text{ or } 0]}{\text{maximum} \quad [[\chi^2_h - df_h], [\chi^2_n - df_n], \text{ or } 0]} \tag{9}$$

The numerator is the maximum of: (a) The chi-square value for the hypothesized model (**h**) minus its degrees of freedom, or (b) zero, if the former is negative. The denominator is the maximum of: (a) The chi-square value for the hypothesized model minus its degrees of freedom, (b) the chi-square value for the more restricted model (i.e., null model = **n**) minus its degrees of freedom, or, (c) zero, if the former two are both negative.

When Bentler (1990) compared findings for the CFI and NFI for model fit, the CFI was shown to underestimate fit less often than did the NFI.

Relative noncentrality index. McDonald and Marsh (1990) developed the relative noncentrality index (RNI). This index compares the reduction in noncentrality by the hypothesized model relative to the null model. Similar to many of the previous fit measures, the RNI is expected to range between 0.00 and 1.00 (although values beyond the range are possible), with values of .90 or greater suggesting acceptable fit.

The RNI appears to have several desirable features including independence from sample sizes and being an unbiased estimator of its population value. The RNI is defined by the following equation:

$$\mathrm{RNI} = \frac{\left(\chi^2_{\text{null}} - df_{\text{null}}\right) - \left(\chi^2_{\text{hypothesized}} - df_{\text{hypothesized}}\right)}{\chi^2_{\text{null}} - df_{\text{null}}} \tag{10}$$

To date, research examining the RNI has been promising. For example, although both the NNFI and RNI are both capable of producing values outside of the expected 0.00 to 1.00 range, the RNI is less likely to do so than is the NNFI (Bentler, 1990). Furthermore, when the RNI does exceed 1.00, it has exceeded it in smaller increments than the NNFI. Another appealing feature of the RNI is that the standard error of the RNI tends to be smaller than the standard error for the NNFI, which suggests a more precise index.

Existing Research on Fit Indices

Over time, many indices have been developed resulting in an extensive choice for the researcher. The abundance of indices has led many researchers to use and report values for multiple fit indices when evaluating their models. The majority of researchers provide readers with values for three to four fit indices, however, there is a great deal of inconsistency in the selection and interpretation of fit indices. Although most researchers routinely report the chi-square statistic, many other goodness-of-fit indices are reported such as the CFI, Critical N, GFI, NFI, NNFI, RMSEA, and RNI.

Mulaik et al. (1989) have suggested that consistency across indices should be regarded as the most reliable indicator of goodness of fit. However, using Monte Carlo procedures, other researchers have shown that goodness-of-fit indices can yield different interpretations of model fit (e.g., Hu & Bentler, 1995; La Du & Tanaka, 1989; Tanaka, 1987).

Although a substantial body of research has examined the behavior of goodness-of-fit indices (see Gerbing & Anderson, 1993 for an extensive review), most of these studies have focused on the effects of sample size and estimation method. Some researchers also have examined the effects of number of latent variables, indicators per latent variable, and model misspecifications (e.g., Anderson & Gerbing, 1984; Boomsma, 1982; Marsh et al., 1988). Table 1 presents a summary of findings from research studies examining the effects on fit indices from sample size, number of latent variables, number of indicators per latent variable, model misspecifications, and model complexity.

Sample Size

One of the primary findings from these studies is that the value of many fit indices, such as Bentler and Bonett's (1980) NFI, Jöreskog and Sörbom's (1981) GFI, and the chi-square statistic are dependent on sample size. When the sample size is small (e.g., between 25-200), the obtained values for these indices are significantly lower than with larger samples. Not surprisingly, recent guidelines for testing structural equation models often recommend a minimum sample size of 200 (Boomsma, 1982).

Gerbing and Anderson (1985), however, asserted that relatively robust estimates could be obtained in sample sizes less than the recommended size of 200 (Boomsma, 1982). Further, Tanaka (1987) reported that sample size effects are more acute when estimation methods are used that do not assume a multivariate normal distribution (e.g., generalized least-squares and unweighted least-squares). Tanaka also found that confirmatory factor analysis using maximum likelihood estimation methods are least affected by changes in sample size.

Table 1

Summary of Findings about Goodness-of-Fit Indices as a Function of Sample Size, Number of Latent Variables, Number of Indicators per Latent Variable, Model Misspecifications, and Model Complexity

Issue	Findings	References
Sample Size	Smaller sample size decreases value of chi-square statistic; Larger sample size increases value of GFI and NFI; Larger sample size decreases value of RMSEA but not usually below .05; CN accepted all models when sample sizes were 500 or greater; CFI, NNFI, and RNI not affected by sample size.	Anderson & Gerbing, 1984; Bearden et al., 1982; Bentler, 1990; Boomsma, 1982; Browne & Cudeck, 1993; Gerbing & Anderson, 1993; Hu & Bentler, 1995; Hu et al., 1992; La Du & Tanaka, 1989; Tanaka, 1987.
Number of Indicators per Latent Variable	Chi-square, GFI, and NFI adversely affected by increases in number of indicators; CFI, NNFI, RMSEA, and RNI appear stable; CN never examined.	Anderson & Gerbing, 1984; Browne & Cudeck, 1993; Ding et al., 1995; Mulaik et al., 1989.
Model Misspecifications	NNFI and RNI accurately sense misspecifications; Chi-square, GFI, and NFI exhibit extreme variability, whereas CFI exhibits slight variability under misspecified conditions; CN and RMSEA never examined.	Bandalos, 1993; Bentler, 1990; Gerbing & Anderson, 1993; La Du & Tanaka, 1989; Marsh et al., 1988.

Table 1 concluded

Issue	Findings	References
Number of Latent Variables	Chi-square, GFI, and NFI adversely affected by increases in number of latent variables; RMSEA decreases in value as sample size increases and number of latent variables increases beyond 6 variables; CFI, NNFI, and RNI appear stable; CN never examined.	Anderson & Gerbing, 1984; Browne & Cudeck, 1993; Gerbing & Anderson, 1993; Mulaik et al., 1989.
Model Complexity	NNFI and CFI penalize complex models; RNI has no penalty for model complexity; Chi-square, CN, GFI, NFI, and RMSEA never examined.	Bearden et al., 1982; Cudeck & Henly, 1991; Marsh & Balla, 1994; Marsh et al., 1996.

Anderson and Gerbing (1984) conducted a comprehensive Monte Carlo study that examined the effects of sample size, number of indicators (2, 3, and 4), and number of latent variables (2, 3, and 4) on several indices, including the GFI and NNFI. Results indicated that the GFI was significantly affected by sample size with larger sample sizes yielding improved model fit values. Overall, the NNFI appears to be relatively unaffected by sample size (Anderson & Gerbing, 1984; Bollen, 1986; Marsh et al., 1988). However, Bentler (1990) noted that when the sample size was small (e.g., 100 or less), the NNFI exhibited greater variability in standard errors than did the CFI, GFI, NFI, and RNI. For example, at a sample size of 50, the NNFI exhibited a standard error of .16 and had a range from .42 to 1.26. In contrast, the NFI and CFI had standard errors that were less than half of the NNFI's (i.e., .056, .058, respectively).

Another important finding by Anderson and Gerbing (1984) was a decrease in the fit indices when the sample was small and the number of latent variables was large. For example, when the sample size was 50 and four latent variables were specified, the GFI yielded values between .85 and .77. Thus, all models would have been rejected! This is an especially troubling finding because all models were correctly specified.

Hu and Bentler (1995) found that the CN also was affected by increases in sample size. Specifically, the CN accepted almost all models when the sample size was 500 or larger. They recommended that a cutoff value greater than 200 was needed to evaluate model fit appropriately in most situations.

Browne and Cudeck (1993) investigated the effects of sample size and number of latent variables on several indices, among them the RMSEA. They showed that as the sample size increased, the point values of the RMSEA decreased but generally not below .05. Interestingly, they noted that this decrease was more pronounced with increases in the number of latent variables and increases in sample size. That is, as the sample size increased and the number of latent variables increased above six, the point estimate of the RMSEA would be more likely to drop below .05.

Number of Indicators per Latent Variable

Another area of research has examined the effects of the number of indicators per latent variable on the fit indices (Anderson & Gerbing, 1984; Ding et al., 1995). Anderson and Gerbing noted that the chi-square statistic, GFI, and NFI suggested poorer fit as the number of latent variables increased in a model, and as the number of indicators per latent variable increased. For example, as the number of indicators increased from two to four, the average value of the GFI decreased from .94 to .81.

Ding et al. (1995) studied the effects of estimation method, number of indicators per latent variable, and sample size on the chi-square, CFI, NFI, NNFI, and RNI. They found that NFI was the most seriously affected as the number of indicators increased. The mean NFI value was .979 with two indicators, whereas it dropped to .905 with six indicators. In addition, the standard deviation for the NFI exhibited greater variability when the number of indicators increased (e.g., from .037 for two indicators to .132 for six indicators).

Similarly, there was a slight decrease for the CFI, NNFI, and RNI values with increases in the number of indicators, although these decreases in value were less pronounced than for the NFI. In contrast to the NFI, increases in the number of indicators per latent variable resulted in decreased standard deviations for the chi-square statistic and NNFI.

They also found significant interaction effects between number of indicators per latent variable and sample size. When the sample size was small (i.e., N = 50 or 100), an increase in the number of indicators adversely affected the values of the fit indices. However, once the sample size reached 200, the negative effects began to decrease and were no longer statistically significant for the CFI, NNFI, and RNI.

Model Misspecifications

Several studies have examined the effects of model misspecifications on fit indices (e.g., Gerbing & Anderson, 1993; Marsh et al., 1988; Mulaik et al., 1989; Williams & Holohan, 1994). Marsh et al. examined the behavior of the NFI, GFI, NNFI, chi-square, and 25 other indices under five conditions of model misspecification (i.e., 1 correct, 4 misspecified). They found that the NNFI was able to detect model misspecifications accurately. In contrast, the NFI often failed to detect misspecifications. NFI values for two misspecified models were higher (i.e., .93 and .89) than for the correctly specified model (i.e., .83).

La Du and Tanaka (1989) examined the effects of model misspecification and estimation method on the GFI and NFI. Similar to Marsh et al. (1988), they noted that the NFI and GFI exhibited undesirable variability under conditions of model misspecifications.

La Du and Tanaka (1989) also noted that the type of misspecification impacted the behavior of the indices. That is, when a path was added to the model that did not appear in the correct model, the behavior of the fit indices remained relatively stable. In contrast, omitting a path that did appear in the correct model led to a substantial decrease in the values of the fit indices.

Model Complexity

Relatively few studies have examined the effects of model complexity on the goodness-of-fit values (Bearden et al., 1982; Cudeck & Henly, 1991; Marsh & Balla, 1994; Marsh et al., 1996). Results have indicated that the NNFI exacts a penalty for model complexity and is more likely to reward parsimonious models. Similarly, the chi-square test statistic was shown to reward simpler models over complex models. In contrast, the RNI does not adjust for model complexity. The CFI exhibited only slight variability when the model was complex and when the sample size was small (e.g., 200 or lower). Unfortunately, each study has evaluated goodness-of-fit performance only for confirmatory factor analysis models.

Clearly, a sufficient sample size is not a guarantee that model fit can be interpreted appropriately. Although it appears that a minimum sample size of 200 is a reasonable starting point, there is little information available on the most appropriate sample size under complex modeling conditions. Furthermore, researchers wishing to test complex structural models will find there are few guidelines regarding selection and interpretation of goodness-of-fit indices under conditions that approximate a "typical" modeling application.

The Research Studies

The current research is conducted in two studies. Study 1 consists of a review of confirmatory factor analysis and structural equation applications in four journals (i.e., Journal of Applied Psychology, Journal of Educational and Psychological Measurement, Journal of Personality and Social Psychology, and Structural Equation Modeling) to represent a cross-section of psychological disciplines. The articles are reviewed and coded to determine the "typical" structural modeling application.

The information gathered in the review is utilized for three purposes: First, to establish the "typical" modeling application based on frequencies, means, and standard deviations; second, to recreate the eight goodness-of-fit indices based on published research; and third, to provide a representative sample of studies for model selection in Study 2. The goodness-of-fit indices are examined to determine whether changes in the reported values of the goodness-of-fit indices could be predicted as a function of sample size, number of latent variables, number of indicators per latent variable, or other coded variables.

Based on the findings from Study 1, Study 2 is a Monte Carlo simulation designed to evaluate the performance of goodness-of-fit indices under conditions that more closely approximate the "typical" structural modeling application. Data for Study 2 conform to assumptions of multivariate normality. Hypothesized structural models are chosen from the representative sample of studies to depict varying degrees of model complexity typically encountered in psychological research.

Models are correctly and incorrectly specified in order to evaluate whether the prevailing rule of acceptable model fit with goodness-of-fit values of .90 or greater is appropriate across varying conditions of sample size, model misspecifications, number of indicators per latent variable, and model complexity. For the CN, a model was deemed acceptable if the value was 200 or greater, whereas a model was acceptable for the RMSEA if it yielded a value of .08 or less.

CHAPTER II

STUDY 1:

Background

Several articles have reviewed the growth and applications of structural equation modeling in psychological journals (e.g., Breckler, 1990; James & James, 1989; MacCallum, Wegener, Uchino, & Fabrigar, 1993; Medsker, Williams, & Holahan, 1994; Tremblay & Gardner, 1996). Tremblay and Gardner examined 1,050 abstracts on PsycLit (PsycINFO, 1973-1995) from 1987 to 1995. They coded articles by year, journal, type of article (i.e., substantive or technical), and type of analysis (i.e., confirmatory factor analysis, path analysis, or structural equation modeling).

Tremblay and Gardner (1996) reported several noteworthy findings, including an increase in the number of journals publishing articles that utilized structural equation modeling procedures, and an overall increase of structural equation modeling articles by year. Although the number of technical articles remained fairly stable across the years, there was a significant increase in the number of substantive articles.

From 1987 to 1994, 40 journals published at least six substantive structural modeling articles. The journals covered six broad psychological disciplines: Clinical; Developmental; Educational; Industrial/Organizational; Personality; and Social Psychology. The top four journals in their review published 20 or more articles utilizing structural equation modeling. Specifically, 45 articles had been published in the Journal of Applied Psychology (JAP), 39 in Educational and Psychological Measurement (EPM), 21 in Personality and Individual Differences (PID), and 20 in the Journal of Personality and Social Psychology (JPSP).

In a 1993 study, MacCallum et al. evaluated equivalent models in structural equation modeling articles from 1988 to 1991. They chose JAP, JPSP, and the Journal of Educational Psychology as likely to have a large number of substantive structural equation modeling articles. In contrast, Breckler's (1990) study focused specifically on structural equation modeling applications in personality and social psychology journals from 1977 to 1987. He noted that in these journals, JPSP accounted for 63 of the 72 articles.

Based on these three reviews, there appears to be some consensus on the journals that would be expected to publish the majority of substantive applications of structural equation models. The Journal of Personality and Social

Psychology was mentioned in all 3 reviews, the Journal of Applied Psychology in 2 reviews, and Educational and Psychological Measurement in the most recent review. In addition to these journals, a fourth interdisciplinary journal is devoted exclusively to structural equation modeling. Structural Equation Modeling, a quarterly, was first published in 1994.

Unfortunately, although these reviews documented the frequency of structural equation applications, there has been little documentation of features that would help to describe the typical modeling application. For example, the most descriptive feature examined by Breckler (1990) and Tremblay and Gardner (1996) was the type of application. Breckler coded articles by specific applications but grouped the majority as either confirmatory factor analysis models (i.e., measurement models alone) or structural models. Tremblay and Gardner's review classified articles as either technical (i.e., one that explains or examines an aspect of the structural equation modeling procedure) or substantive (i.e., one that applies structural equation modeling procedures to data).

Two studies have provided some descriptive information regarding the typical modeling application. James and James (1989) conducted a review of confirmatory factor analyses and structural equation models in four organizational research journals between 1978 and 1987. They noted that the average sample size was 287. Structural equation models were characterized by an average of 3.2 latent variables and an average of 2.1 indicators per latent variable. In addition, James and James noted that 75% of the articles examined the correlation matrix rather than the covariance matrix. However, because their review was based on 16 articles, there is some concern whether the findings would generalize to the larger body of modeling applications.

Medsker et al. (1994) conducted a review of multiple indicator structural models between 1988 and 1992. As a follow-up to James and James (1989), they reviewed the same four organizational research journals. Among the features coded were the choice of goodness-of-fit indices, number of indicators per latent variable, and sample size. The chi-square test statistic was utilized in all articles, and the GFI was reported in about 65% of the articles. The average number of indicators per latent variable was 2.9, with a range of 1.3 to 6.1. Sample sizes ranged from 64 to 5,078, with a mean of 299. Interestingly, there was an increase in the number of articles using the covariance matrix (i.e., 57%) as compared to 25% in James and James.

Unfortunately, although Medsker et al. identified more articles than James and James, their total sample was only 28 articles.

Although this information provides a starting point, it is questionable whether it captures the defining features that characterize the "typical" model. Important characteristics of the typical modeling application would include the complexity of the model, the number of latent variables, and the number of indicators per latent variable. Additional features that also should be considered are the sample size, composite reliability of the latent variables, the choice of goodness-of-fit indices, and number of estimated paths.

Model complexity would need to be determined by assessing the number of latent variables and the number of estimated paths. Models with a greater number of latent variables and a greater number of estimated paths would be classified as more complex than models with fewer latent variables and fewer estimated paths. An example of a simple model might be two or three latent variables using confirmatory factor analysis. In contrast, a very complex model might be characterized by a structural equation modeling application with 15 or more latent variables and 20 or more estimated paths.

Method

Sample of Studies

A computer-based information search was conducted using the key phrases *structural equation modeling, confirmatory factor analysis, measurement models, structural models,* and *goodness-of-fit*. These key phrases were used to search the following data bases: *Psychological Abstracts* (PsycINFO), 1986 to 1996; and *PsycLit* (PsycINFO), 1986 to 1996. A manual search of every volume of *EPM*, *JAP*, *JPSP*, and *SEM* was conducted to ensure that all appropriate articles were captured in the computer-based search.

Inclusion Criteria

Studies were included in the sample if they performed confirmatory factor analysis or structural equation modeling procedures. Articles that included multiple model comparisons were coded only once if the same data were utilized for all model comparisons. Generally, the model initially hypothesized by the researcher was used. Articles that proposed models for multiple data sets (e.g., a model for supervisors and a model for employees) were coded separately if sufficient information was provided for each proposed model. Articles that provided sufficient information to generate goodness-of-fit indices were included even if they did not report goodness-of-fit indices.

Coded Information

Appendix B presents the coding sheet that was used to collect article information. Articles were first coded to indicate the nature of the application (i.e., confirmatory factor analysis, technical procedures, estimation of structural models, and Monte Carlo simulations). A confirmatory factor analysis model was an application that examined a measurement model only. Examples of confirmatory factor analyses include scale development or examination of convergent and discriminant validity among scales. An article was coded as a technical procedure if it discussed a specific technique, compared techniques, or presented illustrative examples of modeling techniques as its focus. An example of a technical procedure might be comparing first-order to second-order confirmatory factor analyses, or a comparison of models with and without correlated residual terms.

Structural equation models were coded based on the usage of single versus multiple indicators for the latent variables. Single indicator models present only the latent variable model information. Multiple indicator models present information regarding the measurement and structural (i.e., latent variable) models.

An article was coded as a Monte Carlo simulation if the data were generated to examine differences in goodness-of-fit indices as a function of manipulated conditions such as sample size, estimation method, and model misspecifications.

Articles were documented for sample sizes, goodness-of-fit indices, number of independent and dependent latent variables, number of indicators per latent variable, and number of paths estimated.

All variables were coded by the author, and 25% of the articles were independently coded by a colleague. Agreement between the two coders was calculated using Kappa (Cohen, 1960) for nominal variables, and Pearson correlation coefficients for interval and ratio variables. The minimum acceptable value was .70 for all variables. Descriptive statistics were calculated to determine the frequency, range, mean, median, mode, standard deviation, and variance of the coded variables.

Post-Hoc Generation of the Fit Indices

Criteria were developed to determine which studies could be utilized to generate complete sets of goodness-of-fit indices. Goodness-of-fit indices were generated using two procedures (a) a reanalysis of the variance-covariance or correlation matrices, or (b) a SAS program written to generate goodness-of-fit indices from reported indices.

Reanalysis of data. First, an attempt was made to recreate the indices through a reanalysis of the matrices reported in the article. Studies were included for reanalysis if: (a) There was either a written explanation or visual depiction of the hypothesized model, and (b) the matrices presented in the study were sufficient to "recreate" the full set of goodness-of-fit indices.

Because measurement error variances are included in structural equation models, studies had to provide sufficient information for their calculation. Multiple indicator model studies had to provide either complete covariance or correlation matrices. Single indicator model studies had to provide estimates of reliability for those indicators, such as coefficient alpha (Cronbach, 1951).

Articles that provided complete covariance matrices were analyzed as covariance and correlation matrices to determine whether values of the goodness-of-fit indices differed as a function of input matrix. If there were no differences in the selected goodness-of-fit values based on the input matrix, then articles that only provided complete correlation matrices also could be included in the reanalysis.[2]

LISREL 8.14 (Jöreskog & Sörbom, 1993a) was then utilized to develop a program that tested the hypothesized model and "recreated" the model's goodness-of-fit indices. The next step was to compare the study's published goodness-of-fit indices to the "recreated" goodness-of-fit indices. Ideally, the published indices and the recreated indices should be identical in magnitude. However, it is possible that discrepancies between the indices could occur for three reasons. First, the article might inaccurately report the covariance or correlation matrix; second, the matrix analyzed might have been different from that reported (e.g., by rounding or only reporting to the second decimal point); and third, raw data may have been analyzed rather than the matrix reported. Differences between published and corresponding indices were considered too large if they differed in absolute value by more than .05 for all indices except the chi-square test statistic and the CN. Differences for the chi-square test statistic and the CN were considered too large if they differed in

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2 Findings examining the effect of matrix type on parameter estimates and standard errors have been mixed. Cudeck (1989) cautioned against the use of correlation matrices in structural modeling in all situations. Boomsma (1987) showed that with small samples (e.g., less than 100) LISREL tended to overestimate the standard errors for model parameters when correlation matrices were analyzed. However, Boomsma noted that when the sample size exceeded 200, the results for correlation and covariance matrices were identical.

absolute value by more than 15.00.

Program generation. A SAS program was written to generate the six goodness-of-fit indices for studies that were insufficient for reanalysis. Appendix C provides the program that recreated the CFI, CN, NFI, NNFI, RMSEA, and RNI values. An article was considered sufficient for program generation if it provided four values: (a) degrees of freedom for the hypothesized model, (b) degrees of freedom for the null model, (c) the chi-square test statistic for the hypothesized model, and (d) the chi-square test statistic for the null model. A program could not be written to recreate Jöreskog and Sörbom's GFI using the four values because the GFI requires traces of several matrices in its computation. Unfortunately, trace values are never reported in published research.

The six goodness-of-fit values generated by the programs were compared to corresponding indices that were provided in the published article. For example, if the article provided a value for the NFI of .84 and the NFI value generated by the program was within .05 in absolute value, then the indices compared favorably. If more than one index could be compared from the published article, then all possible indices were required to compare favorably. If program generated indices compared favorably and the article reported the GFI, then the GFI value was included for the regression analysis.

Regression Analyses

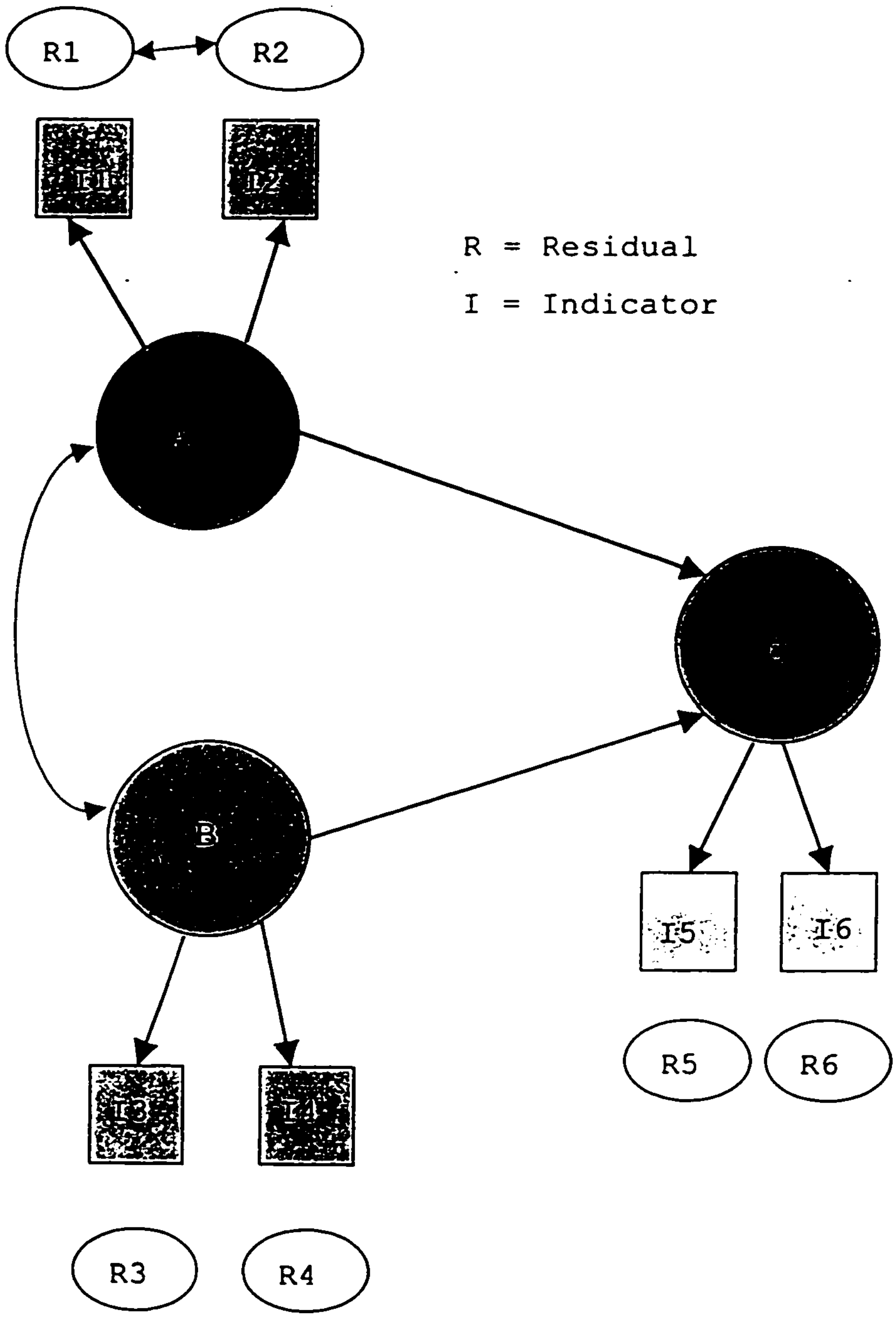
Once all studies were coded, eight multiple regression analyses examining the relationships between the coded variables and the goodness-of-fit indices were conducted. Each regression analysis utilized the values from a single goodness-of-fit index as the criterion variable. The regressions examined whether variations among the goodness-of-fit indices could be explained by the coded variables. For example, if increases in the number of latent variables and number of estimated paths were associated with decreases in value for specific fit indices, then this would lead to specific hypotheses regarding the effect of model complexity on goodness-of-fit indices.

Coding Model Complexity

The articles utilized to recreate the goodness-of-fit indices served as a representative sample of substantive applications for three conditions of model complexity (i.e., simple, moderate, and complex). Based on the variable coding and descriptive statistics from the review, a classification strategy was developed to determine the appropriate placement of an article for model complexity. Model complexity was determined by examining the overall number of latent variables, the number of independent and dependent latent variables, the mean number of indicators for independent and dependent latent variables, and the number and types of estimated paths.

Coding the number of relationships in a model. The number of paths in a model was examined by calculating the total number of relationships (i.e., measured paths + latent paths + correlations) in addition to the individual types of relationships. Figure 1 depicts a model with measured and latent paths, and correlations. Squares are traditionally used in structural equation modeling articles to represent indicator variables (Schumaker & Lomax, 1996). Circles are used to represent latent variables. The small ovals near the measured indicators represent residuals. Lines with single-headed arrows between squares and circles represent measured paths. Lines with single-headed arrows between circles represent latent paths. Lines with two-headed arrows represent latent correlations or correlated residuals.

For example, in Figure 1, there are six measured paths (i.e., from I1 through I6 to the respective latent variables), two latent paths (i.e., from A to C, and B to C), and two correlations (i.e., between A and B, and R1 and R2). Thus, the total number of relationships for Figure 1



<u>Figure 1.</u> Depiction of estimated paths in structural equation models.

is 10 (i.e., 6 measured paths + 2 latent paths + 2 correlations = 10). The number of relationships hereafter will be referred to as number of "paths".

The estimation of paths differs based upon the type of application. For example, confirmatory factor analysis models always estimate measured paths, often estimate latent variable correlations, and may estimate correlated residuals. Because a confirmatory factor analysis examines a measurement model, latent paths are not estimated. In contrast, structural equation models always estimate measured and latent paths, often estimate latent variable correlations, and may estimate correlated residuals. Therefore, descriptive statistics were computed on the total paths, measured paths, latent paths, latent variable correlations, and correlated residuals for the entire sample and by type of application.

Each grouping of model complexity was further examined to provide a single representative model and associated variance-covariance matrix for each of the three levels of model complexity in the Monte Carlo simulation.

Results

Overview

The findings from Study 1 are presented in four sections. The first section gives a description of the coded articles. This description includes information about the type and number of articles, the use of estimation method and data matrix, and the goodness-of-fit indices reported in an article. In addition, the mean number of latent variables and mean number of indicators per latent variable are given. Information about the type of estimated paths and the mean number of each type of estimated path also is provided. Sample sizes are also reported as a function of article type.

The second section gives information about the classification schemes used to code articles into levels of model complexity, as well as the outcomes of these schemes.

The third section provides information about the articles that were used in the regression analysis. This section describes whether articles had sufficient information for reanalysis or program generation of indices. Next, articles in the multiple regression analyses are compared with *t*-tests to the excluded set of articles. The *t*-test analyses ensure that the findings from the regression analyses generalize to the "typical" modeling application.

The fourth section includes the correlative relationships among the predictor and criterion variables in the multiple regression analyses. Finally, the results of the multiple regression analyses are presented.

Description of Articles

Type and number of articles. Three hundred and sixty-six articles met the criteria for inclusion in the present research. A list of the articles appears in Appendix D. Interrater reliability for the coded variables was high, with Kappa (Cohen, 1960) ranging from .76 to .88 on the nominal variables (i.e., application type, estimation method, matrix used), and with Pearson correlation coefficients ranging from .89 to .99 on interval and ratio variables (i.e., mean number of latent variables, mean indicators per latent variable, number of measured, latent, and correlated residual paths, and sample size).

Table 2 indicates that 52% (N = 190) of these applications were confirmatory factor analysis models (i.e., measurement models), 26% (N = 95) were single indicator structural equation models, 6% (N = 23) were technical procedures, 15% (N = 54) were multiple indicator structural equation models, and 1% (N = 4) were Monte Carlo simulations.

Three of the journals, Educational and Psychological Measurement, Journal of Applied Psychology, and Journal of Personality and Social Psychology, were represented in similar proportions. The fourth journal, Structural

Table 2

Type and Number of Structural Equation Modeling Articles between 1986 and 1996 in Educational and Psychological Measurement, Journal of Applied Psychology, Journal of Personality and Social Psychology, and Structural Equation Modeling

Type of Structural Equation Modeling Articles	N	Percent
Confirmatory factor analysis	190	52
Single indicator structural equation model	95	26
Structural equation techniques[a]	23	6
Multiple indicator structural equation model	54	15
Monte Carlo simulation[b]	4	1
Total	366	100

Number of Structural Equation Modeling Articles per Journal	N	Percent
Educational and Psychological Measurement	112	31
Journal of Applied Psychology	111	30
Journal of Personality and Social Psychology	121	33
Structural Equation Modeling	22	6
Total	366	100

[a]Structural equation techniques were represented by 9 confirmatory factor analyses, 4 single indicator models, and 10 multiple indicator models.
[b]Monte Carlo simulations were confirmatory factor analyses.

Equation Modeling, had many fewer articles. However, Structural Equation Modeling only has been published since 1994.

The type of modeling application also varied based upon which of the four journals published the article. Confirmatory factor analyses were found in 87% (N = 97) of the articles in Educational and Psychological Measurement, 43% (N = 48) of the articles in Journal of Applied Psychology, 29% (N = 35) of the articles in Journal of Personality and Social Psychology, and 45% (N = 10) of the articles in Structural Equation Modeling. Only 13% (N = 15) of the articles in Educational and Psychological Measurement examined structural equation models (i.e., 5 single indicator models versus 10 multiple indicator models). In comparison, 50% (N = 56) of the articles in Journal of Applied Psychology examined structural equation models (i.e., 29 single indicator models versus 27 multiple indicator models). Structural equation models were found in 70% (N = 85) of the articles in Journal of Personality and Social Psychology (i.e., 59 single indicator models versus 26 multiple indicator models). Articles in Structural Equation Modeling were less likely to examine structural equation models (i.e., N = 3, 14%), and more likely to perform technical procedures or Monte Carlo simulations (N = 9, 41%).

Figure 2 presents the frequency of applications between 1986 and 1996 across the four journals. During the years between 1986 and 1990 inclusive, approximately 12-25 articles were published per year. Thereafter, 35 or more articles were published each year. An examination of the graph suggests a linear trend of number of applications

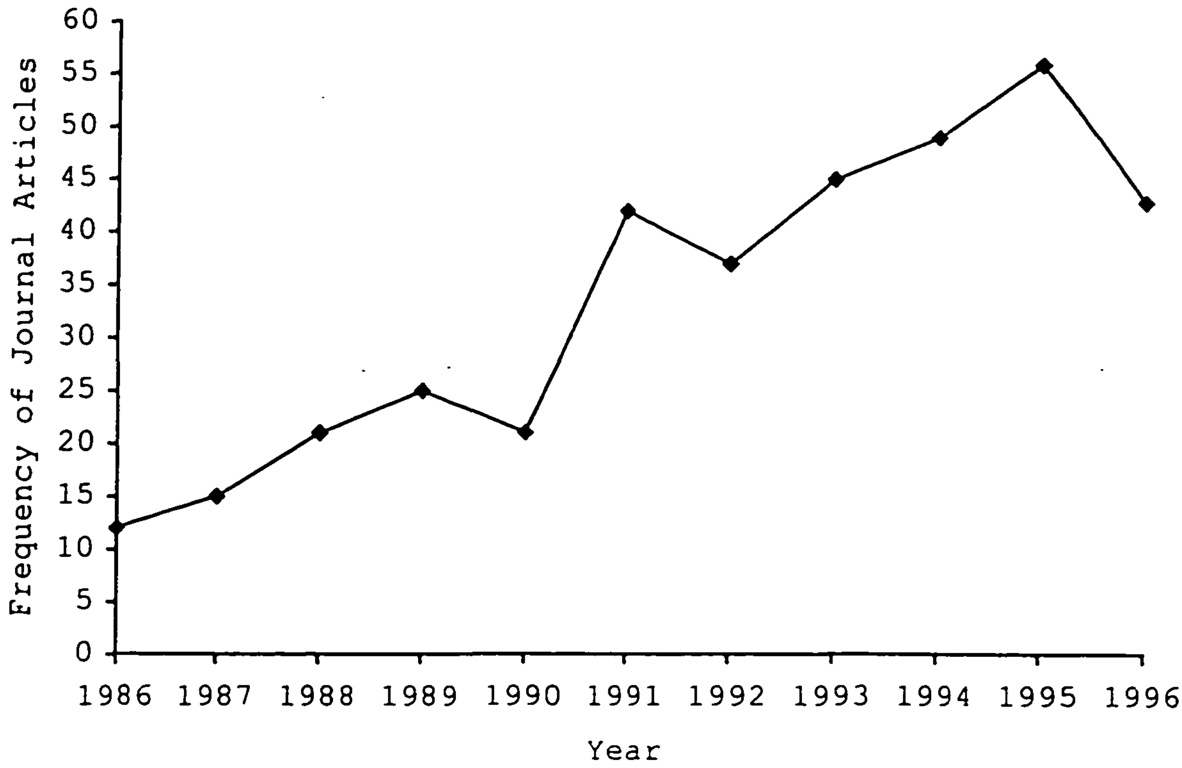


Figure 2. Frequency of journal articles by year.

between 1986 and 1996.

Use of estimation method, matrices, and indices. The majority of applications (N = 334) reported utilizing the maximum likelihood estimation method. Approximately 75% (N = 270) indicated using the covariance matrix for analysis, and the remainder indicated using the correlation matrix.

Table 3 presents information regarding the goodness-of-fit indices reported in the articles. The table

Table 3

Use of Goodness-of-Fit Indices and Number of Indices Reported

Index	N	Percent
Indices Considered in Current Research		
Chi-square test statistic	348	95
Comparative Fit Index (CFI)	76	21
Critical N	9	3
Goodness-of-Fit Index (GFI)	177	48
Normed Fit Index (NFI)	122	33
Nonnormed Fit Index (NNFI)	103	28
Relative Noncentrality Index(RNI)	11	3
Root Mean Square Error of Approximation (RMSEA)	11	3
Additional Indices		
Adjusted Goodness-of-Fit Index	125	34
Chi-Square to Degrees of Freedom Ratio	81	22
Expected Cross-Validation Index	6	2
Information Fit Index	9	3
Noncentrality Parameter	1	0
Parsimony Fit Index	31	9
Root Mean Square Residual	129	35
Number of Indices Reported		
1	38	10
2	79	22
3	91	25
4	75	21
5	43	12
6	27	7
7	11	3
8	1	0
9	1	0

number of goodness-of-fit indices reported was 3.39 (SD = 1.5). However, several articles reported as many as seven goodness-of-fit values and several only reported the chi-square test statistic.

As expected, the most common goodness-of-fit index reported was the chi-square test statistic (N = 348). The second most reported index was Jöreskog and Sörbom's GFIwhich was given in approximately 50% (N = 177) of the articles. The NFI was reported in 33% (N = 122) of the articles, NNFI in 28% (N = 103), and CFI in 21% (N = 76). The RMSEA (N = 11), RNI (N = 11), and CN (N = 9) were reported only in 3% of the articles.

Latent variables and their indicators. The average number of latent variables across all articles was 5.74 (SD = 3.58). As expected, the average number of latent variables differed based on whether the application was a confirmatory factor analysis versus a structural model. Confirmatory factor analysis models had an average of 4.83 latent variables (SD = 2.2), whereas structural equation models had an average of 6.82 latent variables (SD = 2.62). The ratio of independent to dependent latent variables in the structural equation models was approximately 7 to 8 (88%), respectively. Across all articles, the mean number of indicators per latent variable was 3.50 (SD = 2.56). Interestingly, there was a greater number of indicators for independent latent variables (M = 3.59, SD = 2.6) than for dependent latent variables (M = 1.88, SD = 1.29). This result was due to the number of indicators used to measure the independent latent variables in confirmatory factor analysis models. Specifically, confirmatory factor analysis models had a greater number of indicators per independent latent variable (M = 5.52, SD = 3.02) than did structural equation models (M = 2.22, SD = 1.49).

The average number of indicators per independent and dependent latent variable was approximately the same in structural equation models (M = 2.22, SD = 1.49, and M = 2.07, SD = 1.44, respectively). The smaller number of indicators used in structural equation models is explained by the frequent occurrence of single indicator models. Fifty-eight percent (N = 95) of the structural equation models used only one indicator per latent variable.

Number and types of paths. The mean number of total paths was 35.02 (SD = 6.74). The mean number of measured and latent paths, latent correlations, and correlated residuals for the total sample were M = 19.21 (SD = 4.39), M = 8.45 (SD = 3.16), M = 5.29 (SD = 2.27), and M = 2.07 (SD = .88), respectively. Measured paths were estimated in all applications, whereas 47% (N = 171) of the applications estimated latent paths, 77% (N = 282) estimated latent correlations, and 11% (N = 42) estimated correlated residuals.

Because confirmatory factor analysis models contained a greater number of indicators, they tended to have a greater number of measured paths (M = 22.73, SD = 4.78) than did structural equation models (M = 13.42, SD = 3.68). Structural equation models had an average of 10.71 latent paths (SD = 3.28). Structural equation models had a greater number of latent correlations (M = 6.12, SD = 2.3) and correlated residuals (M = 9.53, SD = 3.18) than did confirmatory factor analysis models (M = 8.26, SD = 2.91, and M = 6.69, SD = 2.67, respectively).

Sample sizes. Sample sizes utilized across the articles varied greatly, ranging from a low of 28 (Simonton, 1991) to a high of 40,331 (Rock, Bennett, & Kaplan, 1987). The mean sample size for the entire sample was 765.09 (SD = 398.46), and the median was 289. Confirmatory factor analysis models had a mean sample size of 905.78 (SD = 3107.72) and a median of 333, whereas structural equation models had a mean sample size of 527.81 (SD = 1020.11) and a median of 247.

In Table 4, sample sizes are grouped into eight discrete categories to reflect the frequency of sample sizes by type of application. In this table, 76% (N = 114) of structural equation models had sample sizes of 500 or

Table 4

Frequency of Sample Sizes by Type of Application

Sample Size	CFA	Percent[a]	SEM	Percent[b]	Total	Percent[c]
0 - 99	6	3	27	18	33	10
100 - 199	41	23	46	31	87	26
200 - 300	40	21	18	12	58	18
301 - 500	36	20	23	15	59	18
501 - 999	30	18	19	12	49	15
1000 - 1999	11	6	12	9	23	7
2000 - 4999	12	7	1	1	13	4
5000 +	4	2	3	2	7	2
Total	180	100	149	100	329	100

Note. Ten confirmatory factor analysis models did not report sample size. Technical procedures and Monte Carlo simulations were not included in the table. The following abbreviations were used: CFA = Confirmatory factor analysis; SEM = structural equation models.
[a]Percentage of confirmatory factor analysis articles.
[b]Percentage of structural equation modeling articles.
[c]Percentage of all articles.

smaller. Of particular note is the fact that 49% (N = 73) had less than 200 participants in their sample, and 18% (N = 27) had less than 100 participants. In contrast, only 26% (N = 47) of confirmatory factor analysis models had sample sizes less than 200, and only 3% (N = 6) had less than 100 participants.

Model Complexity Classification Schemes and Outcomes

Classification schemes. Model complexity was determined using two classification schemes that evaluated articles on the basis of (a) the number of latent variables, and (b) the number of latent paths. First, articles were classified into model complexity based on the number of latent variables. Approximately 42% (N = 154) of the articles had between one to four latent variables. These articles were classified as simple. Articles with five to eight latent variables were classified as moderate. Moderate models represented approximately 41% (N = 149) of the entire sample. Articles with nine or more latent variables were classified as complex. Complex models represented approximately 17% (N = 63) of the entire sample.

Second, articles were coded into levels of model complexity based on the number of latent paths. Measured paths, latent variable correlations, and correlated residuals were not used as classifying features because they do not discriminate between confirmatory factor analysis models and structural equation models. In other words, latent paths are found only in structural equation models, whereas measured paths, latent correlations, and correlated residuals can be found in confirmatory factor analyses and structural equation models. Articles that did not estimate any latent paths were classified as simple. Thus, 55% (N = 203) of the articles were classified as simple. Structural equation models that had between one and four latent paths also were classified as simple. Approximately 5% (N = 8) of the structural equation models were categorized as simple. Structural equation models that had between five and nine latent paths were classified as moderate. Sixty-one percent (N = 100) of the structural equation models fell into this classification. The remaining structural equation models (N = 55, 34%) had ten or more latent paths and were classified as complex.

Classification outcomes. The results from the two classification schemes were compared for agreement as to article placement into levels of model complexity. Of the 366 articles, the two schemes agreed for 82% (N = 300) of the articles. When the classification procedures differed for placement of an article into model complexity, the article was evaluated to determine the appropriate placement. Often (N = 57), the difference in placement arose because the article was a confirmatory factor analysis with five or more latent variables that only had measured paths. Thus, the article was classified as moderate or complex based on the number of latent variables, whereas the article was classified as simple based on the number of latent paths. When this type of difference occurred, the article was classified as a simple model.

When structural equation models were classified as moderate based on the number of latent variables, but as complex based on the number of latent paths, the article was classified as complex. When structural equation models were classified as complex based on the number of latent variables, but as moderate based on the number of latent paths, the article was classified as moderate. In sum, when there was a difference between the classification procedures, the placement determined by the number of latent paths was maintained.

The resolution of the discrepancies between the classification schemes led to 58% of the articles (N = 211) being classified as simple, 27% (N = 100) classified as moderate, and 15% (N = 55) classified as complex. This resolved classification was used to select models for Study 2.

Multiple Regression Articles

Computation of article indices. Fifty-one percent (N = 187) of the articles had sufficient information for reanalysis or program generation of indices. Of these, 47% (N = 88) were reanalyzed, and 53% (N = 99) used a program to generate goodness-of-fit indices. Appendix D indicates whether articles were reanalyzed or had indices recreated.

Within the reanalyzed articles, 42% (N = 37) provided complete correlation matrices with standard deviations. For each of these applications, the reanalysis entered the data as a covariance matrix as well as a correlation matrix to compare values of their goodness-of-fit indices. No differences were noted between the indices as a function of type of matrix. Therefore, a decision was made to include applications for reanalysis that only provided correlation matrices.

Although over 50% of the 366 articles could be used in the regression analysis, only 24% could be reanalyzed. Most often (N = 179), the covariance or correlation matrix was not given. In 17% of the cases (N = 61), some matrix information was provided but it was insufficient to recreate the analysis. For example, correlations and standard deviations were provided only for latent variables and not for indicators.

In other situations, an attempt was made to analyze a matrix but the reanalysis was unsuccessful (N = 23). An unsuccessful reanalysis occurred for several reasons. In three attempts, the published and recreated goodness-of-fit indices did not meet the criteria for a successful match. The remainder of the attempts either produced a model implied variance-covariance matrix that was not positivedefinitive or failed to converge after 1000 iterations.

Interestingly, there was a striking difference in whether an article was reanalyzed or had fit indices generated using the SAS program as a function of journal. Only four of the 44 articles from Educational and Psychological Measurement (EPM) in the multiple regression analysis could be reanalyzed. The majority of articles from EPM presented only goodness-of-fit values. Articles from the remaining three journals were more likely to have fit indices generated through reanalysis than with a SAS program. That is, 53% (N = 42) of Journal of Applied Psychology articles; 66% (N = 36) of Journal of Personality and Social Psychology articles, and 60% (N = 6) of Structural Equation Modeling articles were reanalyzed.

Representativeness of multiple regression articles. The type of application used in the regression analysis was representative of the total set of articles. Specifically, 50% (N = 94) were confirmatory factor analysis models (versus 52% in the total set), 32% were single indicator structural models (versus 26% in the total set), and 14% were multiple indicator structural equation models (versus 15% in the total set). Model complexity was representative, in that, 51% of the articles were simple models (versus 58% in the total set), 31% were moderate models (versus 27% in the total set) and 18% were complex models (versus 15% in the total set).

Articles from Journal of Personality and Social Psychology (JPSP), and Structural Equation Modeling (SEM) were represented in similar proportions in the regression analysis to the total set of articles. In particular, 29% (N = 54) of the articles in the regression analysis were from JPSP (versus 33%, N = 121 in the total set), and 10% (N = 10) were from SEM (versus 6%, N = 22 in the total set). However, fewer articles from Educational and Psychological Measurement (EPM) were included in the multiple regression analysis. That is, only 44 of the 112 articles from EPM could be utilized. In contrast, a greater number of articles were utilized from Journal of Applied Psychology (JAP). Almost three-fourths of the articles from JAP (N = 79) were included in the articles in the multiple regression analysis.

t-test Analyses

A series of *t*-tests were performed to compare the articles used in the multiple regression analyses to the set of articles that could not be included in these analyses. Table 5 presents the *t*-test findings.

Specifically, the articles used in the multiple regression analyses were compared to the remaining articles

Table 5

t-tests Comparing Multiple Regression Articles (MRA) and Excluded Articles on Five Predictor and Eight Criterion Variables

	MRA (N = 187)		Excluded (N=179)			
	M	SD	M	SD	N[a]	t
Predictor						
DF	137.97	303.82	180.88	395.73	152	1.13
M indicators[b]	3.50	2.56	4.85	3.82	174	-3.96*
M latent[c]	5.78	3.29	5.75	3.96	175	.07
Paths	23.56	14.03	30.13	25.48	173	-3.05*
Sample Size	602.07	1276.69	920.68	3184.32	175	-1.26
Criterion						
CFI	.93	.09	.95	.06	39	-1.36
Chi-square	379.99	802.60	491.06	1152.92	157	-1.05
CN	425.76	1294.62	445.50	195.04	6	-0.04
GFI	.93	.06	.92	.07	81	0.66
NFI	.88	.11	.90	.09	41	-1.22
NNFI	.89	.14	.90	.10	38	-0.33
RMSEA	.07	.05	.05	.03	7	1.00
RNI	.93	.09	.91	.05	3	0.28

Note. The following abbreviations have been used: Chi-square = Chi-square test statistic; CFI =Comparative fit index; CN = Critical N, DF = Degrees of freedom; GFI = Goodness-of-fit index, MRA = Multiple regression articles; NFI = Normed fit index, NNFI = Nonnormed fit index; RMSEA = Root mean square error Of approximation, RNI = Relative noncentrality index.

[a]Sample size for multiple regression articles was 187, sample size for excluded articles varied as a function of predictor and criterion variables.

[b]Mean number of indicators per latent variable.

[c]Mean number of latent variables.

*= $p < .05$.

on the predictor and criteria variables. The predictor variables were (a) degrees of freedom for the hypothesized model, (b) mean number of indicators per latent variable, (c) mean number of latent variables, (d) number of estimated paths, and (e) sample size. The eight goodness-of-fit indices were used as the criterion variables.

Two significant differences were noted for the predictor variables. Specifically, the multiple regression articles had significantly fewer indicators per latent variable (*M* = 3.51, *SD* = 2.59) than did the excluded articles (*M* = 4.85, *SD* = 3.82). Additionally, the multiple regression articles had significantly fewer estimated paths estimated (*M* = 23.56, *SD* = 14.03) than did the excluded articles (*M* = 30.13, *SD* = 25.48). No significant differences between the multiple regression articles and excluded articles were noted on the eight goodness-of-fit indices.

Multiple Regression Findings

Correlations among predictor and criterion variables.

Table 6 presents the correlation matrix of the predictor (i.e., degrees of freedom, mean number of indicators, number of estimated paths, mean number of latent variables, and sample size) and criterion variables (i.e., the goodness-of-fit values). An examination of the correlation matrix indicates several expected relationships among the predictor variables and the goodness-of-fit indices. In

Table 6

Correlation Matrix of Predictor and Criterion Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. DF	1.00												
2. IND	.31*	1.00											
3. LV	.06	-.40*	1.00										
4. PATHS	.29*	.22*	.63*	1.00									
5. SS	.04	.08	-.12	-.03	1.00								
6. CFI	-.26*	-.13	-.04	-.11	.08	1.00							
7. CHIS	.88*	.29*	.02	.27*	.31*	-.29*	1.00						
8. CN	.03	-.06	-.11	-.15*	.11	.16	-.03	1.00					
9. GFI	-.40*	-.42*	.02	-.28*	.14	.68*	-.30*	.22*	1.00				
10. NFI	-.33*	-.17*	-.06	-.17*	.16*	.91*	-.29*	.20*	.71*	1.00			
11. NNFI	-.12	.01	-.07	-.08	.09	.87*	-.14*	.26*	.53*	.76*	1.00		
12. RMSEA	-.11	-.15*	-.05	.01	-.10	-.53*	-.06	-.24*	-.36*	-.37*	-.71*	1.00	
13. RNI	-.26*	-.14	-.04	.02	.09	.99*	-.29*	.19*	.68*	.91*	.88*	-.54*	1.00

Note. N = 187 except for GFI (N = 135). The following abbreviations have been used: DF = Degrees of freedom; IND = Mean number of indicators per latent variable; LV = Mean number of latent variables; PATHS = Mean number of estimated paths; SS = Sample size; CFI = Comparative fit index; CHIS = Chi-square test statistic; CN = Critical N; GFI = Goodness-of-fit index; NFI = Normed fit index; NNFI =Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; *$p < .05$.

particular, positive relationships occur between the chi-square test statistic and degrees of freedom, mean number of indicators per latent variable, number of estimated paths, as well as sample size.

Degrees of freedom exhibited significant negative relationships with the CFI, GFI, NFI, and RNI. That is, as the degrees of freedom for the hypothesized model increases, the values of the CFI, GFI, NFI, and RNI decrease. Moreover, negative correlations were demonstrated between the GFI, NFI, RMSEA, and mean number of indicators per latent variable. As the mean number of indicators per latent variable increases, values for the GFI and NFI decrease. That is, the GFI and NFI suggest poorer fit as the number of indicators per latent variable increases. In contrast, increases in the mean number of indicators per latent variable are related to decreases in the RMSEA. Thus, the RMSEA suggests better model fit as the number of indicators per latent variable increases.

The mean number of estimated paths was negatively related to the CN, GFI, and NFI. That is, as the mean number of estimated paths increases, values of the CN, GFI, and NFI decrease; thus, suggesting poorer fit. In support of Anderson and Gerbing (1984), the NFI was positively related to sample size. In other words, as sample size increases, NFI values increase.

Several relationships noted by Browne and Cudeck (1993) were not found in the current research. For example, Browne and Cudeck noted a negative relationship between number of latent variables and values for the RMSEA, however, no such relationship was found in the current research.

The findings in the current research may be explained by considering differences between the data utilized by Browne and Cudeck (1993) and the current research. Browne and Cudeck only utilized multiple indicator models, whereas the current research was represented by single and multiple indicator models. Moreover, in the current research, articles that were characterized by a greater number of latent variables often were single indicator structural models. In particular, single indicator models had a mean of 8.19 latent variables (SD = 2.66), whereas multiple indicator models had a mean of 5.47 latent variables (SD = 1.67).

An examination of the subset correlations (i.e., for single indicator and multiple indicator models separately) showed that single indicator models exhibited no significant relationships between the RMSEA, degrees of freedom, number of latent variables, or number of indicators per latent variable. However, for the multiple indicator models, significant relationships were noted between the RMSEA and degrees of freedom ($r = -.32$, $p < .05$), and the RMSEA and number of indicators per latent variable ($r = -.26$, $p < .05$). That is, as the degrees of freedom increase, values of RMSEA decrease. Similarly, as the number of indicators per latent variable increases, values of the RMSEA decrease.

Additionally, no support was found for Browne and Cudeck's (1993) relationship between sample size and the RMSEA. Browne and Cudeck found that as the sample size increased, values of the RMSEA decreased but not generally below .05. In their study, the sample size ranged from 75 to 11,000, whereas the mean sample size for the multiple regression articles was 602.07, with a median of 238.

In contrast to Hu and Bentler (1995), no relationship was noted between the CN and sample size. They found that the CN accepted all models when the sample size was 500 or greater. However, an examination of subset correlations (i.e., for sample sizes from 0 to 499 versus 500 or greater) showed that sample sizes from 0 to 499 exhibited no significant relationship to the CN. In comparison, there was a significant positive relationship between the CN and sample sizes of 500 or greater ($r = .31$, $p < .05$).

In the current research, a negative relationship was noted for the CN values and number of estimated paths. This finding suggests that the CN rewards simpler models with higher CN values and penalizes complex models with lower CN values.

Further, no relationships were noted between any of the fit indices and number of latent variables. Previous research had indicated that the chi-square test statistic, GFI, and NFI were adversely affected by increases in the number of latent variables (see Anderson & Gerbing, 1984; Gerbing & Anderson, 1993; and Mulaik et al., 1989). However, in the current research, the chi-square test statistic, GFI, and NFI were adversely affected by increases in degrees of freedom and increases in the number of estimated paths.

Multiple regression analyses. Table 7 presents the findings from the multiple regression analyses. In the multiple regression analysis, the same five predictors (i.e., degrees of freedom, mean number of indicators, number of estimated paths, mean number of latent variables, and sample size) were entered and the eight goodness-of-fit indices were used as the dependent or criterion variables.

Five of the eight goodness-of-fit indices (i.e., chi-square test statistic, CFI, GFI, NFI, and RNI) were

Table 7

Summary of Multiple Regression Analyses for Predictor Variables Affecting Goodness-of-Fit Indices

Goodness-of-Fit Index	B	SE B	β
Comparative Fit Index (CFI)			
Degrees of Freedom	-6.954*	2.229	-.241*
Indicators per Latent Variable	- .003	.003	-.089
Latent Variables	- .001	.003	-.055
Total Paths	6.048	7.627	.009
Sample Size	6.387	4.956	.093
			R^2 =.084*
Chi-square Test Statistic			
Degrees of Freedom	2.283*	.081	.864*
Indicators per Latent Variable	5.277	13.143	.016
Latent Variables	-5.259	12.832	-.021
Total Paths	2.474	2.778	.043
Sample Size	.174*	.018	.278*
			R^2 =.855*
Critical N (CN)			
Degrees of Freedom	.083	.338	.019
Indicators per Latent Variable	-55.619	54.683	-.109
Latent Variables	-45.253	53.389	-.111
Total Paths	- 4.997	11.556	-.054
Sample Size	.102	.075	.101
			R^2 =.038
Goodness-of-Fit Index (GFI)			
Degrees of Freedom	-4.768	3.086	-.166
Indicators per Latent Variable	- .007*	.003	-.283*
Latent Variables	6.035	.003	.033
Total Paths	-6.293	5.766	-.151
Sample Size	8.097*	3.574	.174*
			R^2 =.253*
Normed Fit Index (NFI)			
Degrees of Freedom	-9.939*	2.578	-.288*
Indicators per Latent Variable	- .005	.004	-.123
Latent Variables	- .002	.004	-.063
Total Paths	-1.216	8.818	-.016
Sample Size	1.448*	5.729	.176*
			R^2 =.150*

Table 7 concluded

Goodness-of-Fit Index	B	SE B	β
Nonnormed Fit Index (NNFI)			
Degrees of Freedom	5.676	3.614	-.125
Indicators per Latent Variable	.001	.006	.020
Latent Variables	-9.598	.005	-.023
Total Paths	-2.954	.001	-.030
Sample Size	9.512	8.032	.088
			R^2=.027
Root Mean Square Error of Approximation (RMSEA)			
Degrees of Freedom	-1.251	1.336	-.074
Indicators per Latent Variable	- .004	.002	-.187
Latent Variables	- .002	.002	-.104
Total Paths	4.086	4.571	.111
Sample Size	-3.502	2.969	-.087
			R^2=.038
Relative Noncentrality Index (RNI)			
Degrees of Freedom	-6.991*	2.267	-.238*
Indicators per Latent Variable	- .003	.004	-.097
Latent Variables	- .001	.004	-.058
Total Paths	3.203	7.755	.005
Sample Size	6.734	5.039	.096
			R^2=.061*

Note. Sample size was 187 for multiple regression analyses except for Goodness-of-Fit Index (GFI) which had a sample size of 135. *p <.05.

influenced significantly by the predictor variables. Values of R^2 for the chi-square test statistic and GFI were quite large (i.e., .855 and .253, respectively), whereas values of R^2 for the CFI, NFI, and RNI were relatively small (.084, .150, and .061, respectively).

The chi-square test statistic and the GFI are most strongly influenced by the predictors. The chi-square test statistic is positively predicted by the hypothesized model's degrees of freedom (β = .86, p <.05) and sample size (β = .28, p <.05). In other words, a poorer fit is suggested with increases in the hypothesized model's degrees of freedom and sample size.

In contrast, the GFI is negatively predicted by the number of indicators per latent variable (β = -.28, p <.05) but positively predicted by sample size (β = .17, p <.05). That is, as the number of indicators per latent variable increases, values for the GFI decrease. However, as the sample size increases, values of the GFI increase and suggest a better fit.

The NFI is negatively predicted by the hypothesized model's degrees of freedom (β = -.28, p <.05) but positively predicted by increases in sample size (β = .18, p <.05). That is, increases in sample size lead to NFI values suggesting better fit, whereas increases in the hypothesized model's degrees of freedom lead to NFI values suggesting poorer fit.

The CFI and RNI are negatively predicted with increases in the hypothesized model's degrees of freedom ($\beta = -.24$, $p < .05$, and $\beta = -.24$, $p < .05$, respectively). That is, as the hypothesized model's degrees of freedom increase, values for the CFI and RNI decrease. No effects were noted for the CN, NNFI, or RMSEA.

As expected, regression coefficients were in the same directions as exhibited in the correlation matrix. In general, significant correlations were represented by significant regression coefficients in the multiple regression analysis. A few exceptions were noted.

In particular, there was a significant positive correlation between the chi-square test statistic and the number of indicators per latent variable that did not produce a significant regression coefficient. This finding can be explained by considering the strong influence of degrees of freedom on the chi-square test statistic. As the degrees of freedom for the hypothesized model increases, the value of the chi-square test statistic increases. Further, as the number of indicators per latent variable increases, the value of the chi-square test statistic increases. A model with more indicators per latent variable will automatically have more degrees of freedom than a model with fewer indicators. Thus, it appears that the contribution of number of indicators per latent variable can be explained through the influence of the hypothesized model's degrees of freedom.

Further, there was a significant positive influence on the GFI from sample size, although the correlation coefficient between sample size and the GFI was not significant. However, the signs of the correlation and regression coefficients were the same.

Discussion

Overview

The purposes of Study 1 were to (a) Establish the typical modeling application, (b) recreate the selected goodness-of-fit indices for use in the multiple regression analysis, and (c) provide a representative sample of studies for model selection in Study 2.

The discussion is presented in three sections. The first section describes the findings from the review and addresses areas of concern. The second section discusses the findings from the multiple regression analyses and compares these findings to those from previous research. The third section reviews the availability of studies for model selection in Study 2.

Review of Journal Articles

The review of the four journals indicates the extensive use of modeling applications. As expected

(Breckler, 1990; Tremblay & Gardner, 1996), the majority of applications (52%, N = 190) were confirmatory factor analysis models, however, structural equation models (42%, N = 149) have increased in use.

In agreement with Tremblay and Gardner's (1996) review of PsychLit abstracts from 1987 to 1995, the current review found a yearly increase in the number of structural equation modeling articles. However, in the current research, a greater number of articles were identified in Educational and Psychological Measurement (112 vs. 39), Journal of Applied Psychology (111 vs. 45), and Journal of Personality and Social Psychology (121 vs. 20). The exclusive use of abstracts and choice of key words in Tremblay and Gardner's review may explain why they identified fewer articles. The current research also included two additional years in the review, 1986 and 1996, but this is unlikely to explain differences in the number of articles identified.

The current research also extends the findings of James and James (1989) and Medsker et al. (1994) on descriptive features of structural modeling applications. James and James noted that the average sample size was 287, whereas Medsker et al. found a mean sample size of 299. In the current research, the average sample size for all identified articles was 765, with a median of 289. Confirmatory factor analysis models were usually characterized by sample sizes of 200-600, whereas structural equation models often were performed on sample sizes of 200 or less. Given the greater number of parameters estimated in structural equation models, these smaller sample sizes are ill-advised.

James and James (1989) also reported an average of 2.1 indicators per latent variable, whereas Medsker et al. (1994) noted an average of 2.9 indicators per latent variable. In the current research, the average number of indicators per latent variable was 3.5, however, 58% (N = 95) of the structural equation models were represented with single indicators. Moreover, only 35% (N = 19) of the multiple indicator structural equation models were characterized by three or more indicators per latent variable. Sixty-eight percent (N = 65) of the models using one indicator per latent variable had sample sizes of 200 or less.

James and James (1989) also reported an average of 3.2 latent variables. Medsker et al. (1994) did not provide information on the average number of latent variables. In the current research, the average number of latent variables was 5.7. In comparison, confirmatory factor analysis models had an average of 4.8 latent variables, whereas structural equation models had an average of 6.8 latent variables. This finding suggests that researchers are studying increasingly more complex models than they have previously (i.e., 3.2 latent variables in James and James versus 5.7 latent variables in the current research).

In comparison to James and James (1989) and Medsker et al. (1994), an improvement in modeling procedures was noted. That is, 75% of the research applications used the covariance matrix as the input data. In contrast, 25% of the applications in James and James and 50% of the applications in Medsker et al. used the covariance matrix.

As expected, the most common goodness-of-fit index reported in the current review was the chi-square test statistic (N = 348). The second most reported index was the GFI (N = 177). Although the CFI and NNFI are recommended as preferred alternatives to the NFI (Gerbing & Andersen, 1993; Tanaka, 1993), both indices were used less frequently than the NFI (i.e., N = 76 for the CFI, N = 103 for the NNFI, and N = 122 for the NFI). However, when the indices reported are examined by year, use of the CFI and NNFI from 1990 to 1996 is greater (i.e., CFI = 76, NNFI = 79) than for the NFI (i.e., 48).

Surprisingly, recently promoted indices (i.e., Browne

& Cudeck, 1993; Gerbing & Andersen, 1993) such as the RMSEA and the RNI were infrequently reported (N = 11, N = 11, respectively). However, an examination of the RMSEA and RNI by year shows that the RMSEA was not reported prior to 1993, whereas the RNI was not reported prior to 1991.

Areas of Concern

The current findings indicate that many researchers performing structural equation analyses are not adhering to the recommended guidelines for sample size or number of indicators per latent variable. That is, about 50% of the studies (N = 73) had less than 200 participants in the sample, and 18% (N = 27) had less than 100 participants. Furthermore, when the sample size was 200 or less, researchers often used only one indicator per latent variable.

One possibility is that the majority of the studies using smaller sample sizes were found in the early years of the review (i.e., from 1986 to 1991). However, an examination of sample size by year showed that this was not the case. That is, between 1992 and 1996, 63 studies had less than 200 participants, and 18 studies had less than 100 participants.

Testing a structural equation model with a small sample size raises several troubling issues. For example, interpretation of the fit indices, obtained parameter estimates, and standard errors are less stable in small samples (Raykov & Widaman, 1995). In particular, researchers are cautioned that the chi-square test statistic follows a central chi-square distribution only when: (a) The correct estimation method is chosen, (b) the true model is specified, and (c) the sample size is large.

The combination of a small sample size with few indicators per latent variable exacerbates an already difficult situation. From a theoretical standpoint, reducing the number of indicators decreases the quantity of empirical information about the latent variable(s) in question (Raykov & Widaman, 1995). A single indicator is rarely as informative as multiple indicators. Moreover, when a single composite of several indicators is constructed, the composite variable has limited, and potentially misleading information about the latent variable. Furthermore, using fewer indicators per latent variable can lead to problems with evaluation of model fit and interpretation of parameter estimates and standard errors.

There are several reasons why researchers might use one indicator per latent variable. As noted earlier, using one indicator per latent variable with a small sample size may increase the utility of the sample (i.e., by meeting sample size to parameter ratio requirements). Another reason for using one indicator per latent variable might be due to the latent variable in question. For example, job experience might be measured by a single indicator such as number of years in a position. Finally, based on expert consensus, there are certain measures that are widely accepted as adequately measuring their latent constructs. For example, Anastasi (1988) recommends the Raven Progressive Matrices (Raven, 1983) as a measure of general intelligence, and the Minnesota Multiphasic Personality Inventory (University of Minnesota, 1982) as a measure of psychopathology. Similarly, Landy (1985) recommends the Job Description Index (Smith, Kendall, & Hulin, 1969) as a measure of job satisfaction.

However, many widely used measures are known to exhibit measurement error. For example, GRE and SAT scores are likely to demonstrate some measurement error. Furthermore, creating single composite indicators from multiple items does not remove potential measurement error. Thus, the use of single indicators with potential measurement error reduces the reliability of a hypothesized model and weakens confidence in the model findings.

Therefore, although it is possible that some latent variables can be measured logically with single indicators, the likelihood that any latent variable can be measured adequately with only one indicator per latent variable is extremely unlikely. Instead, the use of fewer indicators per latent variable with small samples is more than likely an attempt to increase the possibility of publication.

Findings from Study 1

Overall, the correlations and multiple regression analyses support the findings from previous research. Table 8 presents a summary of prior findings with those from the current research.

Sample size. Sample size was found to influence the chi-square test statistic, GFI, and NFI. In agreement with Andersen and Gerbing (1984), Boomsma (1982), and Gerbing and Andersen (1993), a smaller sample size was found to decrease the value of the chi-square test statistic. Additionally, the current findings concurred with Browne and Cudeck (1993), Gerbing and Andersen, and La Du and Tanaka (1989), in that increases in sample size were related to increases in the values of the GFI and NFI.

As in prior research, no influence was noted on the CFI, NNFI, and RNI from sample size. This supports research conducted by Bentler (1990), Gerbing and Andersen (1993), and Hu et al. (1992) demonstrating that the CFI,

Table 8

Summary of Findings Comparing the Performance of Goodness-of-Fit Indices as a Function of Sample Size, Number of Latent Variables, and Number of Indicators per Latent Variable from Prior Research to Study 1 Results

Issue	Prior Research	Study 1 Results
Sample Size	Smaller sample size decreases value of chi-square test statistic; Larger sample size increases value of GFI and NFI; Larger sample size decreases value of RMSEA but not usually below .05; CN accepted all models when sample sizes were 500 or greater; CFI, NNFI, and RNI not affected by sample size.	Smaller sample size decreases value of chi-square test statistic; Larger sample size increases value of CN, GFI and NFI; No significant relationships noted between sample size and RMSEA; CFI, NNFI, and RNI not affected by sample size.
Number of Latent Variables	Chi-square, GFI, and NFI adversely affected by increases in number of latent variables; RMSEA decreases in value as sample size increases and number of latent variables increases beyond six variables; CFI, NNFI, and RNI appear stable. CN never examined.	No relationships noted between number of latent variables and chi-square, GFI, NFI, and RMSEA; CFI, CN, NNFI, and RNI appear stable.

Table 8 concluded

Issue	Prior Research	Study 1 Results
Number of Indicators per Latent Variable	Chi-square, GFI, and NFI adversely affected by increases in number of indicators; CFI, NNFI, RMSEA, and RNI appear stable; CN never examined.	Chi-square test statistic, GFI, and NFI related to increases in number of indicators; Increases in number of indicators related to decreases in value for the RMSEA; CFI, CN, NNFI, and RNI appear stable.

NNFI, and RNI are independent of sample size.

Only partial support was found for Hu and Bentler's (1995) findings of sample size effects on the CN. Hu and Bentler's study demonstrated that the CN accepted all models when the sample size was 500 or greater. In the current research, a positive significant correlation was exhibited between sample size and the CN, suggesting that as the sample size increases CN values also increase. However, sample size did not exert a significant influence on the CN in the multiple regression analysis. Further examination of the multiple regression articles indicates that although the mean sample size was 602.07 (SD = 1276.69), the median was only 238. Thus, the multiple regression articles were skewed on sample size, which may explain the lack of significance.

Additionally, no support was found for Browne and Cudeck's (1993) relationship between sample size and the RMSEA. They found that as the sample size increased, values of the RMSEA decreased. However, Browne and Cudeck examined sample sizes ranging from 75 to 11,000. The more thorough examination of sample size in Study 2 should shed additional light on the relationships between sample size, CN, and RMSEA.

Number of latent variables. Prior research had demonstrated that the chi-square test statistic, GFI, and NFI were significantly influenced by increases in the number of latent variables (Andersen & Gerbing, 1984; Gerbing & Andersen, 1993; Mulaik et al., 1989). That is, with increases in latent variables, values on the chi-square test statistic increased, whereas values on the GFI and NFI decreased.

Prior research also had demonstrated that values on the CFI, NNFI, and RNI were relatively stable with increases in the number of latent variables (Andersen & Gerbing, 1984; Gerbing & Andersen, 1993; Mulaik et al., 1989). Browne and Cudeck (1993) noted that the RMSEA decreased in value as the sample size increased and the number of latent variables increased beyond six variables. The relationship between the CN and number of latent variables had not been examined in prior research.

In the current research, no significant relationships were noted between number of latent variables and the indices. One explanation for the lack of significance may be due to differences in the models examined in prior research compared to those in the multiple regression articles. Overall, prior research has used confirmatory factor analysis models when examining effects of number of latent variables (e.g., Gerbing & Andersen, 1993; Mulaik et al., 1989). In comparison, the multiple regression articles were characterized by 43 single indicator models, 45 multiple indicator models, and 97 confirmatory factor analysis models.

A follow-up regression analysis examining only the confirmatory factor analysis models also failed to yield significant findings for the chi-square test statistic, GFI, and NFI. Similarly, regression analyses examining the single indicator and multiple indicator structural equation models individually and jointly, did not produce significant findings for the chi-square test statistic, GFI, and NFI. The examination of model complexity in the Monte Carlo simulation in Study 2 may provide insight into the relationship between number of latent variables and the indices.

Number of indicators per latent variable. In the current research, only the GFI was significantly influenced by number of indicators per latent variable in the regression analysis. That is, as the number of indicators increased, values on the GFI decreased, thus supporting research by Andersen and Gerbing (1984), and Mulaik et al. (1989). In addition, the correlation matrix demonstrated a significant positive relationship between number of indicators and the chi-square test statistic, and significant negative relationships between number of indicators and the NFI and the RMSEA.

Prior research also had demonstrated that values on the chi-square test statistic and NFI were significantly influenced by increases in the number of indicators per latent variable (Andersen & Gerbing, 1984; Ding et al., 1995; Mulaik et al., 1989). That is, as the number of indicators per latent variable increased, values on the NFI decreased, thus suggesting poorer fit. Similarly, increases in the number of indicators per latent variable results in increases in the value of the chi-square test statistic, again suggesting poorer fit.

However, in the current research, neither the chi-square test statistic nor the NFI were significantly predicted by number of indicators per latent variable. Interestingly, both the chi-square test statistic and NFI were significantly influenced by the hypothesized model's degrees of freedom. Moreover, these relationships were in the same direction as would be expected from number of indicators per latent variable. As noted earlier, models with a greater number of indicators per latent variable automatically have greater degrees of freedom than models with fewer indicators per latent variable. Therefore, the strong influence of the hypothesized model's degrees of freedom to the chi-square test statistic and NFI may explain the lack of significance from number of indicators per latent variable.

The significant negative relationship between number of indicators and the RMSEA suggests that models with more indicators will produce lower RMSEA values, suggesting better fit. Although no relationship was found between the RMSEA and number of latent variables, Study 2 may demonstrate that increases in the number of latent variables (i.e., more complex models) and increases in number of indicators result in significantly lower RMSEA values than in less complex models with fewer indicators.

Ding et al. (1995) noted that the values of the CFI, NNFI, and RNI remained relatively stable when the number of indicators per latent variable increased. However, they expressed concern that these indices decreased in value when there were five or six indicators per latent variable. In the current research, no significant relationships were found between the number of indicators per latent variable and the CFI, NNFI, or RNI.

The relationship between the CN and indicators per latent variable had not been examined in prior research. In the current research, no significant relationship was noted.

Available Studies for Model Selection

Of the 366 articles identified in the current research, only 24% (N = 88) had sufficient information for reanalysis. The reanalyzed articles from Study 1 provided representative samples for the conditions of model complexity in Study 2.

Model criteria. Each article had to meet or exceed the recommended acceptable cutoff values for goodness-of-fit indices to be considered for model selection. That is, the CFI, GFI, NFI, NNFI, and RNI were required to have values of .90 or greater, whereas the CN was required to have a value of 200 or greater, and the RMSEA was required to have a value of .08 or less. Due to the noted effect of sample size on the chi-square test statistic, a significant chi-square value for the article was ignored as a criterion for model selection.

Each article was required to have sufficient data (i.e., a covariance or correlation matrix with standard deviations) to reproduce the observed covariance matrix. There were two reasons why articles that only provided correlation matrices were not included in the sample of articles for model complexity. First, researchers disagree about the effects of correlation matrices on parameter estimates and standard errors (Boomsma, 1987; Cudeck, 1989). In particular, Cudeck argued that correlation matrices should not be used under any circumstances. In contrast, Boomsma noted that when the sample size exceeded 200, the results of correlation matrices were identical to the results from covariance matrices. Second, because the smallest size in the Monte Carlo simulation would be less than 200, there was concern that using correlation matrices would introduce uncontrolled variation into the simulation.

Of the 88 reanalyzed articles, 50% (N = 44) met or exceeded the recommended cutoff values for the goodness-of-fit indices. Covariance matrices or correlation matrices with standard deviations were available in 73% (N = 32) of the articles meeting the recommended cutoff values.

Classification outcomes. When applied to the 44 articles, the latent variable classification procedure yielded 12 simple models, 13 moderate models, and 7 complex models. Within the moderate and complex conditions, confirmatory factor analysis studies were removed. This procedure resulted in the removal of three confirmatory factor analysis studies from the complex condition. No studies were removed from the moderate condition. In the simple condition, 10 articles were represented by confirmatory factor analyses, whereas two articles were structural equation models. Thus, from the original set of 366 identified articles, only 8% (N = 29) were available for model selection in Study 2.

Implications

Unfortunately, almost 75% (N = 267) of the total articles identified could not be reanalyzed. Within these articles, 99 articles gave sufficient information to generate six of the goodness-of-fit indices (i.e., CN, CFI, NFI, NNFI, RMSEA, and RNI). Although the final sample size for the multiple regression analyses were acceptable (N = 187 for the Chi-square test statistic, CN, CFI, NFI, NNFI, RMSEA, and RNI; N = 135 for the GFI), it is troubling that so few articles provided sufficient information for reanalysis.

The lack of sufficient data to recreate analyses is a serious concern regarding published research. Hoyle and Panter (1995) have suggested that a general set of guidelines is needed for presenting structural equation modeling information. Specifically, they recommended guidelines for the presentation of models at both a conceptual and statistical level.

At the conceptual level, they recommend that researchers provide readers with a diagram that refers to constructs and hypothesized relations along with a written discussion of the relations that are supported by theory.

About 90% of the articles under review provided both a diagram and written explanation of the research model. Another 5% of the articles provided a written explanation of the research model but failed to provide a diagram.

At the statistical level, Hoyle and Panter (1995) recommend that estimation of structural models always be based on covariance, rather than correlation matrices. Moreover, they recommend that researchers provide readers with a correlation matrix of all measured variables accompanied by standard deviations of the variables. Almost all software programs can recover the covariance matrix when provided a correlation matrix and standard deviations.

The benefits of including a covariance or correlation matrix with standard deviations should be readily apparent. First, it allows other researchers to replicate models (e.g., as in the present research). Second, it provides other researchers the opportunity to fit alternative models to the data.

Of the 88 articles that were reanalyzed in Study 1, 66 provided either covariance matrices or correlation matrices with standard deviations. The remaining 22 articles that were reanalyzed provided complete correlation matrices but failed to provide standard deviations. Of the articles that could not be reanalyzed, many articles provided correlation matrices and standard deviations only for latent variables when the model used multiple indicators. Another reason articles could not be reanalyzed was because an incomplete correlation matrix was given (e.g., for only the independent or dependent variables).

Article authors often noted that data were not provided to conserve space. However, it was unclear whether data were not provided due to the author's decision to omit data or due to a decision of the journal editor. Examination of the four journals reviewed suggest that articles in Journal of Applied Psychology and Structural Equation Modeling are more likely to provide data than are articles in Educational and Psychological Measurement or Journal of Personality and Social Psychology.

All journals accepting structural equation modeling should include consistent submission requirements for: (a) Visual and written explanation of structural models, (b) covariance matrices or correlation matrices with standard deviations for all measured variables, (c) information about the measurement and/or structural models (e.g., parameter estimates, standard errors, squared multiple correlations), and (d) information about the chosen fit indices with a rationale for their choice (Hoyle & Panter, 1995). Although there is often a discrepancy between the results that should be reported and the results that editors allow to be reported, Hershberger (1997) argued that Hoyle and Panter's recommendations are extremely reasonable and should be acceptable to any editor's standards. Clearly, the research literature would be much improved if Hoyle and Panter's guidelines were followed.

CHAPTER III

STUDY 2:

Background

Building on the results of Study 1 and the previous literature examining the performance of goodness-of-fit indices, Study 2 examines issues relevant to evaluations of overall model fit in structural equation models. In particular, Study 2 focuses on four issues:

First, the effects of sample size on the goodness-of-fit indices are considered. Levels of sample size are based on recommended sample sizes from prior research (e.g., Boomsma, 1982; Ding et al., 1995), and the range of sample sizes noted in Study 1.

Second, the results from Study 1 documented the widespread use of single indicators in structural equation models. In particular, 26% (N = 95) of the structural equation models in Study 1 are classified as single indicator models. However, prior research has only examined multiple indicator models (e.g., Andersen & Gerbing, 1984; Ding et al., 1995). Study 2 extends the accumulated knowledge about the effects of number of indicators per latent variable on the fit indices by examining single and multiple indicator models.

Third, prior examinations of model misspecifications have been limited to a few fit indices (primarily the chi-square test statistic, GFI, NFI, and NNFI) and generally confined to confirmatory factor analysis models (e.g., Gerbing & Andersen, 1987; La Du & Tanaka, 1989). By examining structural equation models, Study 2 provides new information about the performance of the fit indices in true and misspecified models.

Fourth, Study 2 provides an opportunity to examine the appropriateness of the recommended cutoff values for the goodness-of-fit indices. Hu and Bentler (1995) showed that the .90 cutoff value is inadequate and often inappropriate. Study 2 extends Hu and Bentler's research in that the appropriateness of cutoff values is considered for the fit indices under a wider range of conditions. Further, the current research presents information regarding the assessment of model fit using alternative cutoff values. This information will be useful in evaluating structural equation models across a variety of research applications.

Hypotheses

Three Monte Carlo simulations were conducted in Study 2. Each simulation study examined the following conditions: (a) sample size, (b) number of indicators per latent variable, and (c) model misspecifications. The simulations differed in the complexity of the chosen model (i.e., simple, moderate, and complex). Table 9 presents the proposed hypotheses for the eight goodness-of-fit indices as a function of the study conditions in the three simulations. The findings from Study 1 and the literature relating to each hypothesis in Table 9 can be found in the following sections which are represented as conditions in the table.

Sample Size

Previous research has shown that increased sample sizes result in improved model fit and higher rates of model acceptance for many indices. In particular, the GFI and NFI (Andersen & Gerbing, 1984; Browne & Cudeck, 1993) are significantly affected by sample size with larger sample sizes yielding improved model fit values. Moreover, Hu and Bentler (1995) noted that the CN accepts all models when the sample size is 500 or greater. Furthermore, Browne and Cudeck demonstrated that as the sample size increases, RMSEA values decrease, but generally not below .05. In contrast, an increase in sample size results in values suggesting poorer model fit and higher rates of model rejection for the chi-square test statistic (Boomsma, 1982; Jöreskog & Sörbom, 1981). Sample size was found to have little or no effect on the CFI, NNFI, and RNI (Marsh et al., 1988; Mulaik et al., 1989). However, Bentler

Table 9

Study 2 Hypotheses for the Goodness-of-Fit Indices for the Monte Carlo Study Conditions In the Simple, Moderate, and Complex Models

Condition	Hypotheses
Sample Size	As sample size increases, chi-square values increase, suggesting poorer fit. As sample size increases, CN, GFI and NFI values increase, suggesting better fit. As sample size increases, RMSEA values decrease, suggesting better fit, but not generally below .05. When the sample size is 100, the NNFI is expected to exhibit larger standard deviations than the CFI, GFI, NFI, and RNI. No sample size effect is expected for the CFI, NNFI, and RNI.
Number of Indicators per Latent Variable	As number of indicators increase, chi-square values increase, suggesting poorer fit. As number of indicators increase, GFI and NFI values decrease, suggesting poorer fit. As number of indicators increase between three and five, CFI, NNFI, and RNI values decrease, suggesting poorer fit. As number of indicators increase, RMSEA values decrease, suggesting better fit. No indicator effect is expected for the CN.

Table 9 continued

Condition	Hypotheses
Model Misspecifications	When the model is specified correctly, all indices (i.e., chi-square, CFI, CN, GFI, NFI, NNFI, RMSEA, and RNI) should yield values suggesting acceptable fit. When the misspecification is an inclusion, the fit indices are expected to yield the same values as for the true condition. When the misspecification includes an omitted path, the indices are expected to yield values that suggest a poorer fit than for the true or inclusion condition.
Sample Size X Number of Indicators per Latent Variable Interaction	As sample size increases, the effects of number of indicators increase on chi-square values to suggest poorer fit. When the sample size is small (N = 100) and number of indicators increase, CFI, GFI, NFI, NNFI, and RNI values decrease to suggest poorer fit, whereas when the sample size is large (N = 200+) and number of indicators increase, CFI, GFI, NFI, NNFI, and RNI values are stable. As sample size increases, the effects of number of indicators increase on RMSEA values to suggest better fit. No interaction effect is expected for the CN.

Table 9 continued

Condition	Hypotheses
Sample Size X Model Misspecifications Interaction	As sample size decreases, the chi-square is expected to detect misspecifications more accurately, whereas when the sample increases, the chi-square is expected to detect misspecifications less accurately. As sample size increases, the GFI and NFI are expected to detect misspecifications more accurately, whereas when the sample size decreases, the GFI and NFI are expected to detect misspecifications less accurately. No interaction effect is expected for the CN, CFI, NNFI, RMSEA, and RNI.
Number of Indicators per Latent Variable X Model Misspecifications Interaction	As the number of indicators increase, the chi-square test statistic, GFI, and NFI are expected to detect misspecifications less accurately, whereas as the number of indicators decrease, the chi-square, GFI, and NFI are expected to detect misspecifications more accurately. As the number of indicators increase, the RMSEA is expected to detect misspecifications more accurately, whereas as the number of indicators decrease, the RMSEA is expected to detect misspecifications less accurately. No interaction effect is expected for the CFI, CN, NNFI, and RNI.

Table 9 concluded

Condition	Hypotheses
Sample Size X Number of Indicators per Latent Variable X Model Misspecifications Interaction	As the number of indicators and sample size increase, the chi-square test statistic is expected to detect misspecifications less accurately, whereas as the sample size and number of indicators decrease, the chi-square is expected to detect misspecifications more accurately. No interaction effect is expected for the CFI, CN, GFI, NFI, NNFI, RMSEA, and RNI.

(1990) and Marsh et al. noted that when the sample size was small (e.g., 100 or less), the NNFI exhibited greater variability in standard errors than did the CFI, GFI, NFI, and RNI.

Results from Study 1 supported prior findings demonstrating the effects of sample size on the chi-square test statistic, GFI, and NFI. Similarly, support was found for the lack of sample size effects on the CFI, NNFI, and RNI. In contrast, Study 1 results failed to support prior sample size effects on the CN or RMSEA. In particular, no significant relationships were noted between sample size and the CN or RMSEA. However, prior findings examining the CN and RMSEA were based on Monte Carlo investigations and a wider range of sample sizes (e.g., from 75 to 11,000 in Browne & Cudeck, 1993).

Inspection of the correlation matrix (i.e., on page 83) in Study 1 demonstrates a positive correlation between sample size and the CN and a negative correlation between sample size and the RMSEA. Although these correlation coefficients are not statistically significant, they are in the direction that would be expected based on prior findings. Furthermore, the mean sample size of the Study 1 data was 602.07, with a median of 238 (i.e., indicative of positive skewness).

Number of Indicators per Latent Variable

Prior research has shown that the chi-square test statistic, GFI, and NFI are adversely affected by an increase in the number of indicators per latent variable (e.g., Andersen & Gerbing, 1984; Ding et al., 1995). That is, as the number of indicators per latent variable increases, values on the chi-square test statistic, GFI, and NFI suggest poorer model fit. Ding et al. also noted that the CFI, NNFI, and RNI were negatively affected by increasing the number of indicators per latent variable. However, the effects on the CFI, NNFI, and RNI were relatively small. Importantly, when the sample size was 200 or larger, no effects from indicators per latent variable were found for the CFI, NNFI, and RNI.

Browne and Cudeck (1993) demonstrated that as the number of latent variables increase and the sample size increases, the values of the RMSEA were more likely to decrease below .05. However, no prior research has examined the effects of number of indicators on the RMSEA. Inspection of the correlation matrix in Study 1 demonstrates a significant negative relationship between the number of indicators per latent variable and values of the RMSEA. Thus, it appears logical that as the number of indicators increase and sample size increases, RMSEA values should decrease.

The results from the multiple regression analyses supported the influence of number of indicators per latent variable on the GFI. Moreover, the correlation matrix demonstrated significant relationships between number of indicators, the chi-square test statistic, NFI, and RMSEA. No effects from number of indicators were exhibited for the CN, CFI, NNFI, and RNI.

The hypothesized model's degrees of freedom exerted significant influences on the chi-square test statistic, CFI, NFI, and RNI in the multiple regression analysis. An increase in the number of indicators per latent variable results in increases in the hypothesized model's degrees of freedom.

Model Misspecifications

To date, research examining model misspecifications have primarily focused on the degree (i.e., the number of inappropriate paths added or omitted) to which a model is misspecified (e.g., Bandalos, 1993; Bentler, 1990; Marsh et al., 1988). However, La Du and Tanaka (1989) argued that the type of misspecification is an important consideration. Specifically, they noted that adding an incorrect structural path led to improvements in fit between 1% and 2%, whereas omitting a correct structural path led to decrements in fit between 5% and 15%.

When the model is correctly specified, a useful goodness-of-fit index should yield values suggesting acceptable model fit. Further, when the model is correctly specified, goodness-of-fit indices should be influenced only minimally or not at all by sample size, model complexity, and number of indicators per latent variable. When the model is misspecified, a useful goodness-of-fit index should yield values that suggest poorer fit than for the correct specification. The misspecification(s) should be detected irrespective of the sample size, model complexity, and number of indicators per latent variable.

Appropriateness of the Recommended Cutoff Values

Following the analyses of the Monte Carlo simulations, the data were examined to determine the percentages of model acceptance using recommended and alternative cutoff values. The recommended cutoff values for model acceptance are: (a) .90 for the CFI, GFI, NFI, NNFI, and RNI (Bentler & Bonett, 1980; Jöreskog & Sörbom, 1993a; Mulaik et al., 1989); (b) 200 or greater for the CN (Hoelter, 1983); (c) .08 or less for the RMSEA (Steiger, 1990); and (d) a non-significant chi-square value for the chi-square test statistic (Tanaka, 1993).

The likelihood of model acceptance using the recommended cutoff values will differ as a function of the Monte Carlo study conditions and model complexity. The effects of the Monte Carlo study conditions on the percentages of model acceptance are expected to mirror the effects on the values of the fit indices (refer to Table 9 for Monte Carlo hypotheses).

Model Complexity Hypotheses

More complex models are characterized by a greater number of estimated paths, and by increases in the hypothesized model's degrees of freedom. In particular, although model complexity was not studied specifically in Study 1, results demonstrated that the chi-square test statistic, GFI, and NFI were adversely affected by increases in the total number of estimated paths and by increases in the hypothesized model's degrees of freedom. Thus, the chi-square test statistic, GFI, and NFI should have lower percentages of model acceptance as the model becomes more complex.

The CN was negatively related to the total number of estimated paths. That is, as the number of estimated paths increase, values on the CN decrease. Complex models will have more estimated paths than moderate models, and moderate models will have more estimated paths than simple models. Therefore, the CN should yield higher percentages of model acceptance for simple models than for moderate and complex models. And, the CN should yield higher percentages of model acceptance for the moderate rather than for the complex model.

Although the CFI, NNFI, and RNI were not affected by the total number of estimated paths, each was negatively influenced by increases in the hypothesized model's degrees of freedom. As the number of indicators per latent variable increase, the hypothesized model's degrees of freedom will increase. Because a more complex model will have a greater number of latent variables than less complex models, increases in the number of indicators will result in larger degrees of freedom for the hypothesized model. Therefore, the CFI, NNFI, and RNI should yield lower percentages of model acceptance as the model becomes more complex and as the number of indicators per latent variable increases.

In contrast, the RMSEA was not affected by the total number of estimated paths or by the hypothesized model's degrees of freedom. However, Browne and Cudeck (1993) noted that RMSEA values decreased as the number of latent variables increased and as the sample size increased. Moreover, Study 1 demonstrated a significant negative relationship between number of indicators per latent variable and the RMSEA. Therefore, more complex models with increased numbers of indicators and larger sample sizes should yield higher percentages of model acceptance than less complex models or complex models with smaller sample sizes.

Method

Monte Carlo Simulations

Each simulation had three conditions: (a) sample size, (b) number of indicators per latent variable, and (c) model misspecifications. These conditions were studied in three simulation models of differing complexity: (a) simple, (b) moderate, and (c) complex.

The Data

Sample size. Although a minimum sample size of 200 is generally agreed upon for structural equation modeling, there is considerable variation in the sample sizes typically used. For example, sample sizes may range from a low of 80 (e.g., Marcoulides, 1989) to a high of over 50,000 (e.g., Mumford, Weeks, Harding, & Fleishman, 1988). Prior research has shown that, in many cases, goodness-of-fit values improve with increased sample sizes.

Based on sample size recommendations from prior research (e.g., Boomsma, 1982; Ding et al., 1995; Marsh et al., 1988, Tanaka, 1987) and the findings from Study 1, six sample sizes were considered: 100, 200, 500, 1000, 2000, and 5000. The smallest sample size, 100, was chosen because many structural equation models, especially single indicator models, are characterized by 100 or less observations in each group. Among the Study 1 articles, 10% (N = 33) had sample sizes of less than 100.

A sample size of 200 was chosen because it has been recommended as the minimum sample size to conduct structural equation modeling (e.g., Boomsma, 1982; Marsh et al., 1988). Ding et al. (1995) characterized a sample size of 200 as "good." Sample sizes between 101 and 300 were noted in 40% (N =145) of the Study 1 articles.

The next size, 500, was chosen because previous research suggests it is an "excellent" sample size used for performing structural equation modeling (e.g., Andersen & Gerbing, 1984; Ding et al., 1995). Approximately 16% (N = 59) of the Study 1 articles had sample sizes between 301 and 500, whereas 13% (N = 49) had sample sizes between 501 and 999.

A sample size of 1000 was chosen because 6% (N = 23) of the Study 1 articles had sample sizes ranging from 1000 to 1999. A sample size of 2000 was chosen because MacCallum and Tucker (1991) have proposed that variability among standard errors becomes asymptotic at this sample size. Among the Study 1 articles, 4% (N = 13) had sample sizes between 2000 and 4999.

Finally, the largest sample size, 5000, was chosen for several reasons: (a) Substantive articles have touted 5000 as an "ideal" sample size (Mumford et al., 1988); and (b) several researchers have suggested using a ratio of either 5:1 (Bentler & Chou, 1986; Bollen, 1989b) or 10:1 (Austin & Wolfle, 1991; SAS Institute, 1990, chap.1) between sample size and estimated parameters. Because the most complex structural equation model found in Study 1 had 15 latent variables and estimated 48 parameters, a sample size of 5000 would be able to meet the 10:1 ratio requirements. Only 2% (N = 7) of the Study 1 articles had sample sizes of 5000 or greater.

<u>Number of indicators per latent variable.</u> Although studies have pointed out that a minimum of two indicators per latent variable is preferred (e.g., Ding et al., 1995; Gerbing & Anderson, 1993), many researchers choose single indicators for latent variables. Study 1 demonstrated that 26% (N = 95) of the complete set of articles, 32% (N = 60) of the multiple regression articles, and 40% (N = 13) of the articles available for model selection were single indicator models. The effect on goodness-of-fit indices due to this choice has not been evaluated in a Monte Carlo

study, thus, a single indicator was selected as the lower bound. Ding et al.'s research suggested that there is little distinction between five and six indicators per latent variable, therefore, five was chosen as the upper bound.

Model misspecifications. Four levels of model misspecification were examined: (a) a correctly specified model (i.e., the true specification); (b) a misspecified model that had one omitted correct structural path (i.e., an omission condition); (c) a misspecified model that had one added incorrect structural path (i.e., an inclusion condition); (d) a misspecified model that had one omitted correct structural path and one added incorrect structural path (i.e., a combination condition). The combination condition used the same omitted and added paths from the omission and inclusion conditions.

The specific added and omitted paths in the simple, moderate, and complex models were determined by examining parameter estimates in the measurement and structural models. Individual parameter estimates in the measurement models were examined (i.e., latent variable weights, standard errors, and squared multiple correlations for the latent variables). The structural coefficients and squared multiple correlations for the structural equations for the structural models were examined to determine the effects of the misspecifications.

Omitted and added paths accounted for approximately the same proportion of variance (i.e., based upon examining the squared multiple correlations for the structural equations) across the three levels of model complexity. As an example, assume the squared multiple correlation for a structural equation prior to omitting a structural path was .60. After a path was omitted from the model, the squared multiple correlation for that same structural equation dropped to .40. Thus, the omission of that path accounted for approximately one third of the variance for that structural equation. In the remaining two models, the omitted paths were expected to account for one third of the variance in their respective structural equations (e.g., from .45 to .30, and from .75 to .50).

Similarly, when an incorrect structural path was added, the squared multiple correlation for that structural equation was evaluated. If there was no change in the squared multiple correlation for the structural equation when a path was added, then the remaining models specified incorrect paths that did not change the squared multiple correlations for their respective structural equations.

Individual parameter estimates and the structural equations were examined before and after paths were omitted and added to ensure that the omissions and inclusions had approximately the same effects across the levels of model complexity. For example, the lambda values and standard errors in the measurement models were examined to ensure that the composite reliability of the latent variables was not affected by the omissions. To ensure consistency, all model misspecifications (i.e., omissions and inclusions) occurred in structural paths.

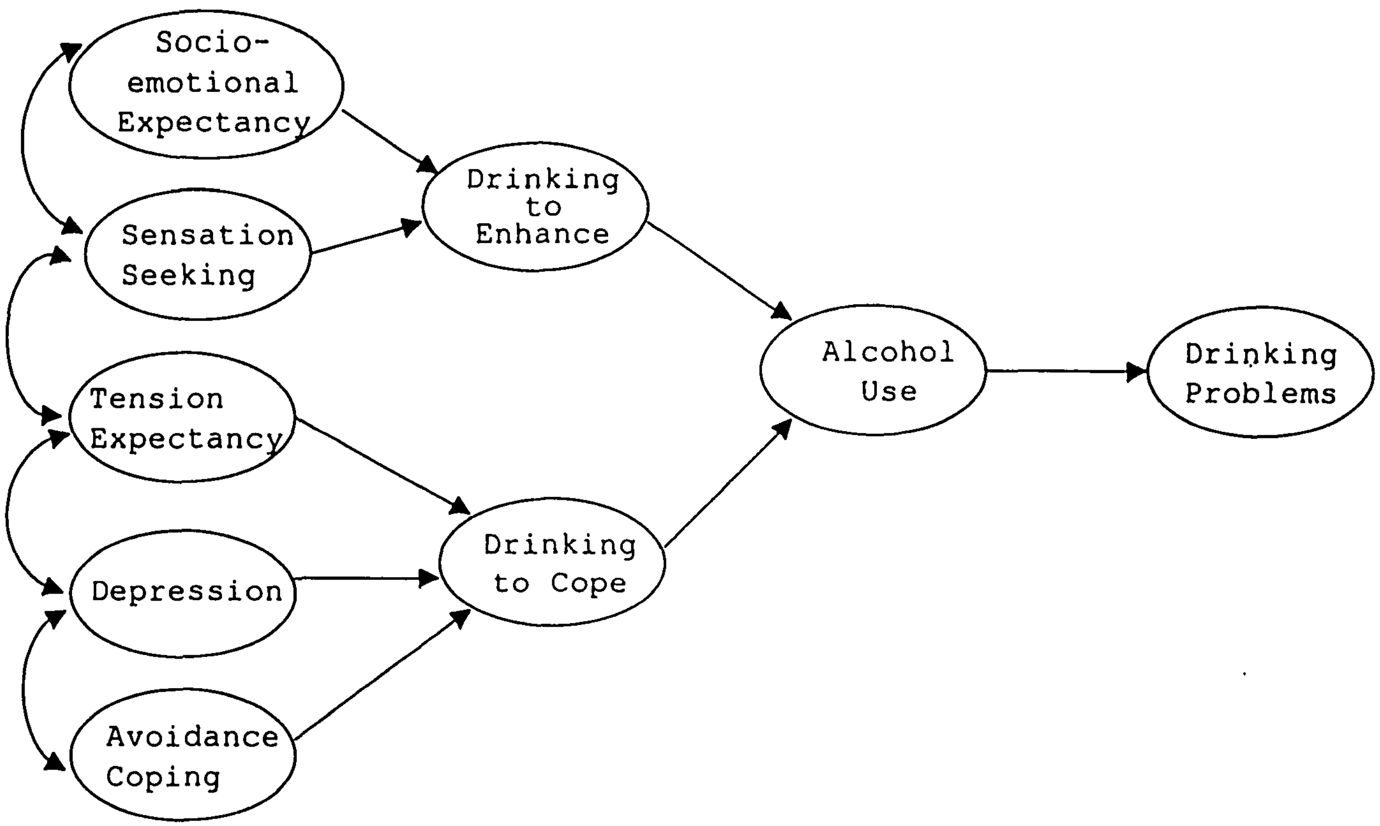
Model Selection

The 29 articles for model selection from Study 1 were examined to choose three specific models to reflect model complexity. Four complex models, 13 moderate models, and 12 simple models were initially available for model selection.

First, the articles in the complex and moderate conditions of model complexity were examined to compare aspects such as the number of latent variables, the hypothesized relations, and the number of latent paths. Ideally, the complex model should have a greater number of latent paths and latent variables than the moderate model. However, some similarities in the hypothesized relations were desirable across the complex and moderate models. That is, the choice of an omitted path should perform more similarly across the models if the omission exerted the same type of influence. For example, if the omitted path in the complex model was from a latent variable that had one hypothesized latent path to another latent variable, then the moderate model would be more similar if the omitted path was also from a latent variable that had one hypothesized path to another latent variable.

Based on these considerations, two models were chosen to represent the complex and moderate conditions of model complexity. The complex model was a structural equation model with nine latent variables examining the relationships between positive and negative emotions and drinking behavior (Cooper, Frone, Russell, & Muldar, 1995). The complex model is presented in Figure 3. The moderate model was a structural equation model with six latent variables examining the relationships between expatriates and the psychological contract (Guzzo, Noonan, & Elron, 1994). A depiction of the moderate model is presented in Figure 4.

Next, the articles in the simple condition of model complexity were examined. Ten of the 12 articles in the simple condition of model complexity were represented by confirmatory factor analyses. The majority of confirmatory factor analyses specified three latent variables (N = 6,



<u>Figure 3.</u> Model for the complex Monte Carlo simulation (Cooper et al., 1995). Although the figure does not depict all possible correlations, they were estimated in this model.

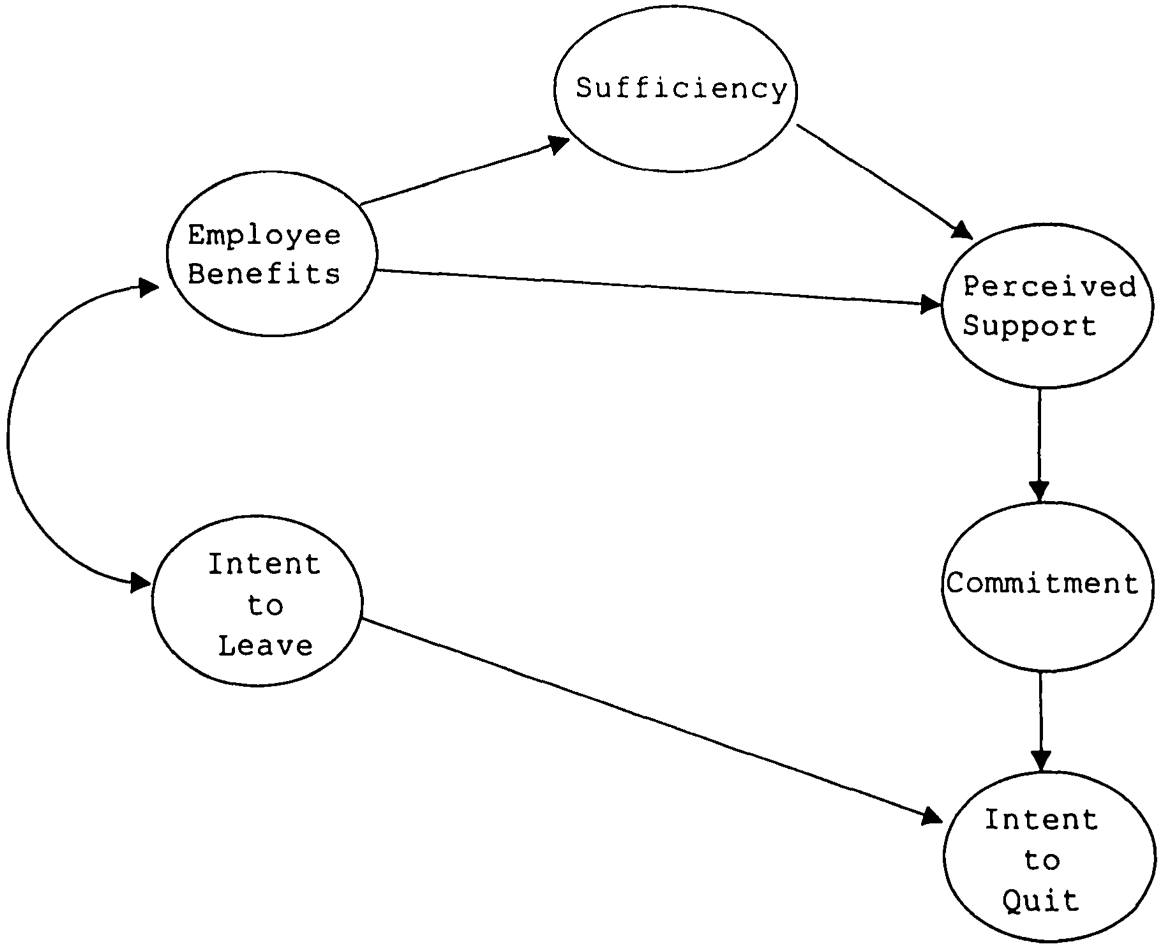


Figure 4. Model for the moderate Monte Carlo simulation (Guzzo et al., 1994).

60%). Because each of the confirmatory factor analyses estimated correlations among the latent variables, none of the confirmatory factor analyses could be used for the simple model. Although it would be possible to create an omission condition for these articles, it would be impossible to create an inclusion or combination condition for model misspecifications.

The removal of the ten confirmatory factor analyses left two remaining articles in the simple condition of model complexity. Unfortunately, both articles also were eliminated. One article (Windle et al., 1989) was eliminated because the composite reliabilities for the four latent variables were low (i.e., from .38 to .62). There was concern that the poor reliabilities of the latent variables would explain differences noted in the Monte Carlo simulation rather than manipulation of the study conditions.

The remaining article (Zebrowitz, Olson, & Hoffman, 1993) was eliminated because it was a longitudinal structural equation model. In other words, the structural paths between the latent variables were sequentially ordered from the first to the fourth latent variable. A longitudinal structural equation model was inappropriate because the omission of any structural path would either create two structural equation models or reduce the longitudinal aspects of the model.

Therefore, the simple model was developed by using a submodel with four latent variables from the model selected for the complex condition. Figure 5 depicts the simple model.

Manipulating the Number of Indicators per Latent Variable

Prior to generating the population variance-covariance matrices, the correlation matrix and standard deviations for each representative model were manipulated to add indicators per latent variable. The original models used one indicator per latent variable.

Two procedures were followed to add indicators. The first procedure was used to increase the number of indicators within a latent variable. For example, a second indicator for each latent variable was initially set to correlate .80 with the first indicator. The value for the standard deviation of the second indicator of each latent variable was set to .01 less than the standard deviation for the first indicator. The composite reliability of the latent variables before and after the addition of a second indicator was compared to ensure consistency.

If the composite reliability of a latent variable after the addition of the second indicator was higher than

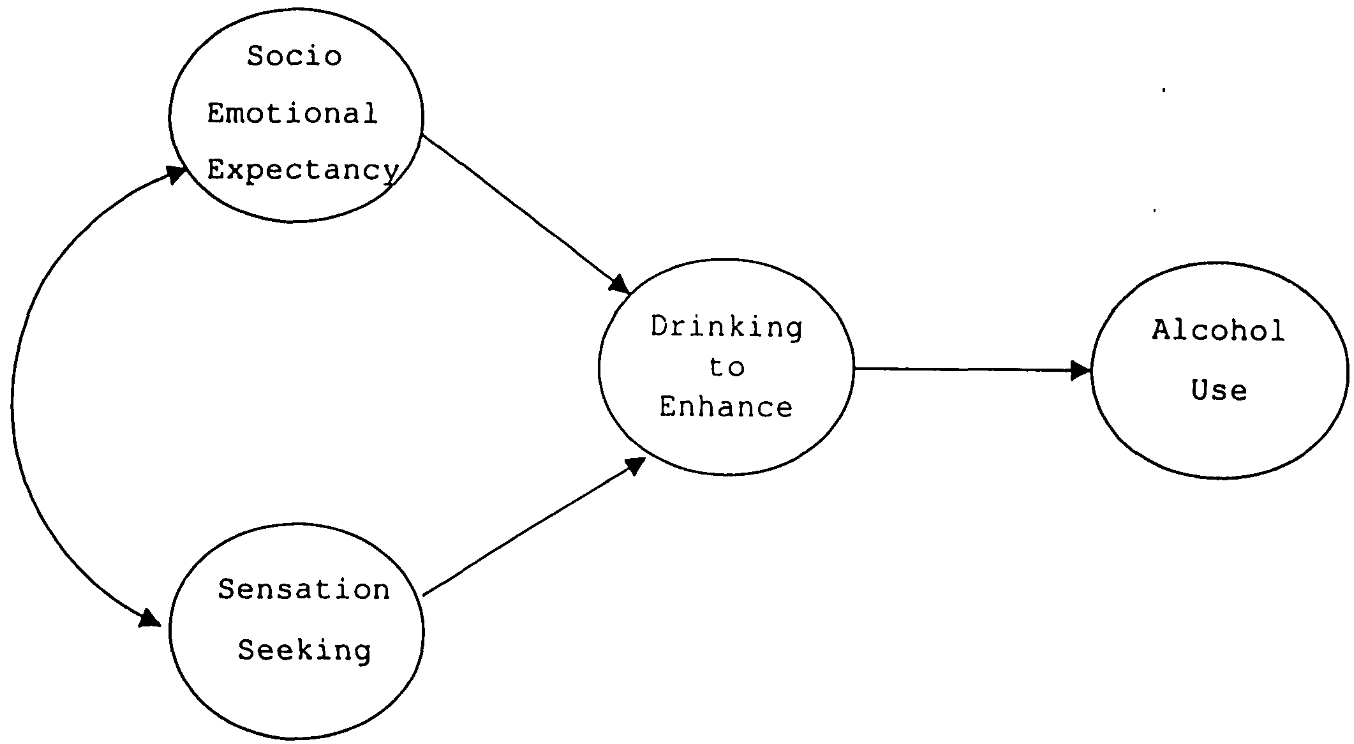


Figure 5. Model for the simple Monte Carlo simulation (adapted from Cooper et al., 1995).

the composite reliability with one indicator, then the correlation between the indicators was reduced .01 to .79. The correlation between the two indicators continued to be reduced in increments of .01 until the composite reliability of the latent variable was within .02 of its original reliability.

If, however, the composite reliability after the addition of the second indicator was lower than the original composite reliability, then the correlation between the indicators were increased in increments of .01. This procedure was repeated until the composite reliability of the latent variable was within .02 of its original composite reliability.

The second procedure was used to generate the correlations between indicators of different latent variables. The correlation between two indicators was increased by systematically holding constant, adding .01, and subtracting .01 from the original correlation between latent variables. For example, when the correlation between the first and second latent variable was .77, the new indicators utilized values of .76, .77, and .78.

Choice of Model Misspecifications

The omitted path in the simple model was between the latent variables of sensation seeking and drinking to enhance. The squared multiple correlation for drinking to enhance dropped from .352 to .264 when this path was omitted. Thus, the omission decreased by 25% the squared multiple correlation in the structural equation for drinking to enhance. The incorrect added path in the simple model was obtained by creating a path from sensation seeking to alcohol use. The squared multiple correlation for alcohol use went from .412 to .424 when this path was included, which represents a 3% increase in the squared multiple correlation.

The moderate model omitted a path between the latent variables of organizational commitment and intent to quit. The squared multiple correlation for intent to quit dropped from .439 to .338 when this path was omitted. The omission decreased by 27% the squared multiple correlation in the structural equation for intent to quit. An incorrect path was added in the moderate model between the latent variables of intent to leave and perceived support. The squared multiple correlation for perceived support went from .334 to .348 when this path was included, which represents a 4% increase in the squared multiple correlation.

The complex model omitted a path between the latent variables of tension expectancy and drinking to cope. The squared multiple correlation for drinking to cope dropped from .668 to .511 when this path was omitted. The omission decreased by 24% the squared multiple correlation in the structural equation for drinking to cope. An incorrect path was added in the complex model between the latent variables of tension expectancy and alcohol use. The squared multiple correlation for alcohol use went from .391 to .402 (i.e., a 4% increase) when this path was included.

The added paths in the simple, moderate, and complex models were represented by structural relationships in the gamma matrix (i.e., relationships from the latent independent variables to the latent dependent variables). The omitted paths in the simple and complex models occurred in the gamma matrix, whereas the moderate model omitted a path in the beta matrix.

According to Hayduk (1987) and Bentler (1995), the distinction between independent and dependent latent variables exists primarily to facilitate understanding of the latent variables in a given model. Both researchers showed that a general model that does not distinguish between beta and gamma matrices is mathematically equivalent to a model that does (e.g., the full LISREL model). Thus, the distinction in omitted paths (i.e., beta in the moderate model versus gamma in the simple and complex models) is superfluous.

Analysis of the Population Matrices

The three simulation models with five levels of indicators per latent variable resulted in 15 population variance-covariance matrices for the Monte Carlo simulations (see Appendix E for presentation of the 15 population matrices).

Two examinations of the population matrices were undertaken to ensure that the characteristics were properly defined for the Monte Carlo simulations. Mooney (1997) noted that careful examination of Monte Carlo conditions is necessary to ensure that appropriate inferences can be drawn from Monte Carlo findings. First, the measurement properties of the population matrices were compared within each level of model complexity. Second, the structural model properties of the population matrices were compared within each level of model complexity.

Population matrices were analyzed with a sample size of 100,000 for two reasons. First, when the sample size is large, the parameter estimates should be stable. Second, in order to analyze the population matrices, LISREL 8.14 required a specified sample size. The size of the population was defined arbitrarily at 100,000.

Measurement properties of the population matrices. Table 10 presents information regarding the measurement properties of the population matrices. In particular, the table shows the composite reliability for each of the latent variables, the average lambda value (i.e., average latent variable weight), average standard error (i.e., average measurement error), and averaged squared multiple correlation (i.e., average proportion of variance accounted for in the latent variable). Table 10 demonstrates that the measurement properties of the simple, moderate, and complex simulation models were maintained across increases in the number of indicators per latent variable. All measurement properties were within .03 of their original values.

Structural properties of the population matrices. Information about the structural model properties of the population matrices can be found in Tables 11, 12, and 13, respectively. These tables present the structural equations for the dependent latent variables and the squared multiple correlation associated with each of the structural equations. The values in these tables show that the structural properties of the simple, moderate, and complex simulation models were maintained across increases in the number of indicators per latent variable. All

Table 10

Measurement Properties of the Population Matrices

Model[a]	Reliability[b]	Lambda Value[c]	Standard Error[d]	SMC[e]
Simple Model				
Alcohol Use				
1 indicator	.900	1.000	.110	.847
2 indicators	.900	.992	.109	.848
3 indicators	.900	.998	.108	.846
4 indicators	.902	1.000	.108	.846
5 indicators	.902	1.002	.109	.845
Drinking to Enhance				
1 indicator	.860	1.000	.159	.840
2 indicators	.863	1.007	.164	.839
3 indicators	.862	1.010	.164	.840
4 indicators	.859	1.014	.164	.840
5 indicators	.859	1.007	.163	.840
Sensation Seeking				
1 indicator	.901	1.000	.107	.790
2 indicators	.903	.997	.107	.789
3 indicators	.900	.989	.109	.790
4 indicators	.902	1.000	.109	.790
5 indicators	.902	1.003	.109	.789
Socioemotional Problems				
1 indicator	.850	1.000	.175	.879
2 indicators	.848	.996	.178	.878
3 indicators	.848	.990	.176	.880
4 indicators	.850	1.000	.176	.880
5 indicators	.850	1.002	.176	.880
Moderate Model				
Employee Benefits				
1 indicator	.946	1.000	.057	.729
2 indicators	.942	.997	.057	.731
3 indicators	.946	1.002	.057	.731
4 indicators	.946	.997	.058	.730
5 indicators	.944	1.002	.058	.731

Table 10 continued

Model[a]	Reliability[b]	Lambda Value[c]	Standard Error[d]	SMC[e]
Moderate Model				
Intent to Leave				
1 indicator	.881	1.000	.146	.863
2 indicators	.873	.993	.145	.860
3 indicators	.870	.997	.148	.856
4 indicators	.874	1.006	.141	.858
5 indicators	.879	1.012	.141	.863
Intent to Quit				
1 indicator	.873	1.000	.140	.900
2 indicators	.876	.992	.139	.893
3 indicators	.881	1.017	.138	.896
4 indicators	.880	1.011	.139	.896
5 indicators	.878	1.007	.141	.894
Organizational Commitment				
1 indicator	.931	1.000	.080	.860
2 indicators	.923	.988	.078	.859
3 indicators	.927	1.002	.078	.860
4 indicators	.927	1.001	.079	.860
5 indicators	.927	1.004	.078	.861
Perceived Support				
1 indicator	.943	1.000	.070	.903
2 indicators	.941	1.011	.064	.900
3 indicators	.944	1.033	.063	.900
4 indicators	.943	1.029	.064	.900
5 indicators	.944	1.025	.063	.901
Sufficiency				
1 indicator	.950	1.000	.056	.802
2 indicators	.949	.970	.051	.800
3 indicators	.951	.995	.052	.800
4 indicators	.950	.993	.052	.800
5 indicators	.952	.995	.050	.804

Table 10 continued

Model[a]	Reliability[b]	Lambda Value[c]	Standard Error[d]	SMC[e]
Complex Model				
Alcohol Use				
1 indicator	.900	1.000	.110	.847
2 indicators	.900	.992	.109	.848
3 indicators	.900	.998	.108	.846
4 indicators	.902	1.000	.108	.846
5 indicators	.902	1.002	.109	.845
Avoidance Coping				
1 indicator	.960	1.000	.048	.789
2 indicators	.959	1.002	.044	.790
3 indicators	.958	.987	.043	.790
4 indicators	.959	1.000	.043	.790
5 indicators	.959	.996	.042	.790
Depression				
1 indicator	.920	1.000	.086	.830
2 indicators	.920	.998	.087	.830
3 indicators	.917	.988	.088	.830
4 indicators	.920	.999	.088	.830
5 indicators	.918	.998	.089	.830
Drink to Cope				
1 indicator	.900	1.000	.119	.840
2 indicators	.899	1.006	.113	.839
3 indicators	.898	.992	.112	.840
4 indicators	.899	.999	.113	.840
5 indicators	.898	.993	.112	.840
Drink to Enhance				
1 indicator	.860	1.000	.159	.840
2 indicators	.863	1.007	.164	.839
3 indicators	.862	1.010	.164	.840
4 indicators	.859	1.014	.164	.840
5 indicators	.859	1.007	.163	.840

Table 10 concluded

Model[a]	Reliability[b]	Lambda Value[c]	Standard Error[d]	SMC[e]
Complex Model				
Drinking Problems				
1 indicator	.940	1.000	.072	.784
2 indicators	.939	1.007	.070	.786
3 indicators	.935	1.010	.071	.785
4 indicators	.936	1.014	.070	.784
5 indicators	.936	1.007	.069	.784
Sensation Seeking				
1 indicator	.901	1.000	.107	.790
2 indicators	.903	.997	.107	.789
3 indicators	.900	.989	.109	.790
4 indicators	.902	1.000	.109	.790
5 indicators	.902	1.003	.109	.789
Socioemotional Problems				
1 indicator	.850	1.000	.175	.879
2 indicators	.848	.996	.178	.878
3 indicators	.848	.990	.176	.880
4 indicators	.850	1.000	.176	.880
5 indicators	.850	1.002	.176	.880
Tension				
1 indicator	.809	1.000	.235	.859
2 indicators	.810	.999	.234	.860
3 indicators	.807	.992	.236	.860
4 indicators	.809	1.000	.236	.860
5 indicators	.806	.994	.237	.859

Note. N = 100,000 for all models. The following abbreviation was used: SMC = Squared multiple correlation.

[a]All original models used one indicator for each latent variable.

[b]Composite reliability, computed as the sum of the squared lambda values divided by the sum of the squared lambda values and their respective standard errors.

[c]Average lambda value.

[d]Average standard error.

[e]Average squared multiple correlation for the latent variable.

Table 11

Structural Properties of the Simple Population Matrices

Model[a]	Structural Equation	SMC
Simple - 1 indicator		
Alcohol Use	AU = .538*DE	.412
Drinking to Enhance	DE = .278*SE+.432*SO	.352
Simple - 2 indicators		
Alcohol Use	AU = .561*DE	.419
Drinking to Enhance	DE = .280*SE+.447*SO	.383
Simple - 3 indicators		
Alcohol Use	AU = .555*DE	.410
Drinking to Enhance	DE = .270*SE+.444*SO	.377
Simple - 4 indicators		
Alcohol Use	AU = .541*DE	.408
Drinking to Enhance	DE = .270*SE+.448*SO	.370
Simple - 5 indicators		
Alcohol Use	AU = .541*DE	.408
Drinking to Enhance	DE = .270*SE+.448*SO	.370

Note. N = 100,000 for all matrices. Assessment of the structural properties is based on the results from the true model. The following abbreviations were used: AU = Alcohol use; DE = Drinking to enhance; SE = Sensation seeking; SMC = Squared multiple correlation for the structural equation; SO = Socioemotional problems.
[a]The original matrix used one indicator per latent variable.

structural properties were within .05 of their original values.

Number of Replications per Simulation Cell

There are no absolute guidelines for the number of replications for Monte Carlo results to be valid (Mooney, 1997). Assuming the simulation has been designed properly,

Table 12

Structural Properties of the Moderate Population Matrices

Model[a]	Structural Equation	SMC
Moderate - 1 indicator		
Intent to Quit	IQ = -.284*IL-.963*OC	.439
Organizational Commitment	OC = .521*PS	.318
Perceived Support	PS = .388*EB+.828*S	.334
Sufficiency	S = .414*EB	.137
Moderate - 2 indicators		
Intent to Quit	IQ = -.300*IL-.939*OC	.451
Organizational Commitment	OC = .537*PS	.316
Perceived Support	PS = .373*EB+.799*S	.334
Sufficiency	S = .394*EB	.121
Moderate - 3 indicators		
Intent to Quit	IQ = -.324*IL-.960*OC	.468
Organizational Commitment	OC = .523*PS	.318
Perceived Support	PS = .344*EB+.784*S	.332
Sufficiency	S = .405*EB	.121
Moderate - 4 indicators		
Intent to Quit	IQ = -.319*IL-.971*OC	.465
Organizational Commitment	OC = .524*PS	.310
Perceived Support	PS = .341*EB+.788*S	.334
Sufficiency	S = .408*EB	.124
Moderate - 5 indicators		
Intent to Quit	IQ = -.323*IL-.963*OC	.464
Organizational Commitment	OC = .524*PS	.310
Perceived Support	PS = .344*EB+.793*S	.336
Sufficiency	S = .405*EB	.122

Table 12 concluded

Note. N = 100,000 for all matrices. Assessment of the structural properties is based on the results from the true model. The following abbreviations were used: EB = Employee benefits; IL = Intent to leave; IQ = Intent to quit; OC = Organizational commitment; PS = Perceived support; S = Sufficiency; SMC = Squared multiple correlation for the structural equation.
[a]The original matrix used one indicator per latent variable.

Monte Carlo results are unbiased for any number of replications (Hope, 1968). However, the power of a Monte Carlo simulation increases with sample size because the efficiency of a test statistic increases with sample size. In other words, Monte Carlo simulations with more replications will have greater power than Monte Carlo simulations with fewer replications. In general, Monte Carlo studies examining the performance of goodness-of-fit indices have recommended a minimum of 100 replications per cell (Andersen & Gerbing, 1984). Recently however, Bandalos (1997) and Ding et al. (1995) argued that 200 replications per cell is necessary to have sufficient power. In particular, they mentioned that the number of replications per cell can be reduced severely when solutions do not converge. Based on the guidelines proposed by Bandalos and Ding et al., the current research generated 200 replications per cell.

Table 13

Structural Properties of the Complex Population Matrices

Model[a]	Structural Equation	SMC
Complex - 1 indicator		
Alcohol Use	AU= .247*DC+.434*DE	.391
Drinking to Cope	DC= .167*AC+.154*D+.385*T	.668
Drinking to Enhance	DE= .261*SE+.419*SO	.360
Drinking Problems	DP= .281*AU+.212*DC	.519
Complex - 2 indicators		
Alcohol Use	AU= .220*DC+.457*DE	.414
Drinking to Cope	DC= .149*AC+.162*D+.422*T	.689
Drinking to Enhance	DE= .245*SE+.441*SO	.383
Drinking Problems	DP= .281*AU+.215*DC	.493
Complex - 3 indicators		
Alcohol Use	AU= .226*DC+.454*DE	.409
Drinking to Cope	DC= .176*AC+.154*D+.417*T	.687
Drinking to Enhance	DE= .236*SE+.455*SO	.378
Drinking Problems	DP= .287*AU+.220*DC	.491
Complex - 4 indicators		
Alcohol Use	AU= .221*DC+.458*DE	.407
Drinking to Cope	DC= .173*AC+.152*D+.418*T	.697
Drinking to Enhance	DE= .231*SE+.459*SO	.371
Drinking Problems	DP= .290*AU+.218*DC	.492
Complex - 5 indicators		
Alcohol Use	AU= .211*DC+.457*DE	.407
Drinking to Cope	DC= .164*AC+.156*D+.419*T	.702
Drinking to Enhance	DE= .230*SE+.460*SO	.371
Drinking Problems	DP= .288*AU+.218*DC	.491

Note. N = 100,000 for all matrices. Assessment of the structural properties is based on the true model. The following abbreviations were used: AC = Avoidance coping; AU = Alcohol use; D = Depression; DC = Drinking to cope; DE = Drinking to enhance; DP = Drinking problems; SE = Sensation seeking; SMC = Squared multiple correlation for the structural equation; SO = Socioemotional problems; T = Tension expectancy.

[a]The original matrix used one indicator per latent variable.

Monte Carlo Design

Each Monte Carlo simulation had three conditions: (a) sample size, (b) number of indicators per latent variable, and (c) model misspecifications. Each simulation was a 6 x 5 x 4 balanced factorial design (i.e., sample size X number of indicators X model misspecifications). Therefore, each simulation study had 120 cells with 200 replications per cell.

There were 15 population variance-covariance matrices (i.e., 3 models X 5 levels of indicators = 15 population matrices) used to generate replications. Replications were generated from a multivariate normal distribution (see Jöreskog & Sörbom, 1993b, p. 192).

Appendix F presents a sample program of those used to calculate the lambda weights from the population variance-covariance matrices. These weights were used to generate samples of raw data with PRELIS 2.14 (Jöreskog & Sörbom, 1993b). Appendix G gives a sample PRELIS 2.14 program of those used to generate the raw data sets. Appendix H presents the FORTRAN program used to generate the random number used to initiate each PRELIS program. Appendix I contains a sample LISREL 8.14 program of those used to generate the goodness-of-fit indices for the raw data sets.

Seven goodness-of-fit indices (i.e., chi-square statistic, CFI, CN, GFI, NFI, NNFI, and RMSEA) were available from LISREL 8.14 output. The output file also contained the degrees of freedom for the hypothesized and null model and information regarding whether a solution had converged. The RNI was calculated using equation 10 (i.e., on page 38) in a separate SAS program.

Analytical Strategy for the Monte Carlo Simulations

As noted by Hendry (1984), Monte Carlo results only apply to the statistical situation explicitly specified by the pseudo-population generated by the Monte Carlo procedures. In other words, when there are differences in the correlation or variance-covariance matrices of the latent variables or error distributions, it is inappropriate to perform analyses across pseudo-populations. Mooney (1997) stated that analyses across multiple experiments could be performed only when the potential sources of variation and interdependencies of these sources were controlled across pseudo-populations.

A review of Monte Carlo research in the social sciences demonstrates that values of goodness-of-fit indices from distinct models are compared to one another through descriptive statistics such as the mean and standard deviation (e.g., Bearden et al., 1982; Bentler, 1990; Curran, West, & Finch, 1996; Gerbing & Anderson, 1985, 1987; Hu et al., 1992; Hu & Bentler, 1995; La Du & Tanaka, 1989; MacCallum, Roznowski, & Necowitz, 1992; Marsh et al., 1988; Mulaik et al., 1989). Within individual simulations, however, researchers may use inferential tests such as analysis of variance to compare across study conditions.

Therefore, analyses of variance were performed to examine the effects of sample size, number of indicators per latent variable, and model misspecifications on the values of each of the goodness-of-fit indices within each simulation (see Appendix J for presentation of the expected mean squares for the analyses). An alpha level of .01 was used for tests of statistical significance.

Given the large sample size, most effects were expected to be statistically significant. Previous Monte Carlo investigations have used a practical significance criterion of 3% (see Anderson & Gerbing, 1984, Bandalos, 1993, Bandalos, 1997). Therefore, the current study calculated eta-squared values (η^2) for all significant effects and adopted the 3% practical significance criterion. An η^2 was calculated as the effect variance divided by the total variance.

Establishing Percentages of Model Acceptance

Percentages of model acceptance were calculated for each cell of each Monte Carlo simulation to determine the appropriateness of the recommended cutoff values for the fit indices. The recommended cutoff values for model acceptance are: (a) .90 for the CFI, GFI, NFI, NNFI, and RNI (Bentler & Bonett, 1980; Mulaik et al., 1989); (b) 200 or greater for the CN (Hoelter, 1983); (c) .08 or less for the RMSEA (Steiger, 1990); and (d) a non-significant chi-square value for the chi-square test statistic (Tanaka, 1993). Percentages of model acceptance were calculated as the frequency of solutions that accepted the model divided by the maximum number of converged solutions. In other words, if 190 replications converged in a cell and 150 solutions yielded goodness-of-fit values that met the recommended cutoff values, the percentage of model acceptance in that cell would be 79% (i.e., 150/190 = .789).

Because model acceptance was measured as percentages, transformations were required prior to performing analyses to reduce departures from normality. Appropriate data transformations were determined using UNICORN (Allison, Gorman, & Kucera, 1993), a computer program that uses Box-Cox-Type transformations to reduce skewness, kurtosis, and overall departures from normality.

Examining Alternative Cutoff Values

Hu and Bentler (1995) argued that the recommended .90 cutoff value is inadequate and often inappropriate. However, they did not recommend more appropriate cutoff values. Therefore, an examination of alternative cutoff values was undertaken. The following alternative cutoff values were examined: (a) For the CFI, GFI, NFI, NNFI, and RNI, cutoff values were examined in increments of .01 from .90 to 1.00; (b) for the CN, cutoff values were examined in increments of 10.00 from 210.00 to 300.00; (c) for the RMSEA, cutoff values were examined in increments of .01 from .01 to .10; and (d) for the chi-square test statistic, the probability value was adjusted in increments of .01 from .05 to .15.

Results

Overview

The results from Study 2 are presented in three sections. The first section includes a random assessment of multivariate normality, and information regarding the number of solutions that failed to converge. The second section describes the findings from the analyses of variance to assess the main effects of sample size, number of indicators per latent variable, and model misspecifications within each simulation. The third section describes the findings using the recommended cutoff values for the goodness-of-fit indices. This latter section also provides information regarding the use of alternative cutoff values.

Tests of Multivariate Normality

Prior to generating the fit statistics, tests of multivariate normality were conducted on the raw data sets. PRELIS 2.14 (Jöreskog & Sörbom, 1993b) was used to test for zero multivariate skewness and zero multivariate kurtosis. These multivariate tests were developed by D'Agostino (1986), Mardia (1970), and Mardia and Foster (1983). Because the tests of multivariate normality are extremely time-consuming, 25% of the Monte Carlo cells (N = 90 total, with 30 cells per simulation study, respectively) were randomly sampled to test for multivariate normality.

Violations from multivariate normality were observed in 10% of the simple and moderate cells (N = 3, 3, respectively) and 13% (N = 4) of the complex cells. Inspection of the matrices showing departures demonstrated that the violations were not particularly extreme. That is, values for multivariate skewness and kurtosis were never greater than 5.00. Similarly, values for univariate skewness and kurtosis were never greater than 8.3.

Nonconvergent Solutions

In the current research, an observation was regarded as nonconvergent if the maximum likelihood estimation procedure did not yield a solution after a predetermined number of iterations. For each LISREL program, the number of iterations was predetermined as three times the number of free parameters (i.e., the default value for LISREL 8.14).

Nonconvergent solutions occurred only in sample sizes of 500 or less, and predominantly when the sample size was 100 or 200. As an example, in the simple model, between 4 to 31 of the solutions failed to converge when the sample size was 100. Similarly, nonconvergent solutions in the moderate and complex models ranged between 1 and 12 when the sample size was 100. The frequency distributions for nonconvergent solutions in the simple, moderate, and complex models are presented in Table 14.

Main Effects

Table 15 presents the η^2 values for each level of model complexity obtained from the analyses of variance. An η^2 less than .03 (presented in the table as 0.00) was considered a negligible effect even though the *F* test may have been significant. All interaction effects were ordinal and are discussed after the main effects.

Table 14

Frequency Distributions of Nonconvergent Solutions for the Simple, Moderate, and Complex Models

	N = 100	N = 200	N = 500
Simple Model			
True	4		
Omission	31	4	1
Inclusion	9		
Combination	16	12	
Moderate Model			
True	6	2	8
Omission	10		
Inclusion	13	4	1
Combination	9	4	
Complex Model			
True	10	2	
Omission	16	2	
Inclusion	4	3	
Combination	17	4	

Note. Each simulation cell generated 200 replications.

Mean scores, standard deviations, and minimum and maximum values for the goodness-of-fit indices as a function of sample size, number of indicators per latent variable, and model misspecifications are presented in Appendices K, L, and M (simple, moderate, and complex conditions of model complexity, respectively).

Sample size. Figures 6, 7, and 8 demonstrate the effects of sample size on the goodness-of-fit indices in the simple, moderate, and complex models, respectively (see

Table 15

η^2 Values for the Fit Indices as a Function of the Study Conditions in the Simple, Moderate, and Complex Models

	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
Simple Model								
Sample Size(S)	.41	.00	.19	.21	.27	--	.00	.00
Indicators(I)	.28	.33	.04	.66	.25	.49	.40	.31
Misspecif-ications(M)	.00	.00	.09	.00	.00	.00	.00	.00
S*I	.31	.00	.06	.08	.00	.00	.00	.00
S*M	.00	.00	.07	.00	.00	.00	.00	.00
I*M	.00	.10	.00	.00	.08	.00	.00	.10
S*I*M	.00	.00	.00	.00	.00	.00	.00	.00
Moderate Model								
Sample Size (S)	.36	.00	.16	.46	.05	.00	.00	.00
Indicators(I)	.23	.39	.05	.14	.35	.39	.25	.38
Misspecif-ications(M)	.09	.18	.10	.14	.18	.16	.40	.19
S*I	.16	.00	.07	.15	.00	.00	.00	.00
S*M	.13	.00	.15	.00	.00	--	.00	.00
I*M	.00	.39	.06	.00	.38	.41	.31	.40
S*I*M	.00	.00	.00	.00	.00	.00	.00	.00
Complex Model								
Sample Size (S)	.35	.00	.22	.42	.32	.00	.00	.00
Indicators(I)	.31	.34	.21	.40	.19	.44	.46	.34
Misspecif-ications(M)	.06	.27	.14	.05	.19	.17	.25	.27
S*I	.30	.00	.16	.11	.05	.00	.00	.00
S*M	.00	.00	.07	.00	.00	.00	.00	.00
I*M	.00	.30	.09	.00	.21	.31	.21	.30
S*I*M	.00	.00	.00	.00	.00	.00	.00	.00

Note. The following abbreviations were used: χ^2 = chi-square test statistic, CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; I = Number of indicators per latent variable; M = Model misspecifications; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; S = Sample size. All η^2 were rounded to the second decimal. All entries were statistically significant (p<.01) except for those omitted (i.e., --).

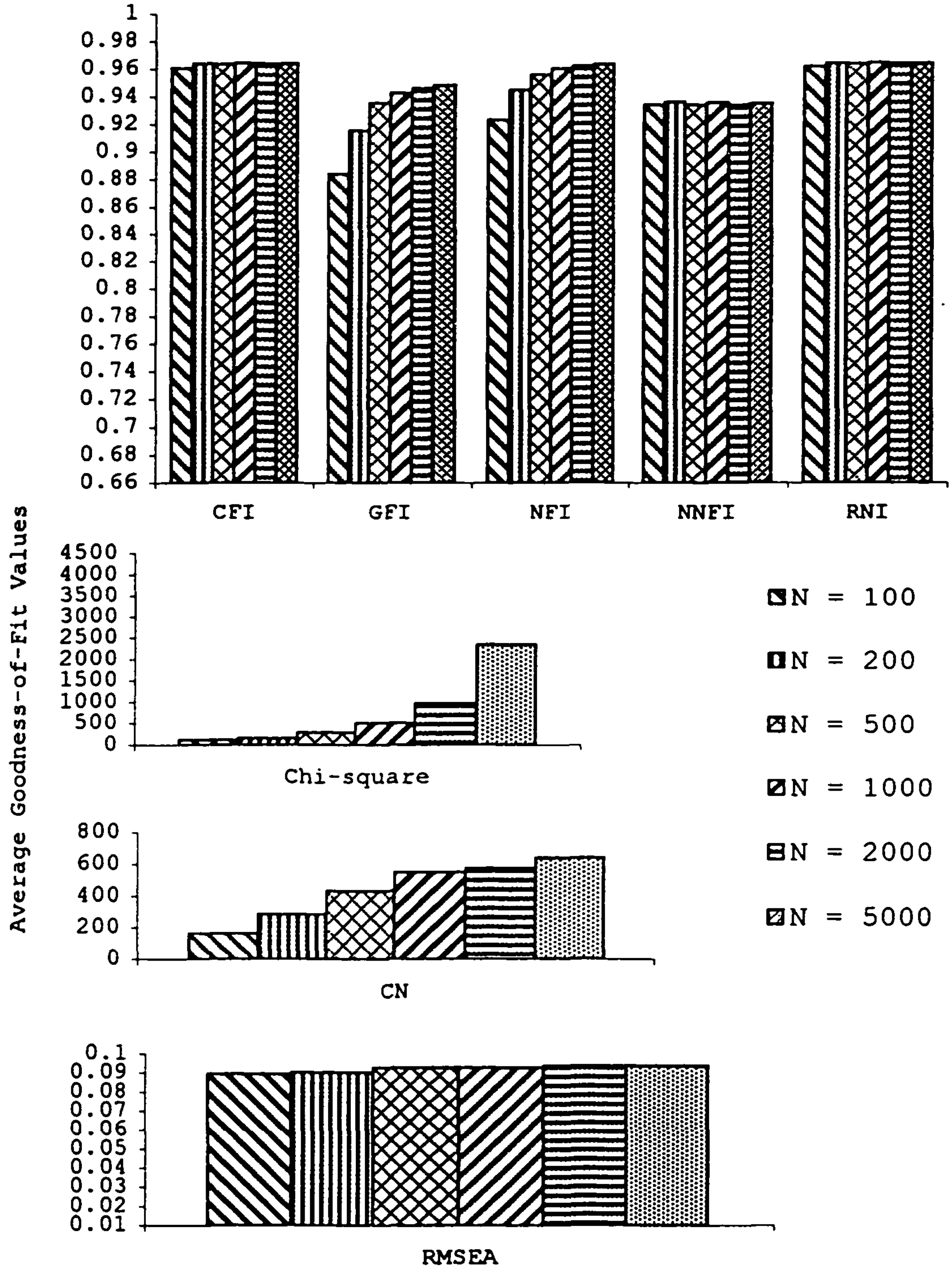


Figure 6. The effect of sample size on the fit indices in the Monte Carlo simulation for the simple model.

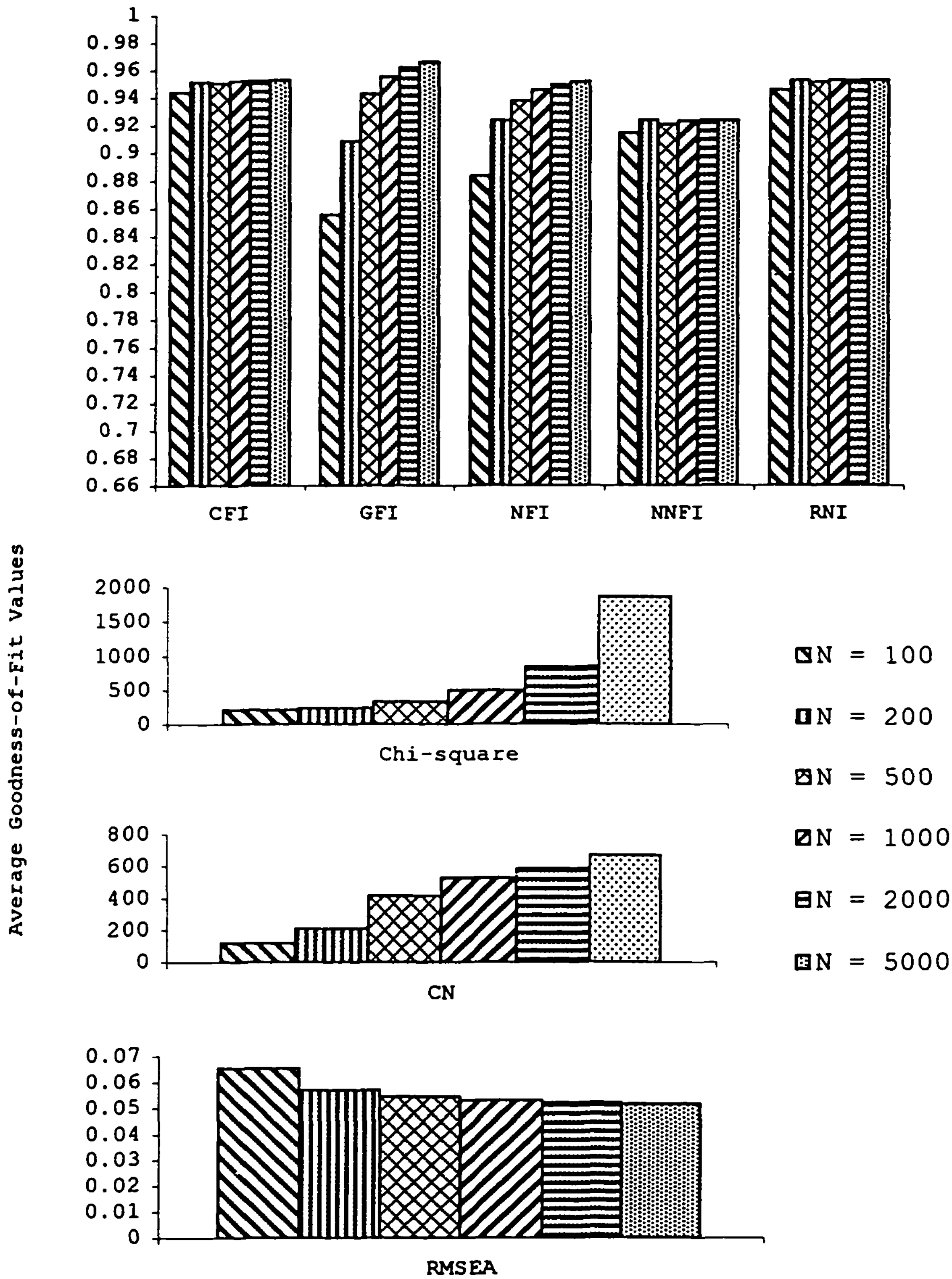


Figure 7. The effect of sample size on the fit indices in the Monte Carlo simulation for the moderate model.

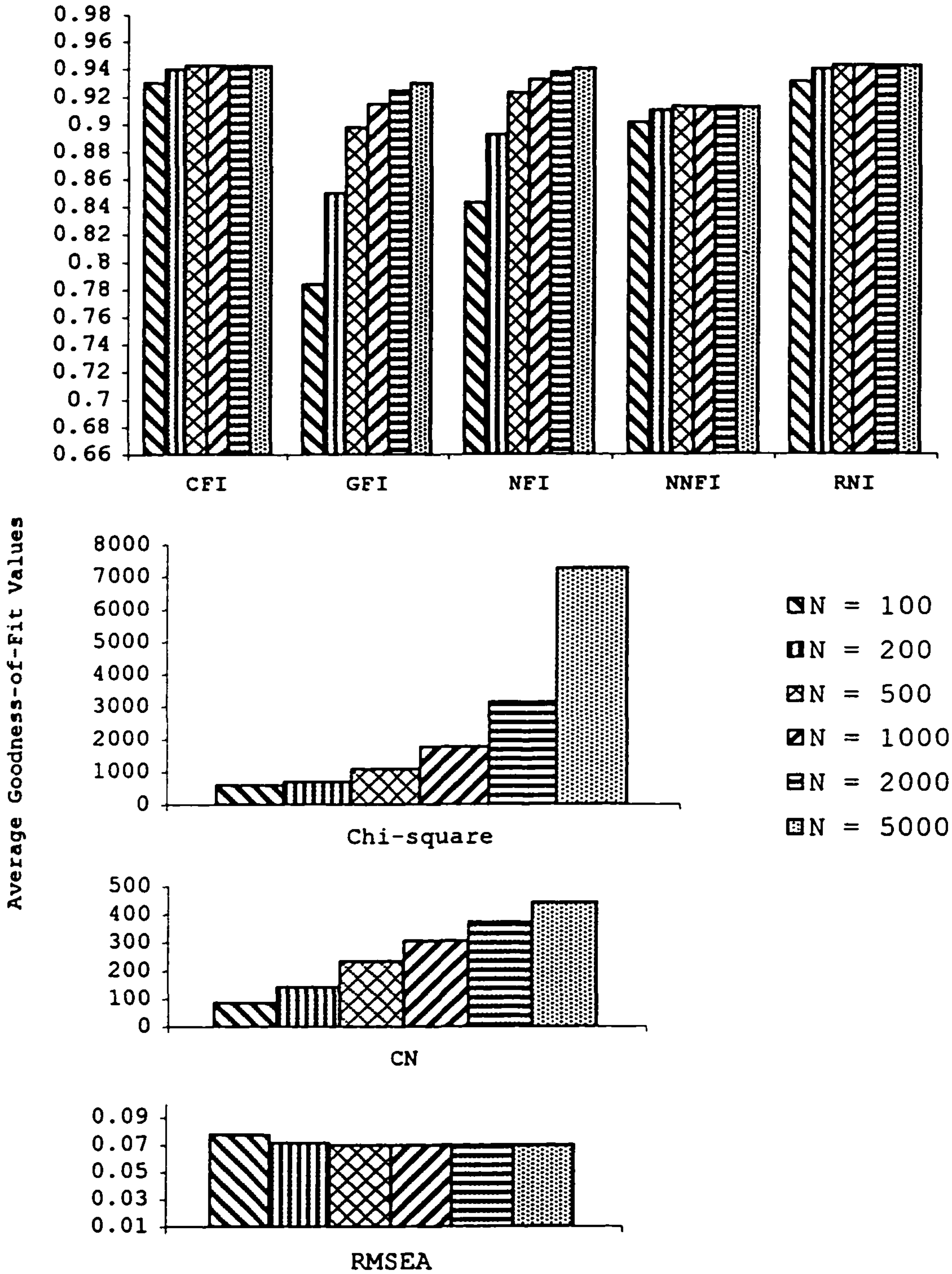


Figure 8. The effect of sample size on the fit indices in the Monte Carlo simulation for the complex model.

Appendix N for mean values of the fit indices as a function of sample size). These sample size effects on the fit indices were primarily replications of previous studies (e.g., Andersen & Gerbing, 1984; Bearden et al., 1982; Bentler, 1990; Marsh et al., 1988).

Across the simple, moderate, and complex models, sample size effects were noted for the chi-square test statistic, GFI, and NFI. As expected, increases in sample size resulted in increases in the values of the chi-square test statistic, suggesting poorer fit. In contrast, increases in sample size resulted in improved values for the GFI and NFI across all models, suggesting better fit. For example in the simple model, the average value for the GFI was .884 when the sample size was 100, whereas a sample size of 5000 resulted in a mean GFI value of .948. A similar pattern was noted with the NFI. The average NFI value in the moderate model was .883 when the sample size was 100, whereas a sample size of 5000 yielded an average NFI value of .967.

Although the same pattern of increasing GFI and NFI values was noted in the complex model, the average values across all sample sizes were lower than those exhibited in the simple and moderate models. For example, the average GFI value for a sample size of 100 was .884, .856, and .784

in the simple, moderate, and complex models, respectively. Similarly, the average NFI value for a sample size of 5000 was .963, .951, and .940 in the simple, moderate, and complex models, respectively.

In support of Hu and Bentler (1995), sample size effects were found for the CN in the simple, moderate, and complex models. That is, increases in sample size led to increases in average CN values. For example, at a sample size of 100, the average CN value was 166, 122, and 86 in the simple, moderate and complex models, respectively. However, increases in the sample size from 200 to 5000 led to CN values ranging from 284 to 640 in the simple model, from 211 to 668 in the moderate model, and from 141 to 444 in the complex model.

In agreement with prior research (e.g., Bentler, 1990; Marsh et al., 1988; Mulaik et al., 1989), no sample size effects were noted for the CFI, NNFI, RMSEA, or RNI in the simple, moderate, or complex models. Although most of these indices exhibited a slight improvement in average values when the sample size increased from 100 to 200, average values changed very little with additional increases in sample size. For example, the average CFI value rose from .93 (N = 100) to .94 (N = 200) in the complex model. However, between a sample size of 500 and

5000, the average CFI values ranged from .942 to .943.

A follow-up one-way analysis of variance supported the hypothesis that standard deviations, analyzed with a square root transformation, at a sample size of 100 were significantly larger for the NNFI than for the CFI, GFI, NFI, and RNI. Results indicated that standard deviations for the NNFI were significantly larger when the sample size was 100, F (4, 295) = 41.06. That is, when the sample size was 100, the average standard deviation for the NNFI was .04 (SD = .059), whereas the average standard deviations for the CFI, GFI, NFI, and RNI were .02 (SD = .022), .015 (SD = .004), .02 (SD = .02), and .022 (SD = .023), respectively.

Number of indicators per latent variable. Figures 9, 10, and 11 demonstrate the effects of number of indicators per latent variable on the goodness-of-fit indices in the simple, moderate, and complex models, respectively (see Appendix O for mean values of the fit indices as a function of number of indicators). A main effect for number of indicators per latent variable was found for each of the indices in the simple, moderate, and complex models.

For the chi-square test statistic, increases in the number of indicators per latent variable resulted in increases in chi-square values for all models, suggesting

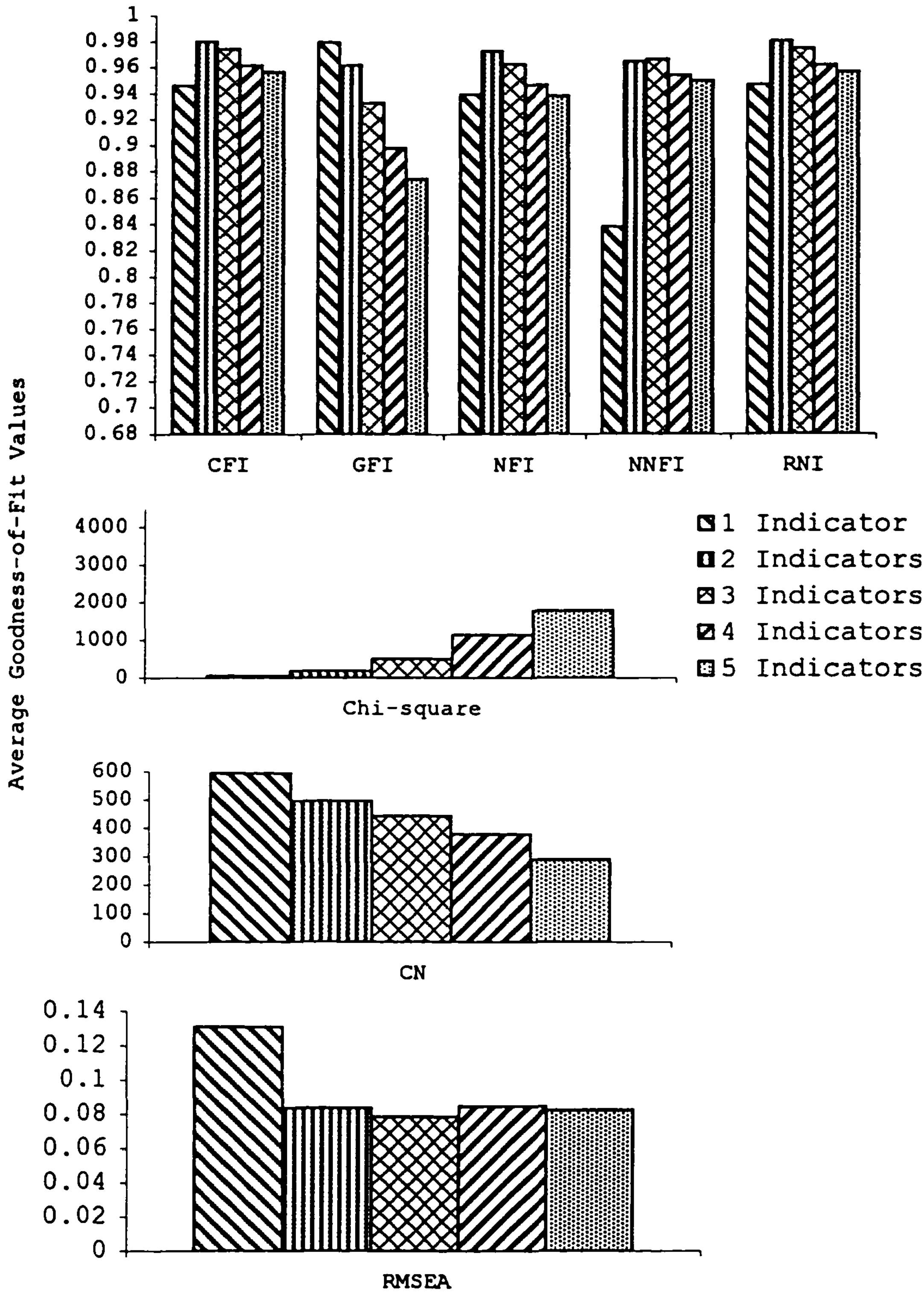


Figure 9. The effect of indicators per latent variable on the fit indices in the Monte Carlo simulation for the simple model.

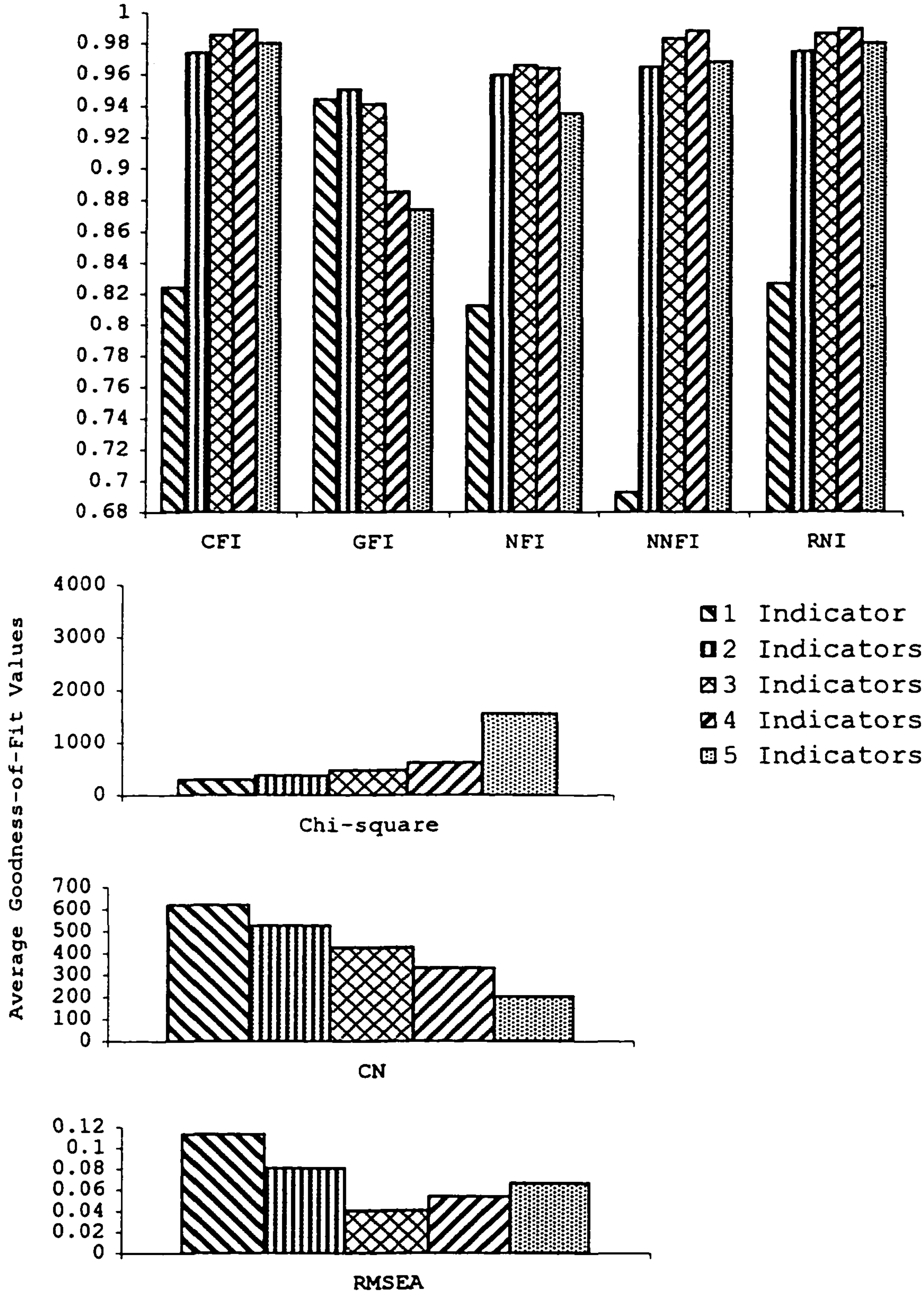


Figure 10. The effect of indicators per latent variable on the fit indices in the Monte Carlo simulation for the moderate model.

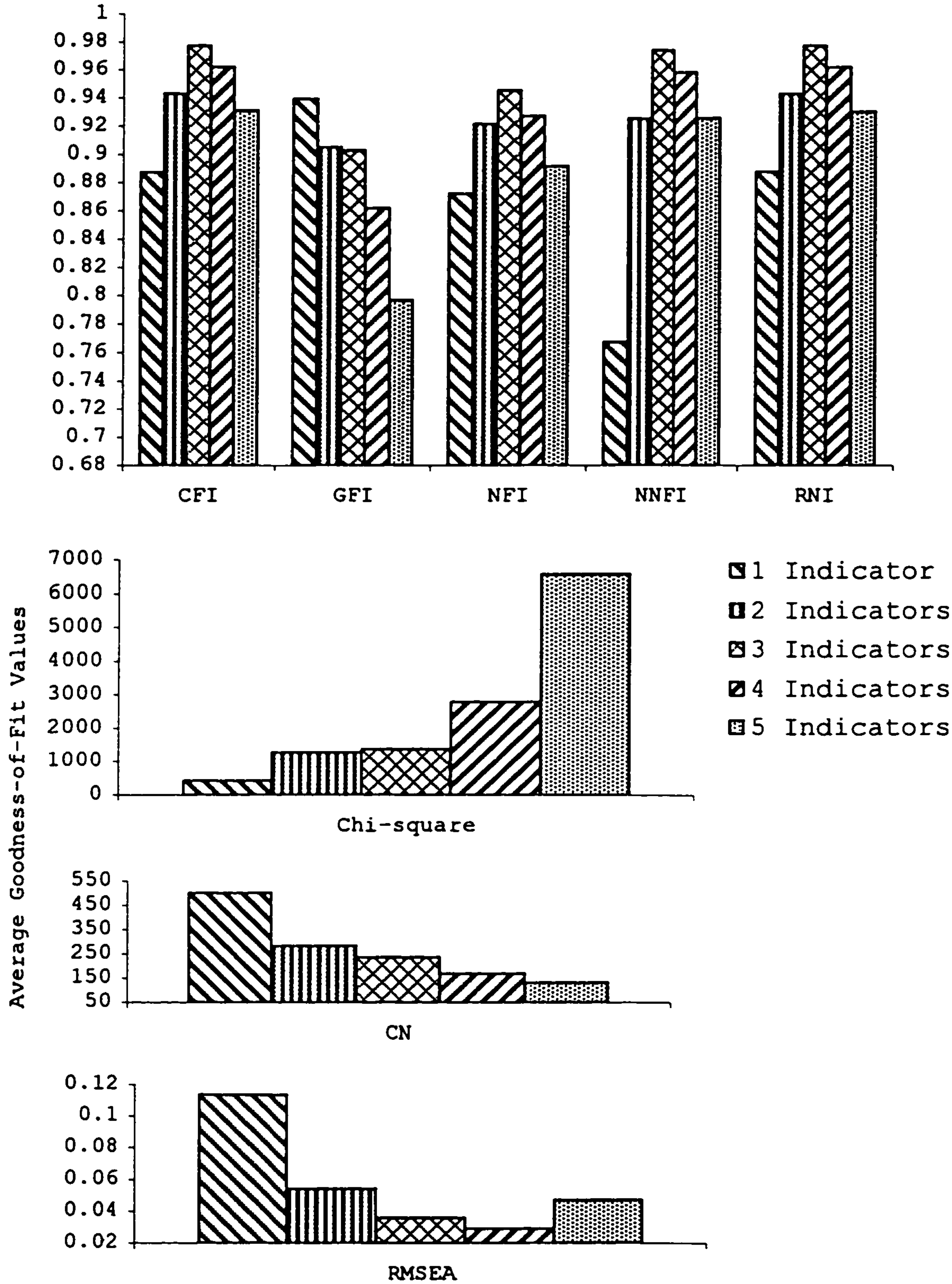


Figure 11. The effect of indicators per latent variable on the fit indices in the Monte Carlo simulation for the complex model.

poorer fit. Similarly, increases in the number of indicators per latent variable resulted in decreases in CN and GFI values for all models, suggesting poorer fit. For example, in the simple model, the average GFI value was decreased from one to five indicators (i.e., from .979, .961, .932, .897, to .874, respectively).

In agreement with Ding et al. (1995), number of indicator effects were found for the CFI, NFI, NNFI, and RNI across the simple, moderate, and complex models. Average values for the four indices were lowest when the model used one indicator and increased when the model specified two indicators. For example, average CFI values for one and two indicator models rose from .946 to .980, from .824 to .974, and from .888 to .943 in the simple, moderate, and complex models, respectively. Much larger increases were noted in average NNFI values from one to two indicator models. In particular, mean NNFI values for one and two indicator models rose from .838 to .964, from .693 to .965, and from .767 to .925 in the simple, moderate, and complex models, respectively.

As the number of indicators increased from two to five, average values for the CFI, NFI, NNFI, and RNI changed very little from two to four indicators. However, when five indicators were specified, average values for the

CFI, NFI, NNFI, and RNI decreased.

For the RMSEA, an increase from one to three indicators resulted in smaller values in the simple and moderate models, suggesting better fit. However, an increase from four to five indicators resulted in larger values in the simple and moderate models, suggesting poorer model fit. In comparison, average RMSEA values in the complex model decreased from one to four indicators, but increased at five indicators.

Model misspecifications. Figures 12, 13, and 14 depict the effects of model misspecifications on the fit indices in the simple, moderate, and complex models, respectively (see Appendix P for mean scores of the indices as a function of model misspecifications).

The CN was the only index to successfully detect omission and combination conditions in the simple model. However, all indices were able to detect omission and combination conditions in the moderate and complex models.

In support of La Du and Tanaka (1989), misspecified models that omitted correct structural paths (i.e., the omission and combination conditions) resulted in fit values suggesting poorer model fit than when the model was correctly specified or included an incorrect structural path. Moreover, indices rewarded models that specified an

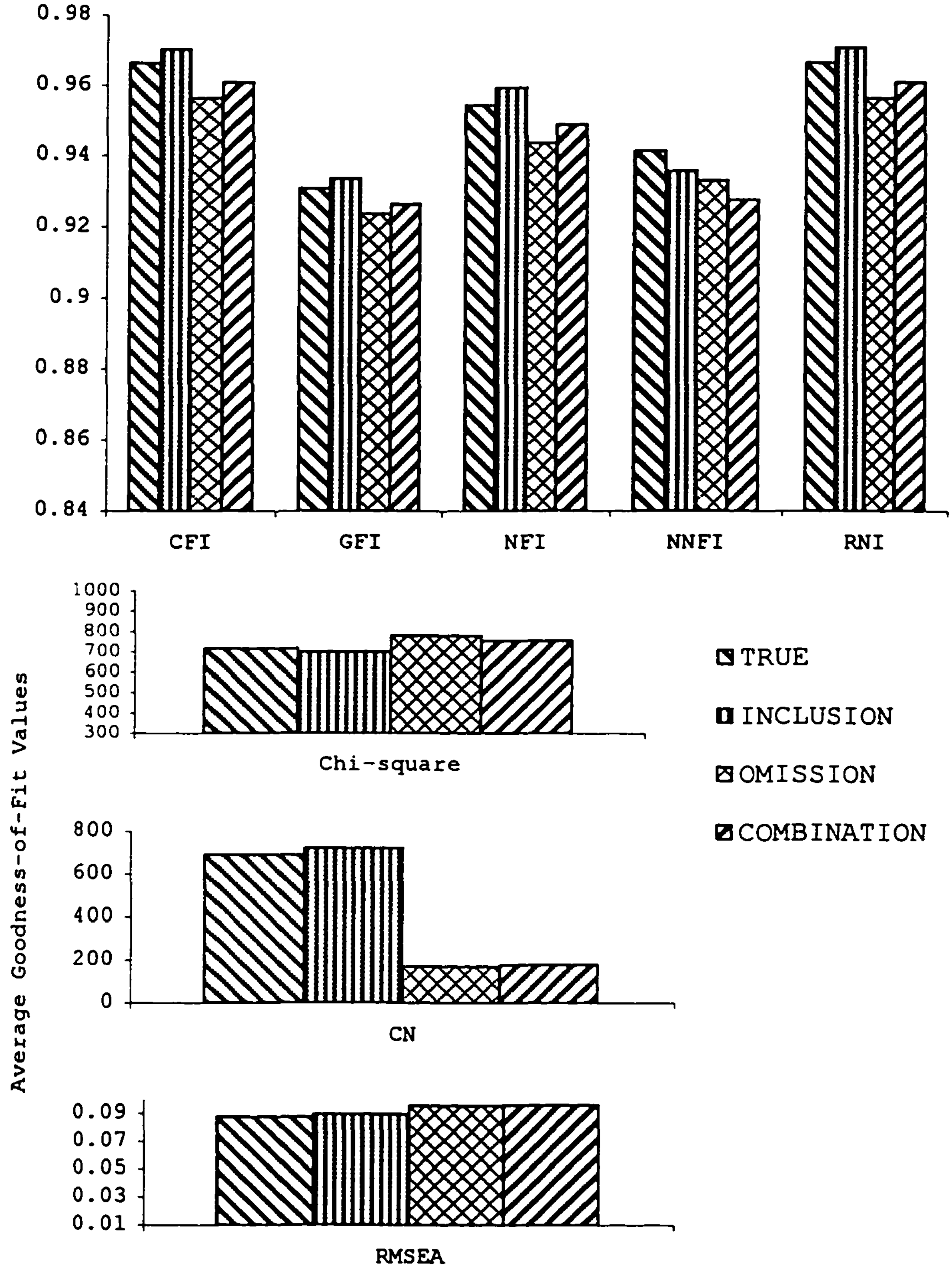


Figure 12. The effect of model misspecifications on the fit indices in the Monte Carlo simulation for the simple model.

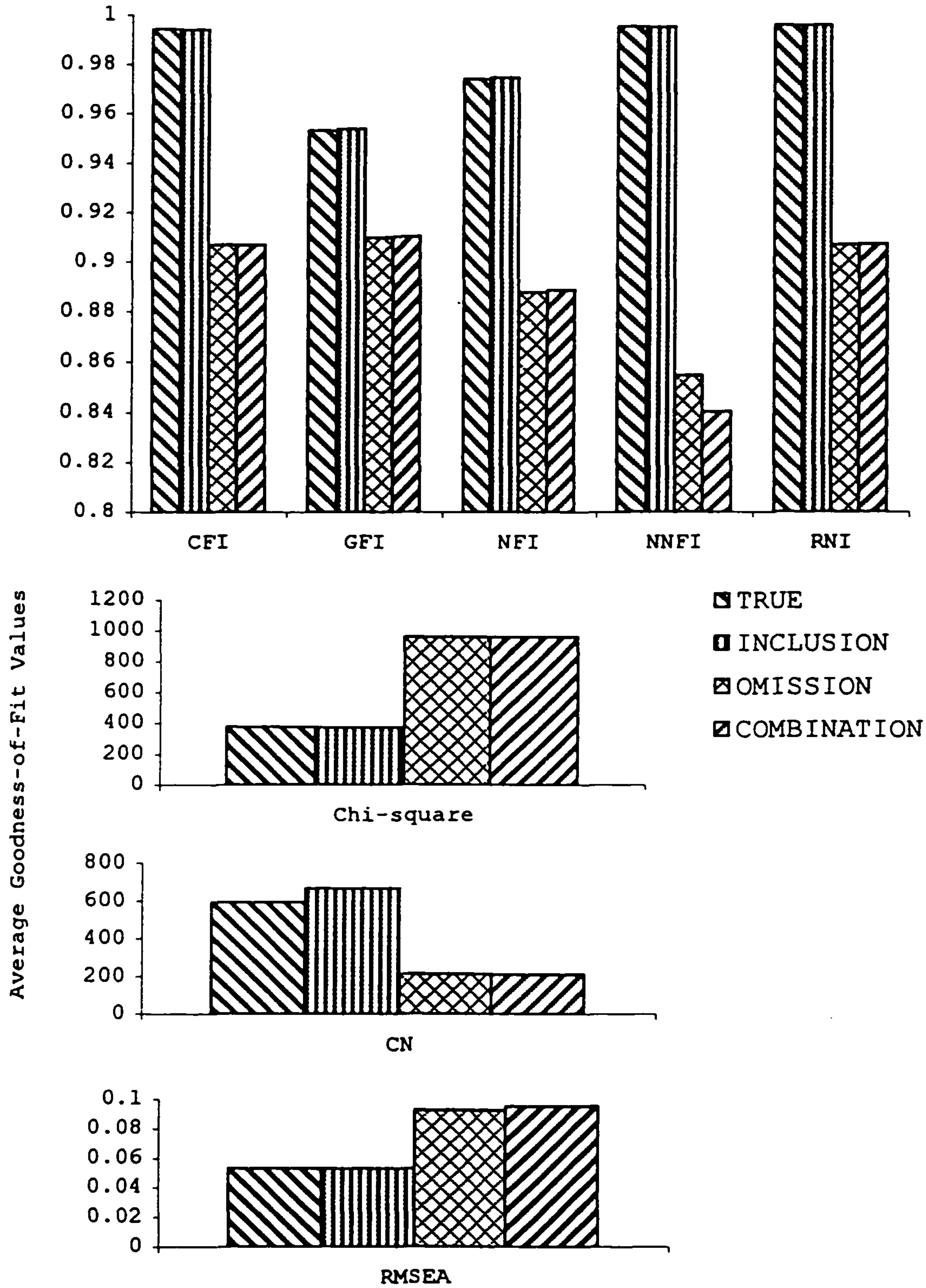


Figure 13. The effect of model misspecifications on the fit indices in the Monte Carlo simulation for the moderate model.

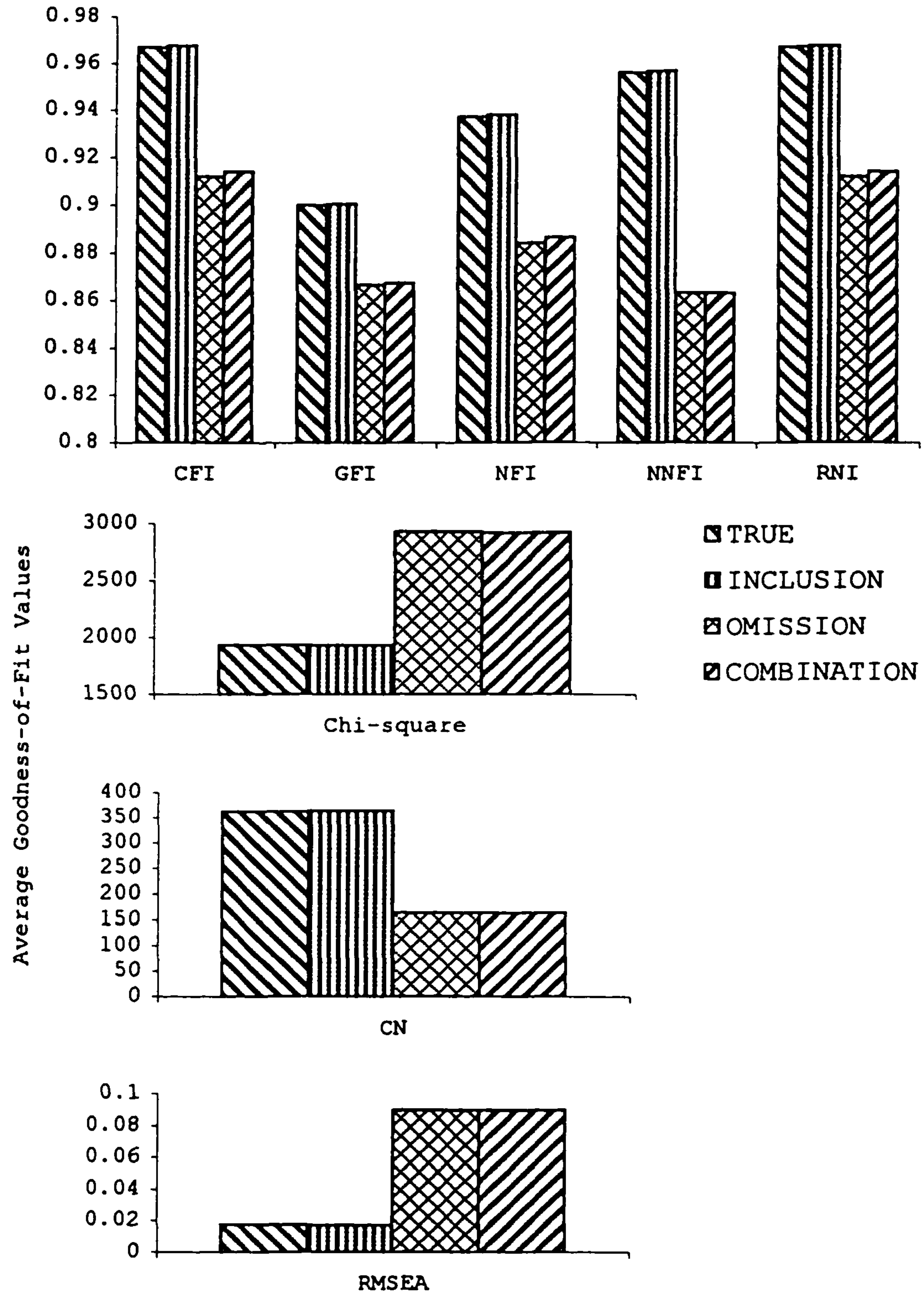


Figure 14. The effect of model misspecifications on the fit indices in the Monte Carlo simulation for the complex model.

incorrect structural path (i.e., an inclusion condition) with values that suggested the same or better fit than the true condition. For the CFI, CN, GFI, NFI, NNFI, and RNI, the average values for the inclusion condition in the moderate and complex models were the same or slightly higher than the values for the true condition. For the chi-square statistic, models that were specified correctly (i.e., true) or had incorrect added paths (i.e., inclusion) had chi-square values that were significantly lower than models with omitted paths.

Interaction Effects

Significant interaction effects were exhibited in each simulation and are presented in Table 15 (see p. 159). Tests of simple main effects were conducted to facilitate interpretation of the interactions. Because all of the interactions were ordinal in nature, they intensified the main effects discussed in the preceding sections.

Sample size by number of indicators per latent variable. Interaction effects were noted for the chi-square test statistic, CN, and GFI in all models, and for the NFI in the complex model.

For the chi-square statistic, increases in the sample size and number of indicators per latent variable resulted in significantly more pronounced increases in the average values of the chi-square test statistic than when the sample size was smaller or there were fewer indicators. Figure 15 depicts the interaction on the chi-square test statistic in the simple model for illustrative purposes.

The profiles of CN values were parallel and increasing in value across levels of indicators when sample sizes were between 500 and 5000. However, when the sample size was small, decreases in the number of indicators led to significantly more pronounced increases in average CN values. Figure 16 depicts the interaction on the CN in the simple model.

For the GFI, when the sample size was large (i.e., 1000 or greater), average values changed very little across levels of indicators (see Figure 17). However, as the sample size decreased, average values decreased significantly as the number of indicators was increased.

For the NFI, the profiles for two to five indicators were parallel and increasing across increases in sample size. The interaction of sample size and number of indicators per latent variable on the NFI in the complex model is presented in Figure 18. However, the one indicator profile differed because NFI values remained flat across increases in sample size.

As hypothesized, no interaction effects were noted for

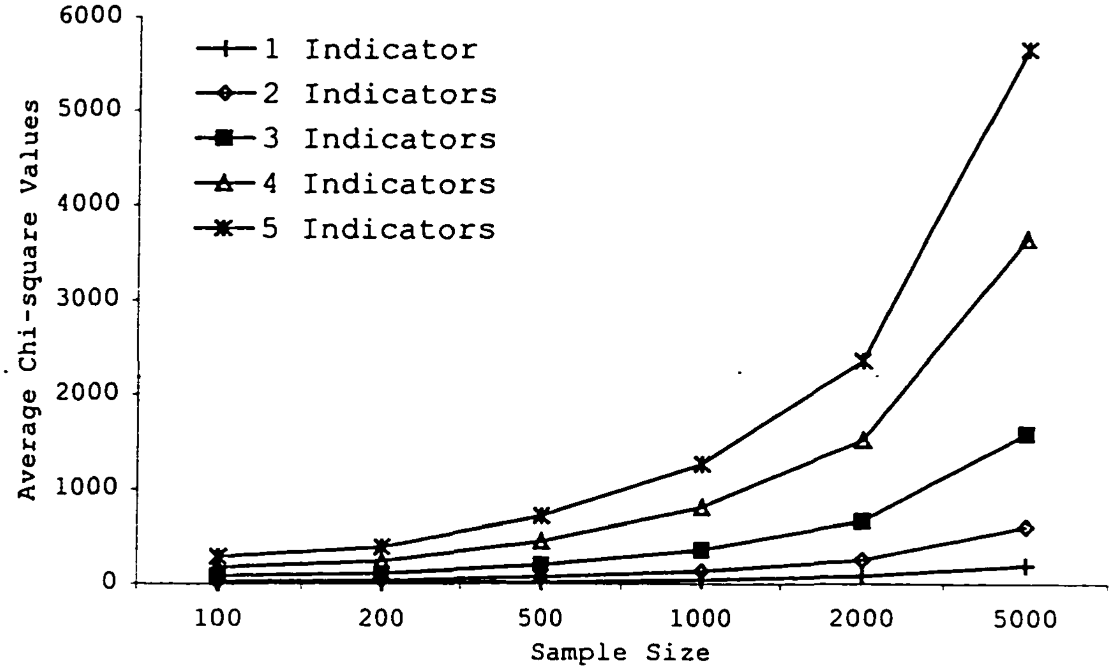


Figure 15. Chi-square test statistic values as a function of sample size and number of indicators per latent variable in the simple model.

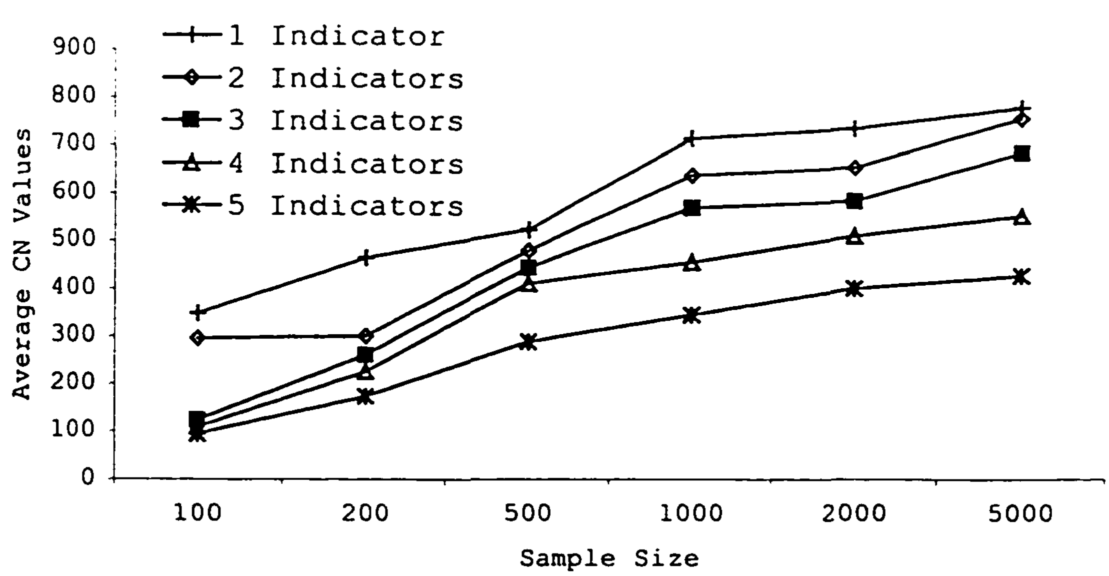


Figure 16. CN values as a function of sample size and number of indicators per latent variable in the simple model.

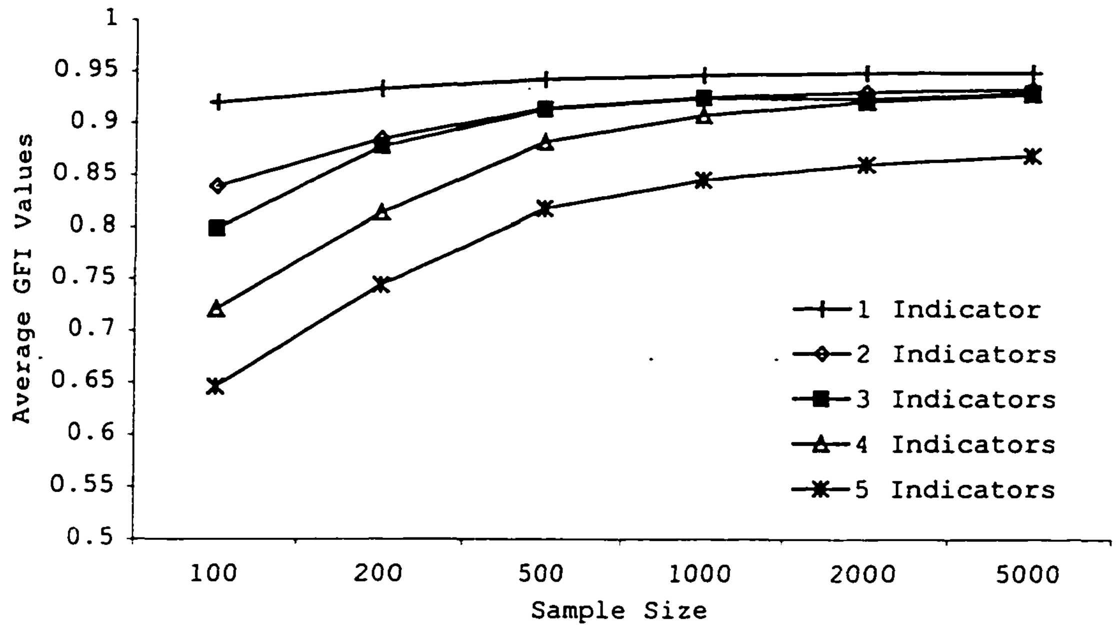


Figure 17. Average GFI values as a function of sample size and number of indicators per latent variable in the complex model.

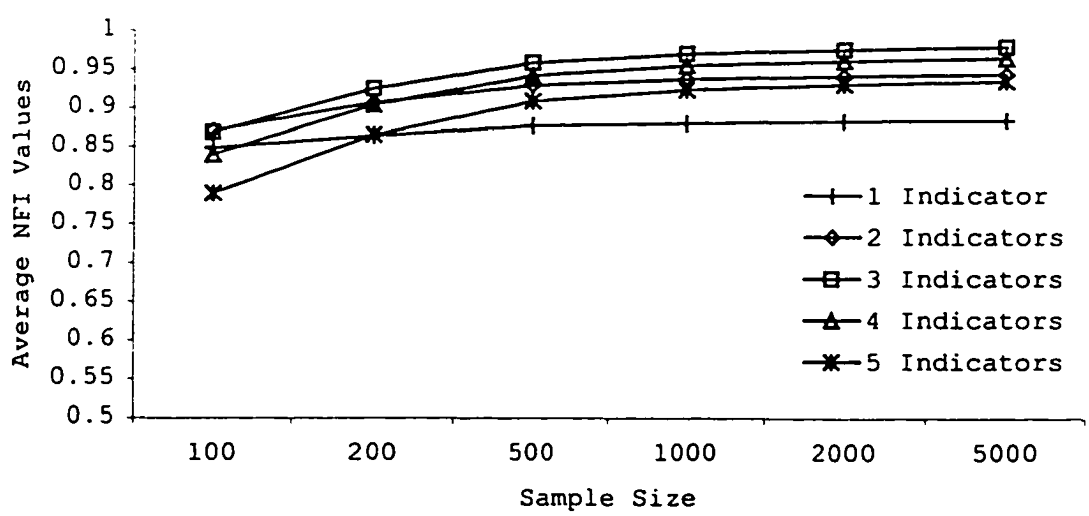


Figure 18. Average NFI values as a function of sample size and number of indicators per latent variable in the complex model.

average RMSEA values. In contrast to Ding et al. (1995) and the current hypotheses, no interaction effects were noted for the CFI, NNFI, or RNI.

Sample size by model misspecifications. Interaction effects were exhibited for the chi-square test statistic in the moderate model, and for the CN in the simple, moderate, and complex models. No other interaction effects were noted, supporting hypotheses regarding the CFI, RMSEA, and RNI. However, no support was found for the expected interaction for the GFI and NFI.

For the chi-square test statistic and CN, increases in sample size led to greater differences in average values for the omission and combination conditions of model misspecifications versus the true and inclusion conditions. Figure 19 presents the effects of sample size and model misspecifications on average chi-square values for illustrative purposes. For example, when the sample size was 100, the average chi-square value for a true specification was 198. Increasing the sample size to 5000 yielded an average value of 868. The average chi-square value for an omission condition when the sample size was 100 was 239. However, increasing the sample size to 5000 resulted in an average chi-square value of 2843. Thus, in contrast to the study hypotheses, as the sample size

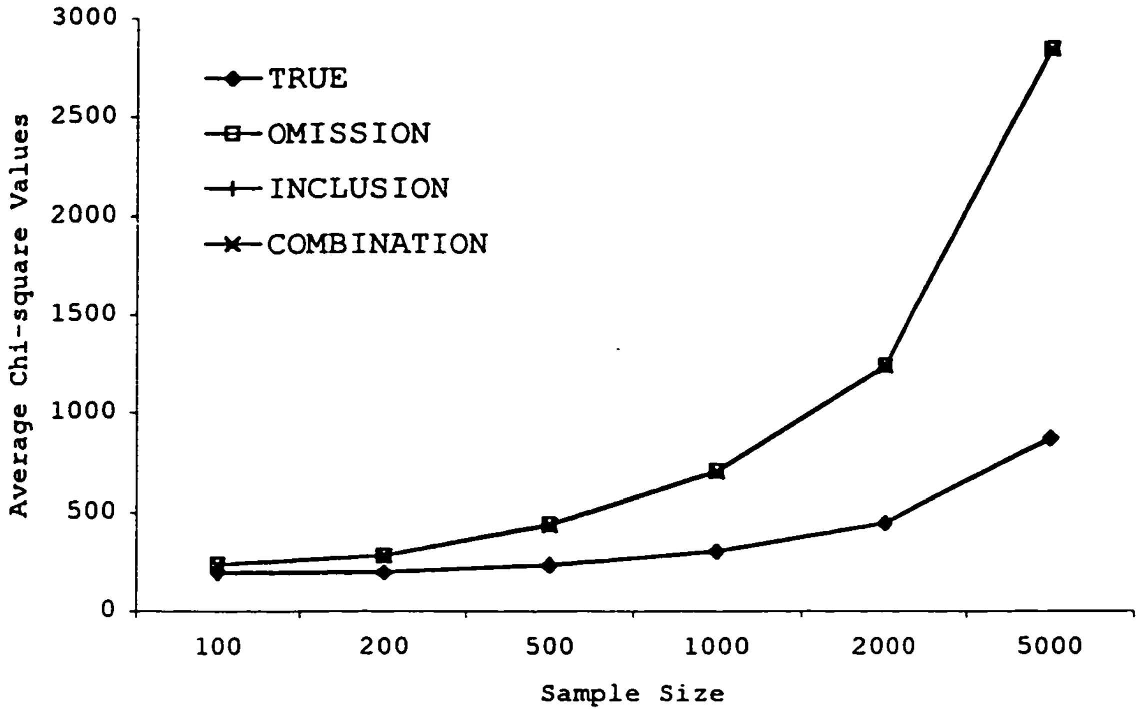


Figure 19. Average chi-square values as a function of sample size and model misspecifications in the moderate model.

increased, the chi-square test statistic detected omitted misspecifications more accurately as evidenced by the increasing discrepancy in average values from true and inclusion conditions versus the omission and combination conditions.

Number of indicators per latent variable by model misspecifications. Interaction effects with η^2 of .03 or greater were demonstrated for the CFI, NFI, and RNI in all models, and the NNFI and RMSEA in the moderate and complex models. In contrast to the study hypotheses, no interaction effects were noted for the chi-square statistic in any of the models.

In particular, for the CFI, NFI, NNFI, and RNI, when two or more indicators were specified, average values within the given indicator level changed very little across the conditions of model misspecifications (see Figures 20 and 21 to view the interaction on average CFI and NNFI values). However, when one indicator was specified, average values for the true and inclusion conditions were significantly greater than for the omission and combination conditions.

The one indicator profile behaved similarly for the CFI, NFI, NNFI, and RNI. However, the discrepancy between average values for the true and inclusion conditions versus omission and combination conditions was most pronounced for the NNFI. That is, the average NNFI values for omission or combination conditions was approximately .60, whereas average values for the remaining indices under omission and combination conditions was .90 or greater.

The profiles of RMSEA values were parallel for two to four indicators across levels of model misspecifications (see Figure 22). The one indicator profile for the RMSEA exhibited more pronounced differences in average values for true and inclusion conditions versus the omission and

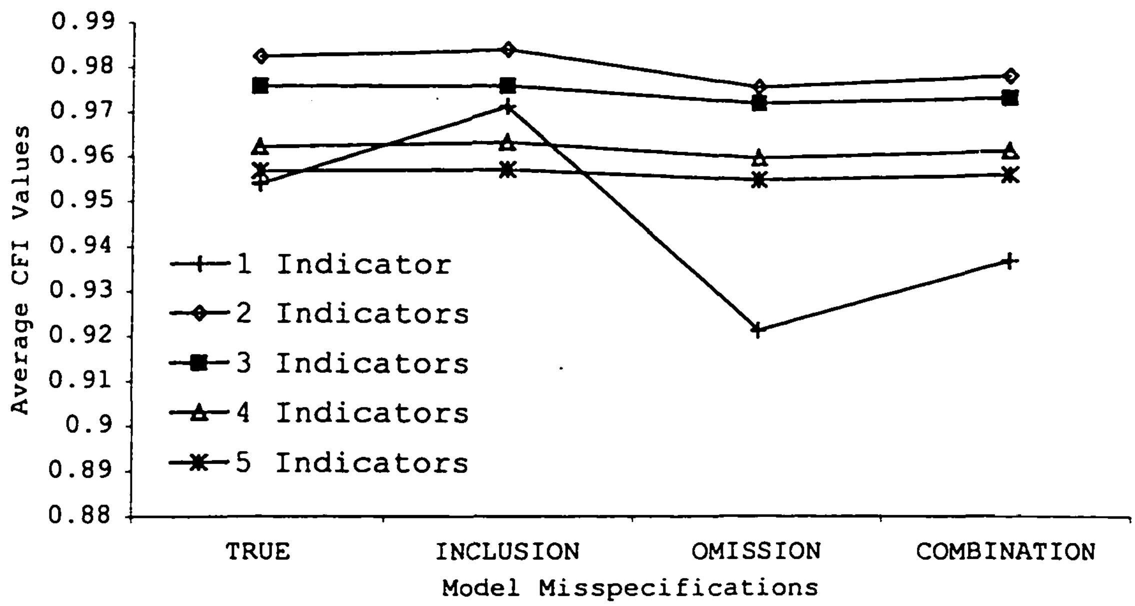


Figure 20. Average CFI values as a function of number of indicators per latent variable and model misspecifications in the simple model.

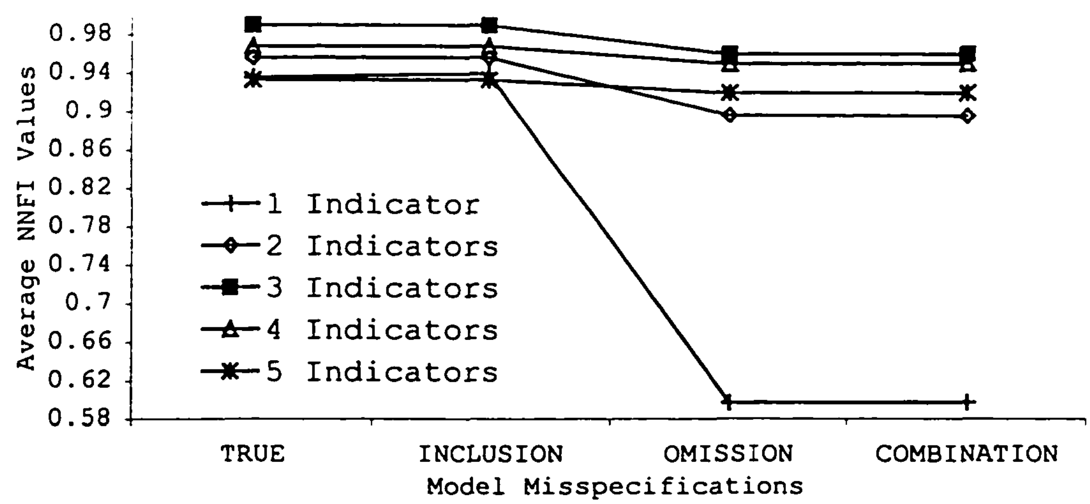


Figure 21. Average NNFI values as a function of number of indicators per latent variable and model misspecifications in the complex model.

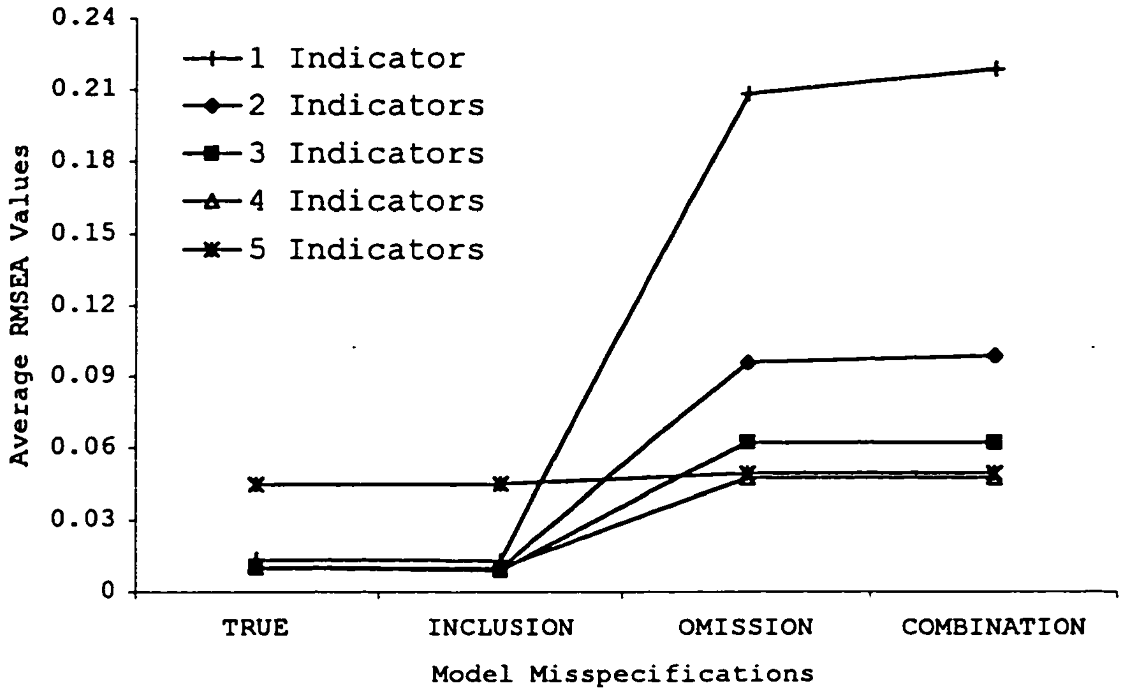


Figure 22. Average RMSEA values as a function of number of indicators per latent variable and model misspecifications in the moderate model.

combination conditions than the two to four indicator profiles. In comparison, the five indicator profile for the RMSEA was flat across levels of model misspecifications.

Summary of Monte Carlo Findings

According to Marsh et al. (1988), an ideal goodness-of-fit index should be independent of sample size, easily interpreted, and replicable when tested with new data. Further, an ideal index should be relatively unaffected by model features such as number of indicators and model complexity (Cudeck & Henly, 1991; Gerbing & Andersen, 1993). Moreover, an ideal goodness-of-fit index should reward true models with values suggesting better fit, and penalize misspecified models with values suggesting poorer fit.

The results from the Monte Carlo simulations demonstrate that none of the indices examined displayed all of these features. However, the results did show that the indices were affected differentially by the study conditions. Table 16 presents a summary of the effects noted in the simulations.

Several of the indices were relatively independent of sample size effects. In particular, the CFI, NNFI, RMSEA, and RNI were unaffected by sample size in the simulations. In other words, values for these indices remained relatively stable across increases or decreases in sample size. However, the chi-square statistic, CN, GFI, and NFI demonstrated sample size effects in the simulations. In particular, chi-square values suggested poorer fit with increases in sample size, whereas values for the CN, GFI, and NFI suggested better fit with sample size increases. Of particular concern is the fact that the chi-square statistic and CN were affected at almost every level of sample size. For the GFI, sample size effects tended to

Table 16

Summary of Findings for the Goodness-of-Fit Indices in the Monte Carlo Simulations

Index	Sample Size	Number of Indicators per Latent Variable	Model Misspecifications
Chi-square statistic	Values increase when sample size increases.	Values increase when number of indicators increase.	Omission and combination conditions detected in moderate and complex models.
CFI	No effect noted.	Values lowest at one indicator; relatively stable from two to five indicators.[a]	Omission and combination conditions detected in moderate and complex models.
CN	Values increase when sample size increases.	Values decrease when number of indicators increase.	Omission and combination conditions detected in all models.
GFI	Values increase when sample size increases, but stabilize when sample size is 500 or greater.	Values decrease when number of indicators increase.	Omission and combination conditions detected in moderate and complex models.
NFI	Values increase when sample size increases, but stabilize when sample size is 200 or greater.	Values lowest at one indicator; relatively stable from two to five indicators.[a]	Omission and combination conditions detected in moderate and complex models.

Table 16 concluded

Index	Sample Size	Number of Indicators per Latent Variable	Model Misspecifications
NNFI	No effect noted, however, index exhibits more variability than CFI, GFI, NFI, and RNI when the sample size is 100.	Values lowest at one indicator; relatively stable from two to five indicators.[a]	Omission and combination conditions detected in moderate and complex models.
RMSEA	No effect noted.	Values decrease when number of indicators increase from one to four.[b]	Omission and combination conditions detected in moderate and complex models.
RNI	No effect noted.	Values lowest at one indicator; relatively stable from two to five indicators.[a]	Omission and combination conditions detected in moderate and complex models.

Note. The following abbreviations have been used: CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index.

[a]Values tended to decrease slightly at five indicators.

[b]Values tended to increase at five indicators.

stabilize when the sample size was 500 or greater, whereas NFI values tended to stabilize when the sample size was 200 or greater.

Effects for number of indicators per latent variable were exhibited for each of the indices in the simulations. For the chi-square statistic, CN, and the GFI, increases in the number of indicators led to values suggesting poorer fit. In comparison, increases in the number of indicators led to values suggesting better fit for the RMSEA. Values for the CFI, NFI, NNFI, and RNI were lowest at one indicator, increased from two to four indicators, and tended to decrease slightly at five indicators.

Importantly, all of the indices detected the omission and combination conditions of model misspecifications in the moderate and complex models. However, the CN was the only index to detect omission and combination conditions in the simple model. As noted by La Du and Tanaka (1989), the inclusion condition of model misspecifications was not detected accurately by any of the indices in the simulations. In fact, the indices often rewarded the inclusion condition of model misspecifications with greater values than the correct specification.

Examining Recommended Cutoff Values

The purpose of examining the recommended cutoff values was to determine whether these values detect model misspecifications. The recommended cutoff values should assist researchers by rewarding true models with values suggesting acceptable model fit, and penalizing misspecified models with values suggesting unacceptable fit. If the values do not penalize misspecified models, researchers will draw erroneous conclusions about model fit.

The percentages of model acceptance using the recommended cutoff values were calculated as the frequency of solutions that accepted the model divided by the maximum number of solutions. A series of analyses of variance were conducted, using an alpha level of .01 for statistical significance. These analyses of variance were conducted on transformations provided by the Unicorn program (Allison et al., 1993). Data transformations can be viewed in Appendix Q. The ANOVA examined the likelihood of model acceptance as a function of the study conditions within each level of model complexity.

All main effects and two-way interactions were estimated in the analyses. The three-way interaction was not estimated because the findings from the Monte Carlo simulations suggested an assumption of zero effects for this interaction. Instead, the three-way interaction was used as the error term in the analyses.

The results regarding the percentages of model acceptance for the fit indices as a function of sample size and number of indicators per latent variable mirrored those in the Monte Carlo simulations (see Appendix R to view percentages of model acceptance as a function of the study conditions). Although the hypotheses regarding model misspecifications also mirrored those in the Monte Carlo simulations, there was interest as to the percentage of misspecified models that would be accepted. Therefore, to avoid repetition of the findings from the Monte Carlo simulations, only the findings regarding model misspecifications are discussed in the following section.

Acceptance of model misspecifications. Figures 23, 24, and 25 present the raw percentages of model acceptance as a function of model misspecifications in the simple, moderate, and complex models, respectively.

Examination of the figures demonstrates that three indices (i.e., the CN, RMSEA, and NNFI) were able to detect misspecifications in the models. The CN was the most successful in detecting misspecifications. In the simple and moderate model, the CN accepted 100% of the true conditions, and rejected approximately 50% of the omission and combination conditions. In the complex model, the CN

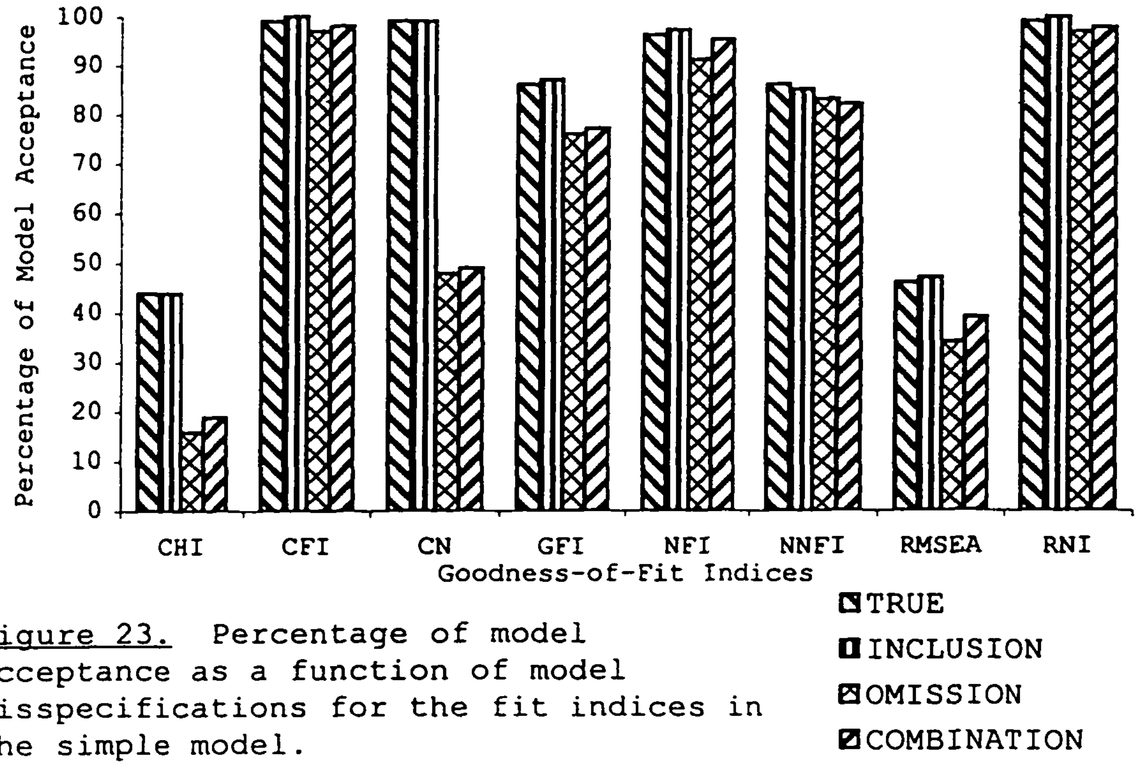


Figure 23. Percentage of model acceptance as a function of model misspecifications for the fit indices in the simple model.

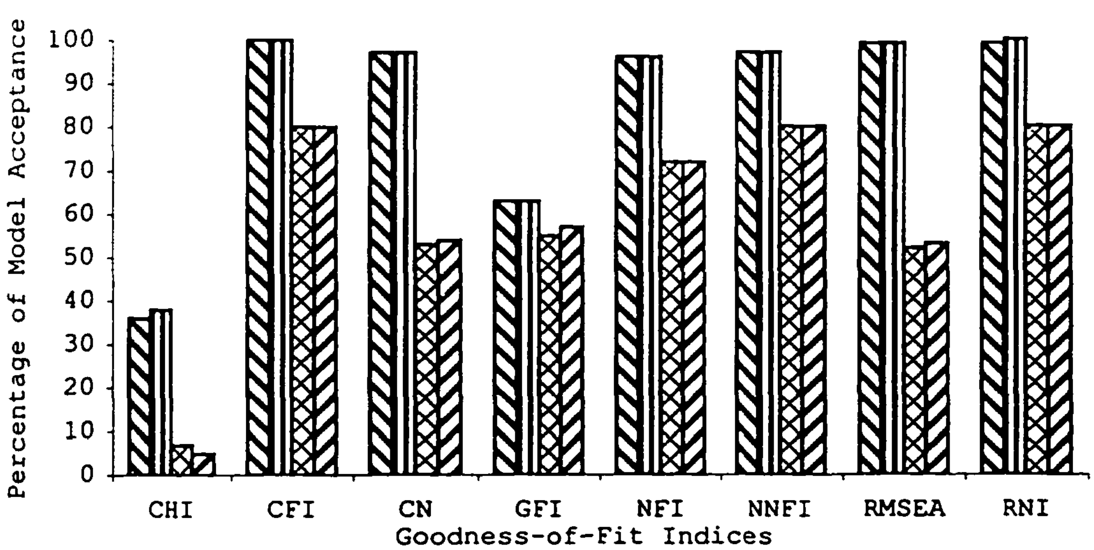


Figure 24. Percentage of model acceptance as a function of model misspecifications for the fit indices in the moderate model.

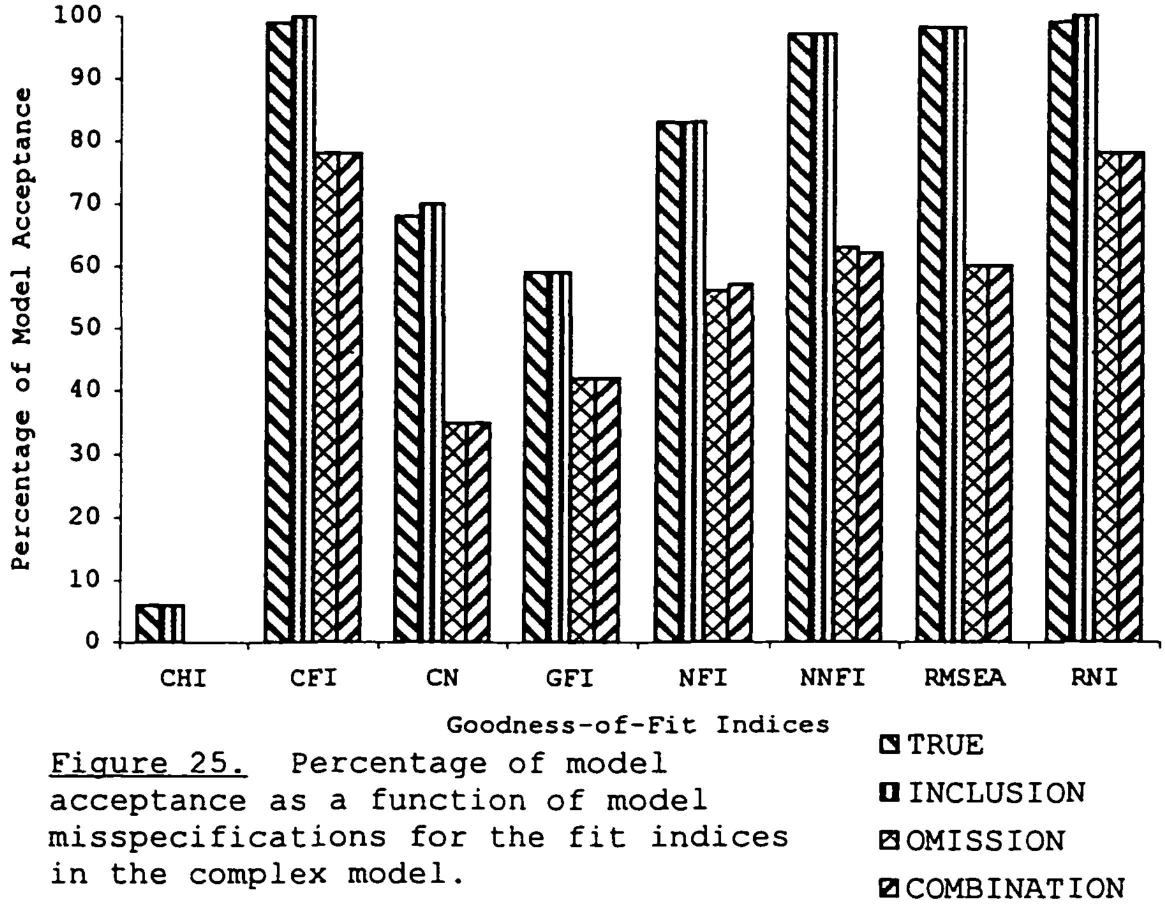


Figure 25. Percentage of model acceptance as a function of model misspecifications for the fit indices in the complex model.

accepted approximately 70% of the true conditions, and rejected approximately 35% of the omission and combination conditions.

The RMSEA detected misspecifications well in the moderate and complex models. In these models, the RMSEA accepted approximately 100% of the true conditions, and rejected approximately 50% of the omission and combination conditions.

The NNFI detected misspecifications well in the complex model. In this model, the NNFI accepted approximately 100% of the true conditions, and rejected approximately 40% of the omission and combination conditions.

As noted by La Du and Tanaka (1989), models that were specified to include an incorrect structural path (i.e., the inclusion condition) were rewarded with index values that were the same or greater than the true condition. Across every simulation, models that included incorrect structural paths had rates of model acceptance that were within 1% of model acceptance for the true condition.

Although each index had significantly higher percentages of model acceptance for true and inclusion conditions, percentages of model acceptance for omission and combination conditions were unacceptably high for several indices. As an example, the CFI and RNI accepted at least 80% of the misspecified omission and combination conditions across the simple, moderate, and complex models. Moreover, in the simple model, the GFI accepted about 80% of the solutions, irrespective of how the model was specified.

<u>Model Complexity</u>

To evaluate differences in percentages of model acceptance as a function of model complexity, an analysis of variance was performed. An alpha level of .01 was used to test for statistical significance.

The majority of main effects and interactions were statistically significant. However, only findings related to model complexity (i.e., main effect and interactions) and that accounted for 3% or more of the variance are interpreted in the following section.

Figure 26 presents the percentages of model acceptance for the fit indices as a function of model complexity. As hypothesized, there were differences in the percentages of model acceptance based on model complexity. Overall, the indices rewarded the simple model with the highest percentages of model acceptance. For the majority of indices (i.e., the chi-square statistic, CN, NFI, NNFI, and RNI), the simple model was awarded the highest percentages of model acceptance followed by the moderate model, and then by the complex model. The CFI and GFI failed to exhibit significantly different percentages in model acceptance between the simple and moderate model, however, the complex model had lower percentages of model acceptance.

As expected, the RMSEA tended to reward more complex models with higher percentages of model acceptance. The complex model received the highest percentage of model

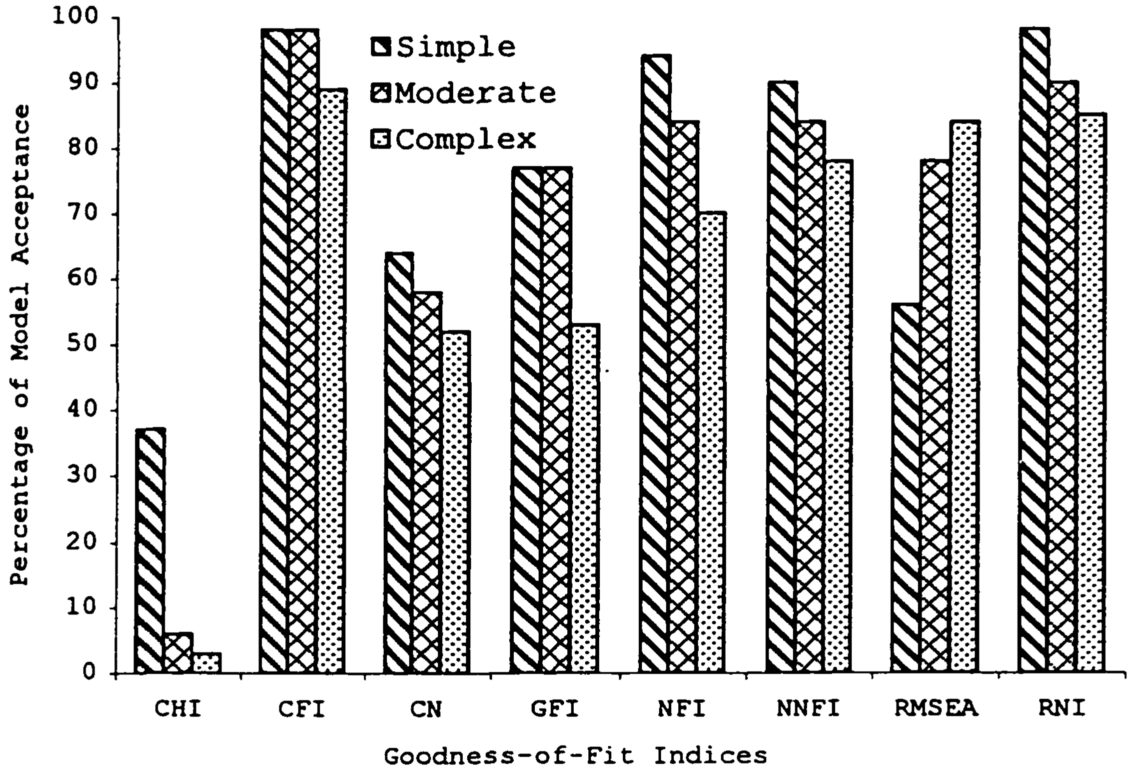


Figure 26. Percentage of model acceptance as a function of model complexity for the fit indices.

acceptance from the RMSEA, followed by the moderate model, and then by the simple model.

Model complexity by number of indicators per latent variable. Interaction effects with η^2 of .03 or greater were noted for the chi-square test statistic, CFI, NNFI, RMSEA, and RNI. No interaction was found for the CN, GFI, or NFI.

The chi-square test statistic had approximately the same percentage (i.e., about 50%) of model acceptance when the model specified one to four indicators in the simple model (see Figure 27). However, when five indicators were specified, none of the models were accepted. In contrast, the percentage of model acceptance in the moderate and complex models was low irrespective of increases in the number of indicators.

For the CFI and RNI (see Figure 28 for the CFI), increases in the number of indicators in the simple model yielded approximately the same percentages (i.e., .90 or greater) of model acceptance. However, in the moderate and complex models, single indicator models had significantly lower percentages of model acceptance than when two through five indicators were specified.

For the NNFI, the lowest percentages of model acceptance occurred when a single indicator model was specified (i.e., from 20% to 50%). However, in the simple and moderate models, increasing the number of indicators from two through to five resulted in almost all models being accepted (see Figure 29). In contrast, increasing the number of indicators from one to two in the complex model only led to a 20% increase in the percentage of models accepted. When three or more indicators were specified in the complex model, almost all models were accepted.

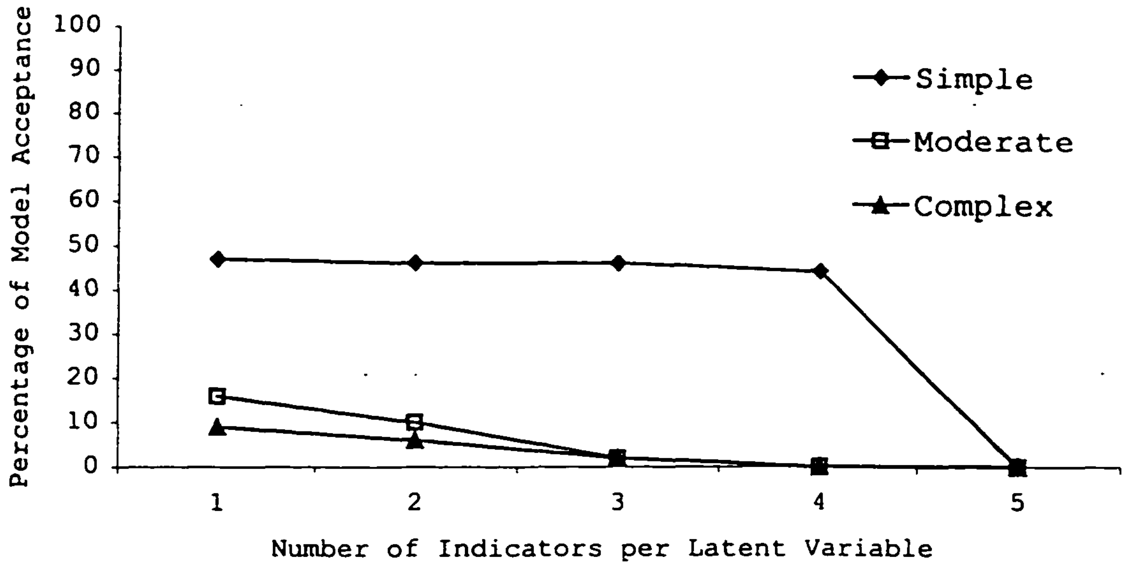


Figure 27. Percentage of model acceptance as a function of model complexity and number of indicators per latent variable for the chi-square test statistic.

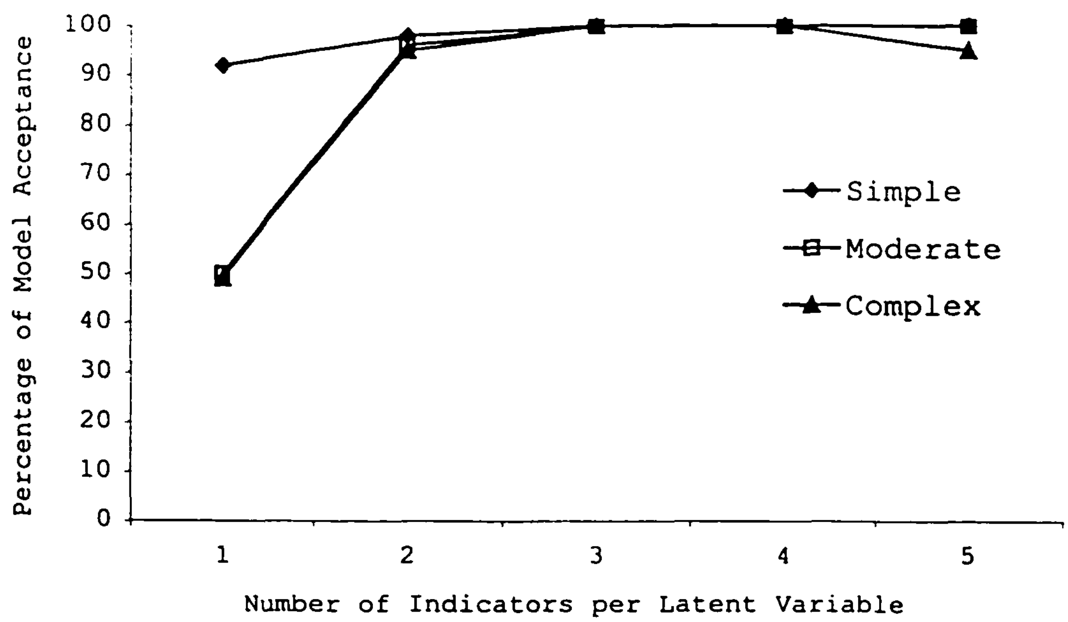


Figure 28. Percentage of model acceptance as a function of model complexity and number of indicators per latent variable for the CFI.

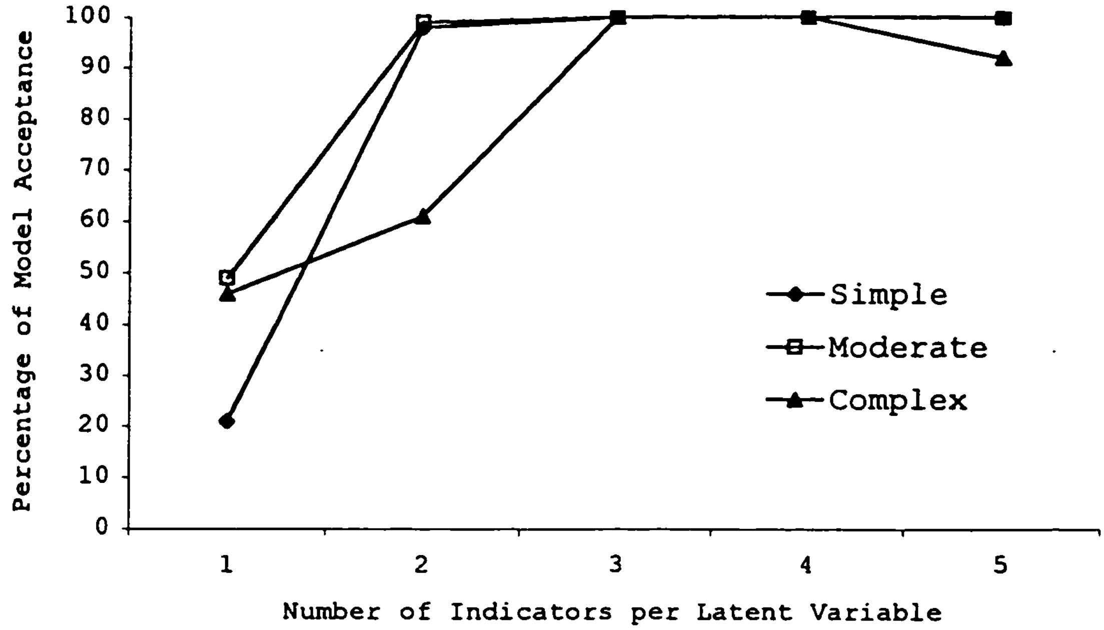


Figure 29. Percentage of model acceptance as a function of model complexity and number of indicators per latent variable for the NNFI.

In contrast to the previously discussed indices, the RMSEA favored more complex models over simple models. For all models, the lowest percentages of models were accepted at one indicator (see Figure 30). Increasing the number of indicators beyond one resulted in significantly higher percentages of model acceptance for the simple, moderate, and complex models. However, in the simple model, a further increase from four to five indicators led to a significant reduction in the percentage of models accepted.

Model complexity by model misspecifications. Interaction effects with η^2 of .03 or greater were noted for

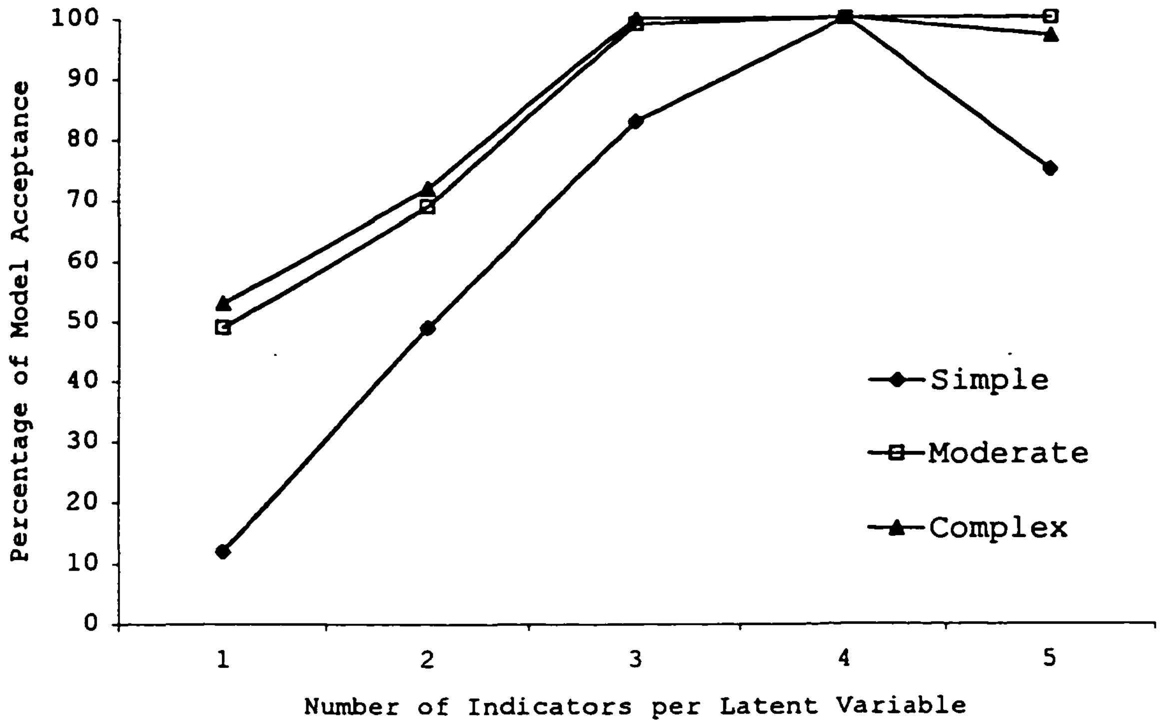


Figure 30. Percentage of model acceptance as a function of model complexity and number of indicators per latent variable for the RMSEA.

the chi-square test statistic, CFI, NNFI, and RNI.

Figure 31 depicts the effect of model complexity and model misspecifications on the chi-square statistic. In the simple model, the chi-square statistic yielded significantly higher percentages of model acceptance for true and inclusion conditions as opposed to omission and combination conditions. In the moderate and complex models, there was little distinction across levels of model misspecifications for the chi-square test statistic.

In contrast, the CFI, NNFI, and RNI were less

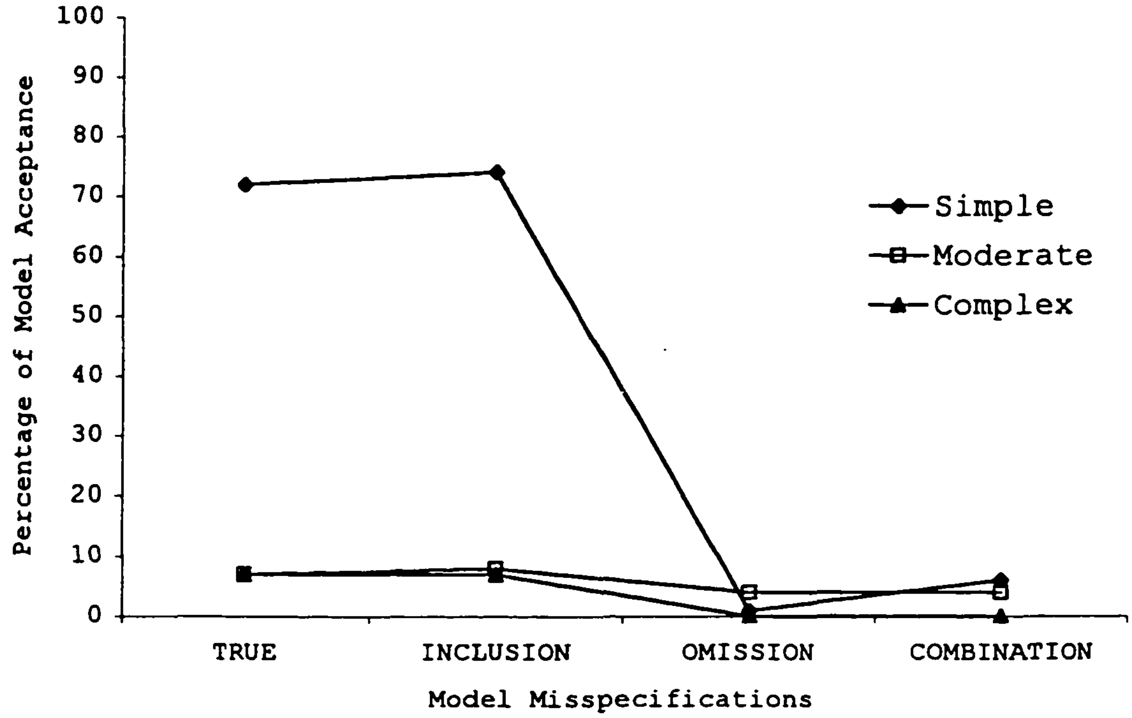


Figure 31. Percentage of model acceptance as a function of model complexity and model misspecifications for the chi-square test statistic.

sensitive to omission and combination conditions when the model was simple. Figure 32 presents the effect of model complexity and model misspecifications on the NNFI for illustrative purposes. In the simple model, the percentage of model acceptance across levels of model specification was approximately the same for the indices (i.e., approximately 85%), whereas for the moderate and complex model, there was a 20% to 40% reduction in the percentage of acceptance for omission and combination conditions.

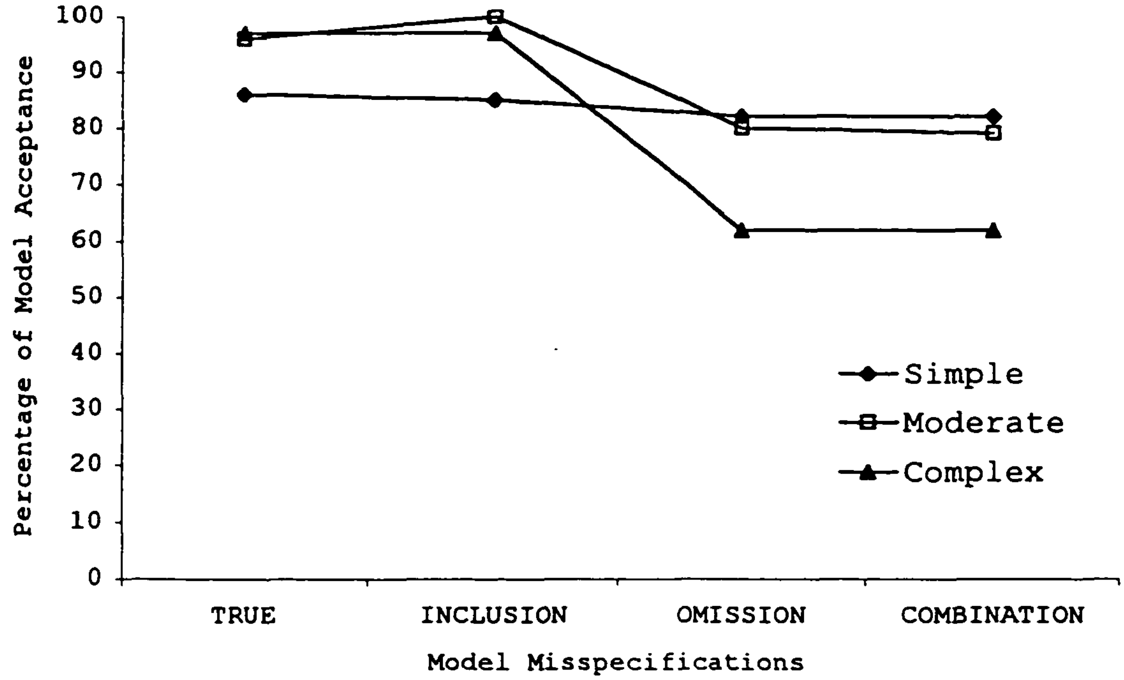


Figure 32. Percentage of model acceptance as a function of model complexity and model misspecifications for the NNFI.

Model complexity by sample size. An interaction effect with an η^2 greater than .03 was noted for the NFI. The NFI yielded approximately the same percentages of model acceptance for the simple and moderate models when the sample size was 200 or larger (see Figure 33). However, the NFI did not yield the same percentages of model acceptance in the complex model until the sample size was 500 or greater.

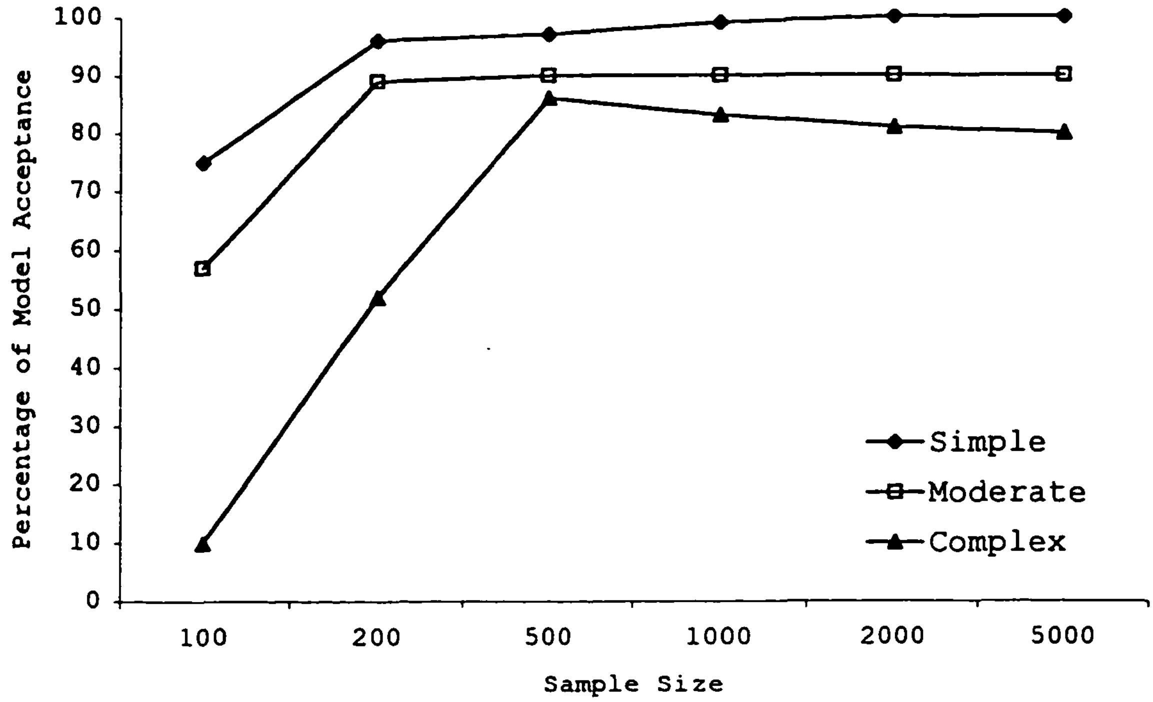


Figure 33. Percentage of model acceptance as a function of model complexity and sample size for the NFI.

Model complexity by number of indicators per latent variable by model misspecifications. Three-way interactions with η^2 of .03 or greater were demonstrated for the CFI, NNFI, RMSEA, and RNI. Appendix S presents the percentages of models accepted as a function of model complexity and number of indicators per latent variable for the CFI, NNFI, RMSEA, and RNI in the true and omission conditions. Tests of simple and complex main effects were performed to interpret the findings.

For each of these indices, true and inclusion conditions had approximately the same percentages of model acceptance. The omission and combination conditions also had approximately the same percentages of model acceptance. Therefore, to facilitate discussion of the findings, the results are described by comparing the true condition to the omission condition.

The interaction effect for the CFI and RNI was the same across the simulations. Therefore, for illustrative purposes, Figures 34 and 35 depict the percentages of model acceptance as a function of model complexity and number of indicators per latent variable for the CFI in the true and omission conditions, respectively. The CFI demonstrated high percentages of model acceptance for the true condition across levels of model complexity and number of indicators per latent variable. Percentages of model acceptance for the omission condition varied as a function of model complexity and number of indicators per latent variable. When the model was moderate or complex and one indicator was specified, the percentage of model acceptance for the omission condition was significantly lower than when additional indicators were specified. However, the simple model did not exhibit this result for one indicator specifications.

For the NNFI, (see Figures 36 and 37) true conditions

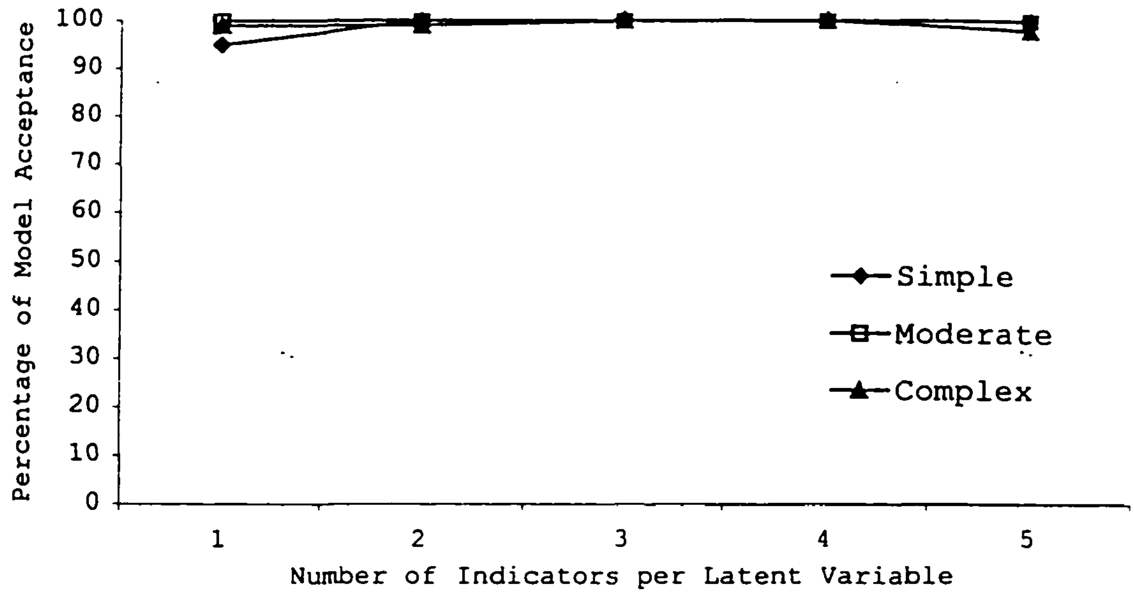


Figure 34. Percentage of model acceptance for the CFI as a function of model complexity and number of indicators per latent variable in the true condition.

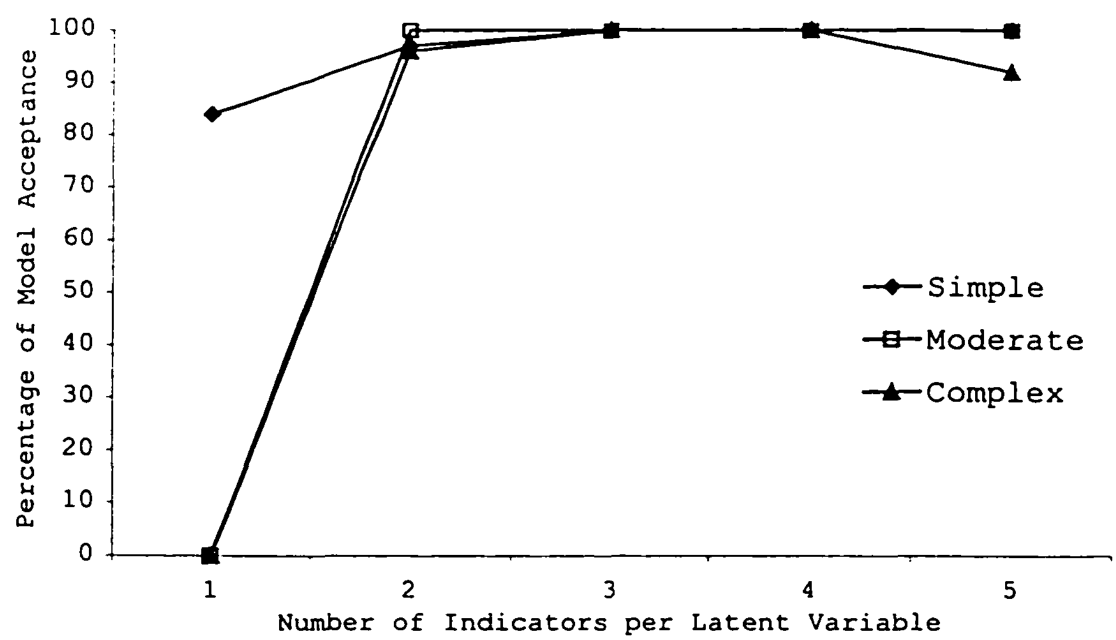


Figure 35. Percentage of model acceptance for the CFI as a function of model complexity and number of indicators per latent variable in the omission condition.

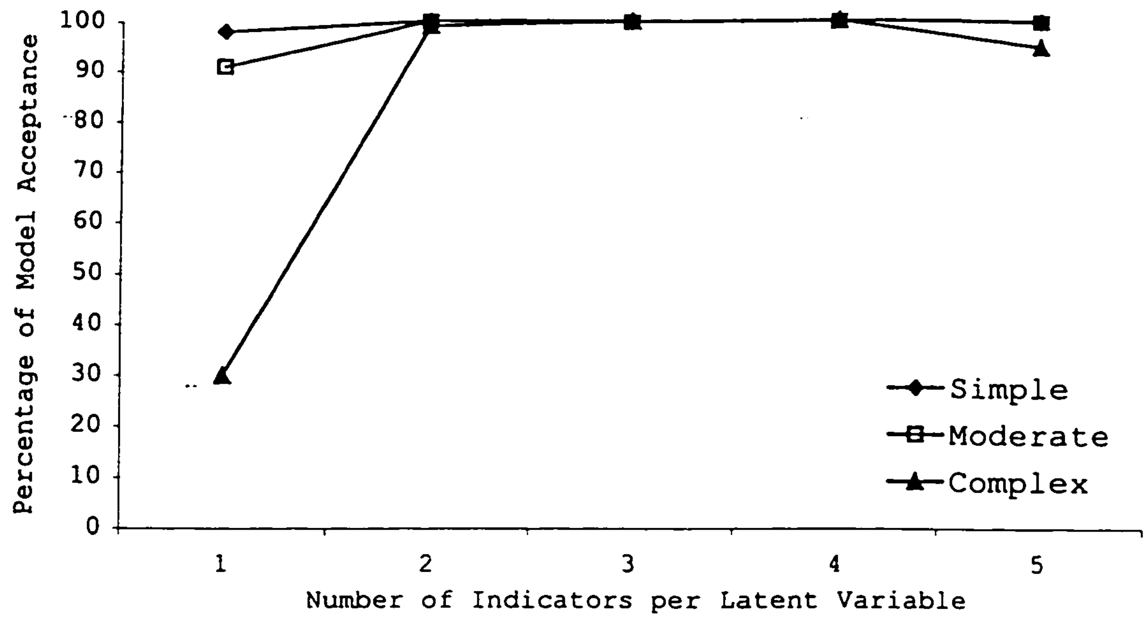


Figure 36. Percentage of model acceptance for the NNFI as a function of model complexity and number of indicators per latent variable in the true condition.

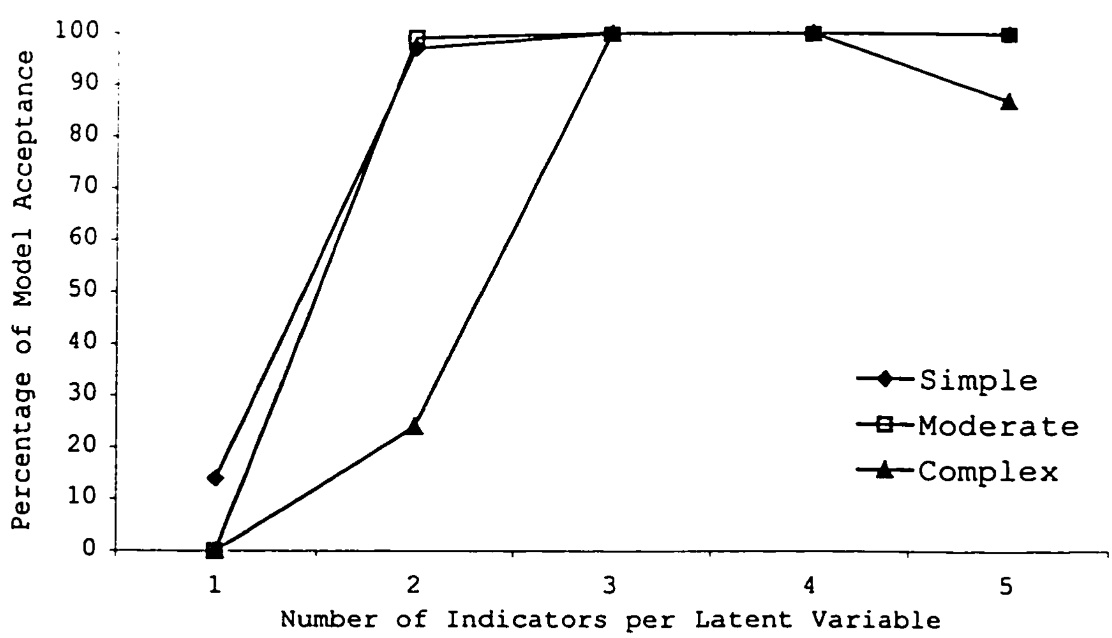


Figure 37. Percentage of model acceptance for the NNFI as a function of model complexity and number of indicators per latent variable in the omission condition.

had approximately the same percentage of model acceptance for all levels of indicators in the simple and moderate model. However, in the complex model, when the model specified one indicator, true conditions had significantly lower percentages of model acceptance.

In comparison, when one indicator was specified, omission conditions resulted in low percentages of model acceptance from the NNFI across all levels of model complexity (i.e., from 0% to 14%). When two to five indicators were specified in the simple and moderate models, nearly all omission conditions were accepted. In the complex model, increasing the number of indicators from one to two only resulted in approximately 20% acceptance of the omission conditions. However, specifying three or more indicators in the complex model led to high acceptance of the omission conditions.

For the RMSEA, in the moderate and complex models, true conditions resulted in high percentages of model acceptance across levels of indicators (see Figures 38 and 39). In contrast, percentages of model acceptance for the true specification in the simple model were lower than the moderate and complex models at all levels of indicators. Moreover, the profile of model acceptance across indicators differed in the simple model. In particular, at one

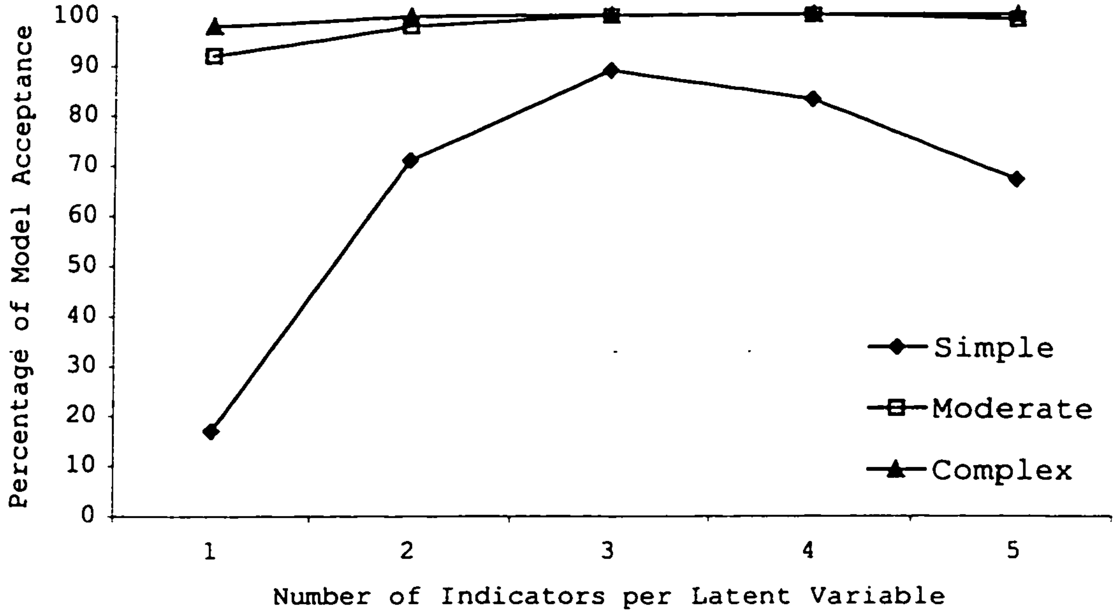


Figure 38. Percentage of model acceptance for the RMSEA as a function of model complexity and number of indicators per latent variable in the true condition.

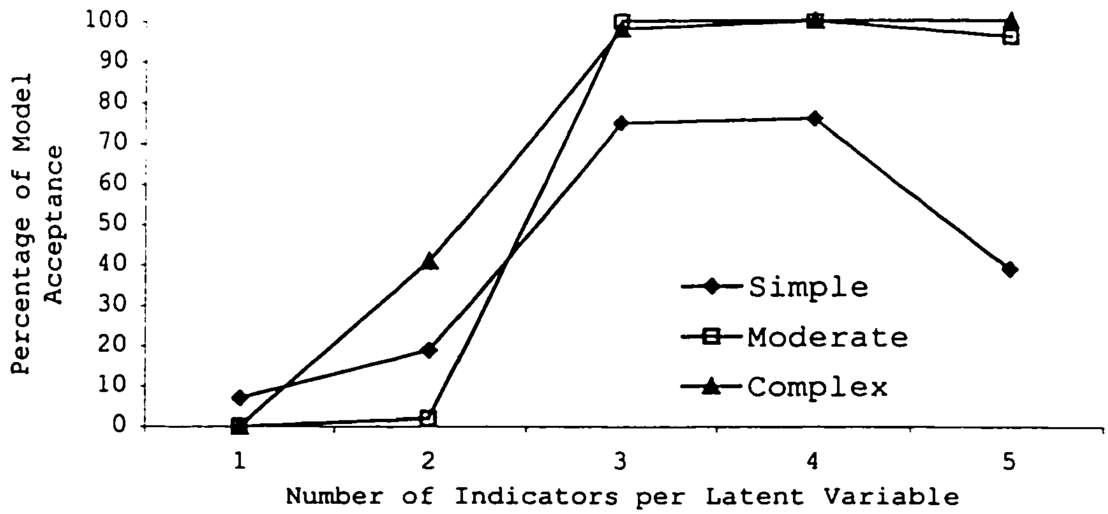


Figure 39. Percentage of model acceptance for the RMSEA as a function of model complexity and number of indicators per latent variable in the omission condition.

indicator, the percentage of model acceptance was exceptionally low for the true condition (i.e., 17% versus 92% and 98% in the moderate and complex models, respectively). In the simple model, increases in indicators from one to three resulted in higher percentages of model acceptance for the true condition, but additional increases in indicators led to decreases in model acceptance.

In the omission condition, when one or two indicators were used, the RMSEA yielded relatively low percentages of model acceptance across the simple, moderate, and complex models (i.e., from 0% to 41%). In the moderate and complex model, increasing the number of indicators to three, four, or five resulted in almost complete acceptance of omission conditions. In the simple model, increases in indicators to three and four also led to substantial increases in acceptance of omission conditions, however, specifying five indicators once more resulted in a decrease in acceptance for omission conditions.

Model complexity by number of indicators per latent variable by sample size. Interaction effects with η^2 of .03 or greater were demonstrated for the GFI and NFI. For the GFI, in the simple model, almost 100% of the one and two indicator models were accepted across all levels of sample size (see Figures 40, 41, and 42 to view the interaction effect on the GFI in the simple, moderate, and complex models, respectively). However, when the model specified 3, 4, or 5 indicators, sample sizes of 500 or greater were required before the majority of models were accepted.

The one indicator profile for the GFI in the moderate and complex models was quite similar across increases in indicators. That is, 60% to 70% of the models were accepted at one indicator irrespective of sample size. However, when the sample size was small (i.e., 500 or less in the moderate model, and 1000 or less in the complex model) increases in indicators led to substantial decreases in the percentage of model acceptance. As an example, in the simple model, when the sample size was 1000, all one to four indicator models were accepted. In the moderate model, when the sample size was 2000, all solutions were accepted. However, when the sample size was 5000 in the complex model, about 10% of the models using one indicator were not accepted, and over 50% of the five indicator models were not accepted.

For the NFI, in the simple and moderate models, the profile of values for two to five indicators was very similar (see Figures 43, 44, and 45). That is, at a sample size of 200, the percentage of acceptance for models with

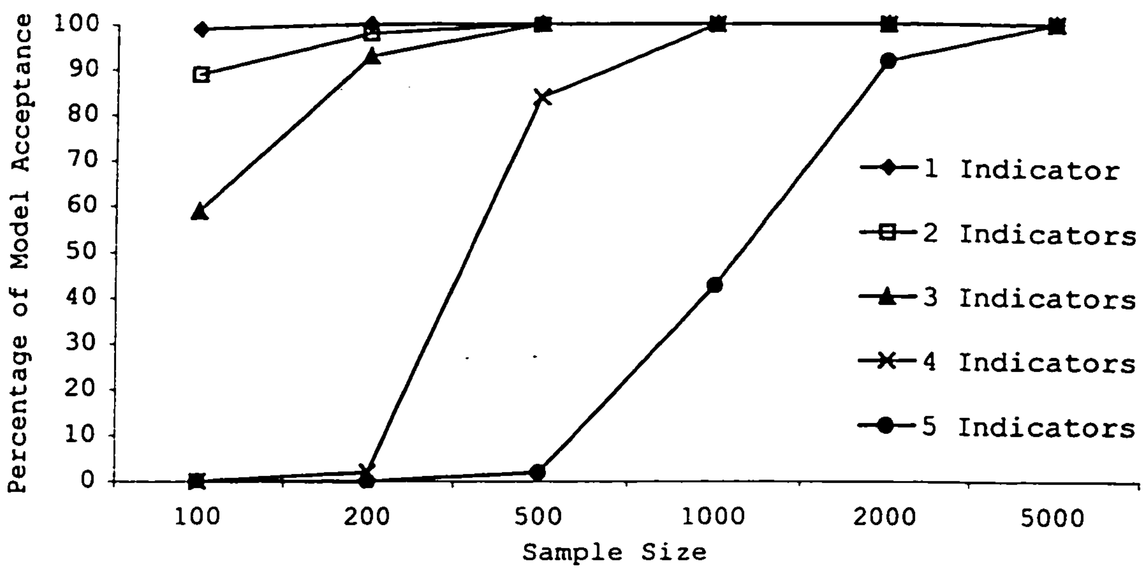


Figure 40. Percentage of model acceptance for the GFI as a function of number of indicators per latent variable and sample size in the simple model.

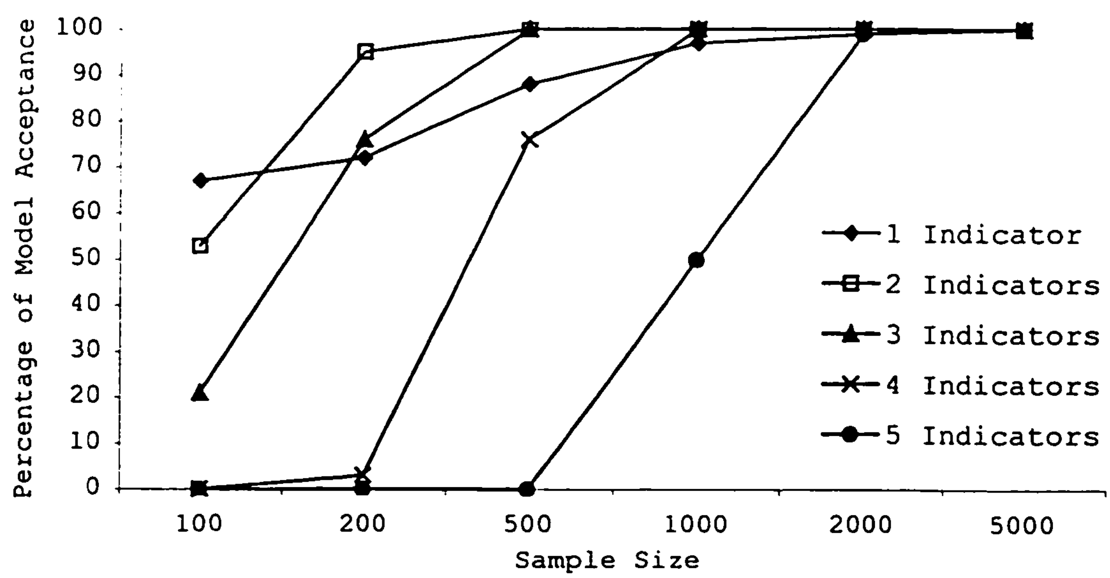


Figure 41. Percentage of model acceptance for the GFI as a function of number of indicators per latent variable and sample size in the moderate model.

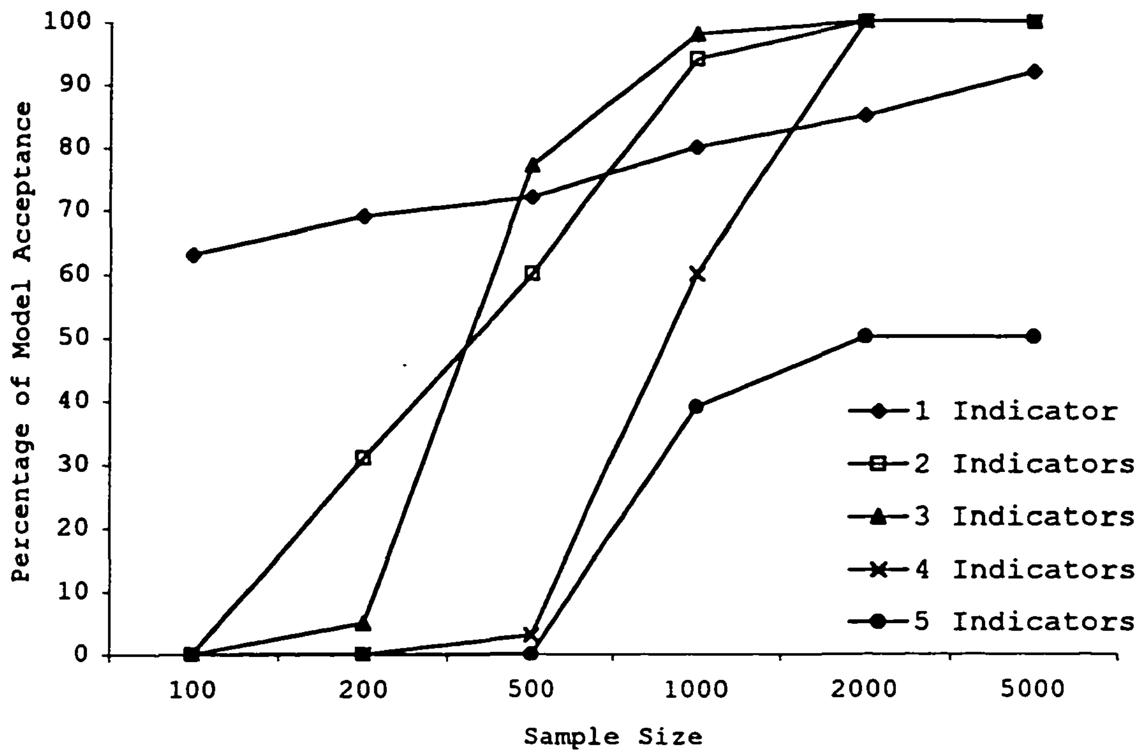


Figure 42. Percentage of model acceptance for the GFI as a function of number of indicators per latent variable and sample size in the complex model.

two to five indicator was approximately 100%. However, at a sample size of 100, there were differences in the percentages of model acceptance as a function of number of indicators.

In comparison, the profile of NFI values for two to five indicators in the complex model differed. In the complex model, the percentage of model acceptance varied across number of indicators until the sample size reached 1000.

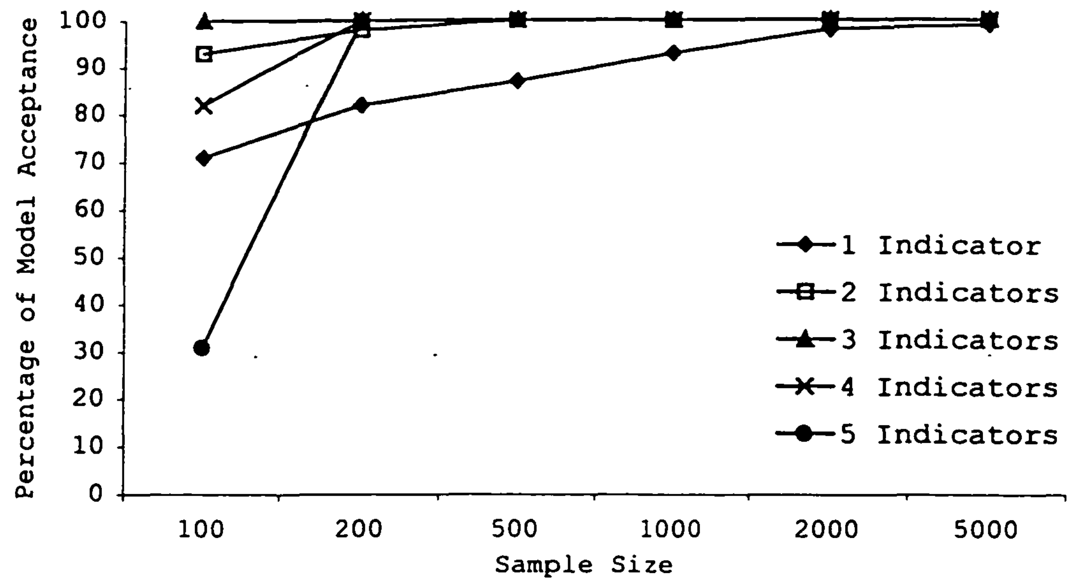


Figure 43. Percentage of model acceptance for the NFI as a function of number of indicators per latent variable and sample size in the simple model.

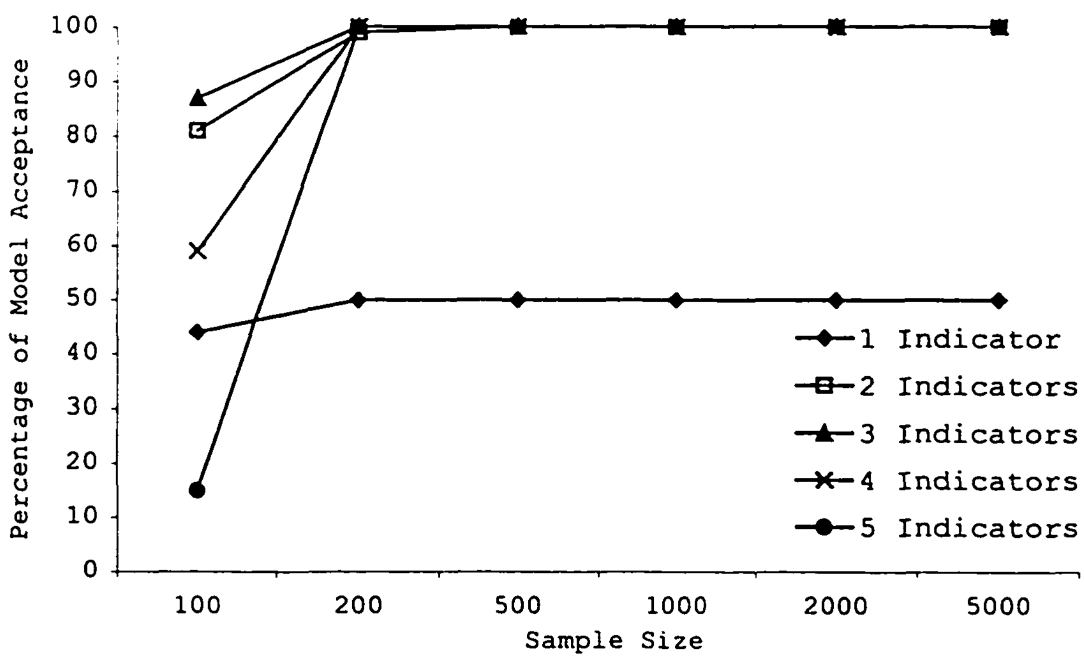


Figure 44. Percentage of model acceptance for the NFI as a function of number of indicators per latent variable and sample size in the moderate model.

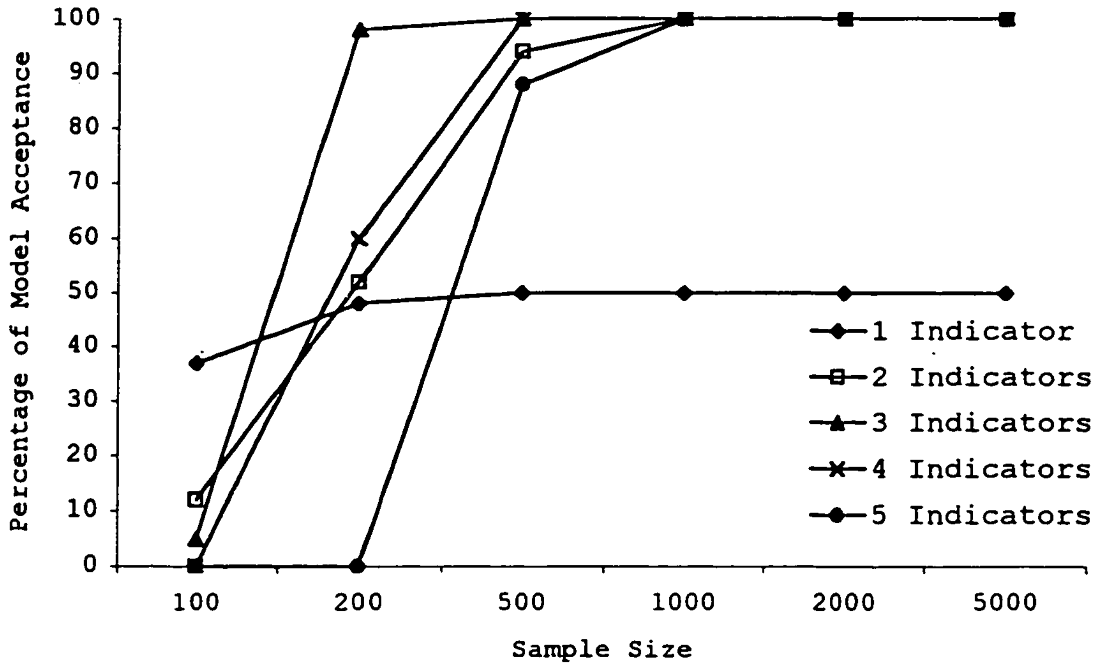


Figure 45. Percentage of model acceptance for the NFI as a function of number of indicators per latent variable and sample size in the complex model.

The one indicator profile for the NFI was similar in the moderate and complex models, but was different in the simple model. That is, in the moderate and complex models, the percentage of model acceptance was relatively flat across increases in sample size. In comparison, the profile of NFI values in the simple model increased with increases in sample size.

Examining Alternative Cutoff Values

Given that use of the recommended cutoff values led to a high percentage of accepted misspecified models (i.e., omission and combination conditions), alternative cutoff values were examined. Results from the Monte Carlo simulations demonstrated that across the simulations the indices rewarded the inclusion condition with approximately the same percentage of model acceptance as the true condition. Therefore, alternative values will not reduce the percentage of model acceptance for inclusion conditions.

Results also demonstrated that for single indicator specifications, the CFI, NNFI, RMSEA, and RNI were extremely sensitive to the omission condition in the moderate and complex model. Thus, because these indices rejected approximately 100% of the omission conditions and accepted between 90% to 100% of the true conditions, the recommended cutoff value for single indicator models is .90 for the CFI, NNFI, and RNI, and .08 for the RMSEA. However, these indices rewarded many of the multiple indicator models with values suggesting acceptable model fit under omission or combination conditions. Alternative cutoff values should minimize the percentage of model acceptance for misspecified models with omissions. A ratio was calculated that compared the frequency of accepted true models to the frequency of accepted misspecified (i.e., omitted) models. The most desirable values were those that maximized the frequency of accepted true models and minimized the frequency of accepted misspecified models. Table 17 summarizes the alternative values that are discussed below. Appendix T presents the percentages of model acceptance for the fit indices across the conditions using the alternative cutoff values.

Suggestions for Alternative Values

Figure 46 depicts the suggested alternative values for the fit indices as a function of simulation model. Suggestions for the simple model could only be offered for the chi-square statistic, CN, and RMSEA.

Three findings regarding the alternative values were evident immediately. First, for the GFI, no alternative value was able to minimize the percentage of model acceptance for misspecified solutions with omitted paths under any condition or simulation. Second, no alternative values were suggested for the fit indices as a function of sample size. Results from the Monte Carlo simulations had demonstrated that several of the fit indices were relatively independent of sample size (i.e., CFI, NNFI, RMSEA, and RNI). Therefore, it is not surprising that no additional benefit was gained by changing the cutoff values across the levels of sample size. For the chi-square statistic, increases in sample size led to decreases in the

Table 17

Suggestions for Alternative Values for the Fit Indices as a Function of Model Complexity and Single Versus Multiple Indicator Models

	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
Model Complexity								
Simple								
1 Ind	.10		250				.08	
2 + Ind	.11		260				.07	
Moderate								
1 Ind		.90	230		.94	.90	.08	.90
2 + Ind		.98	240		.96	.98	.06	.98
Complex								
1 Ind		.90	210		.92	.90	.08	.90
2 + Ind		.94	220		.93	.93	.04	.94

Note. The following abbreviations have been used: χ^2 = Chi-square statistic; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; Ind = Indicators; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index. Blank spaces in the table indicate that no alternative cutoff values are suggested.

percentage of model acceptance overall. In other words, both true and omission conditions were unlikely to be accepted. For the remaining indices (i.e., CN and NFI), changing the cutoff values resulted in very little improvement in discrimination between true and omission conditions as the sample size increased.

Third, when the number of indicators per latent

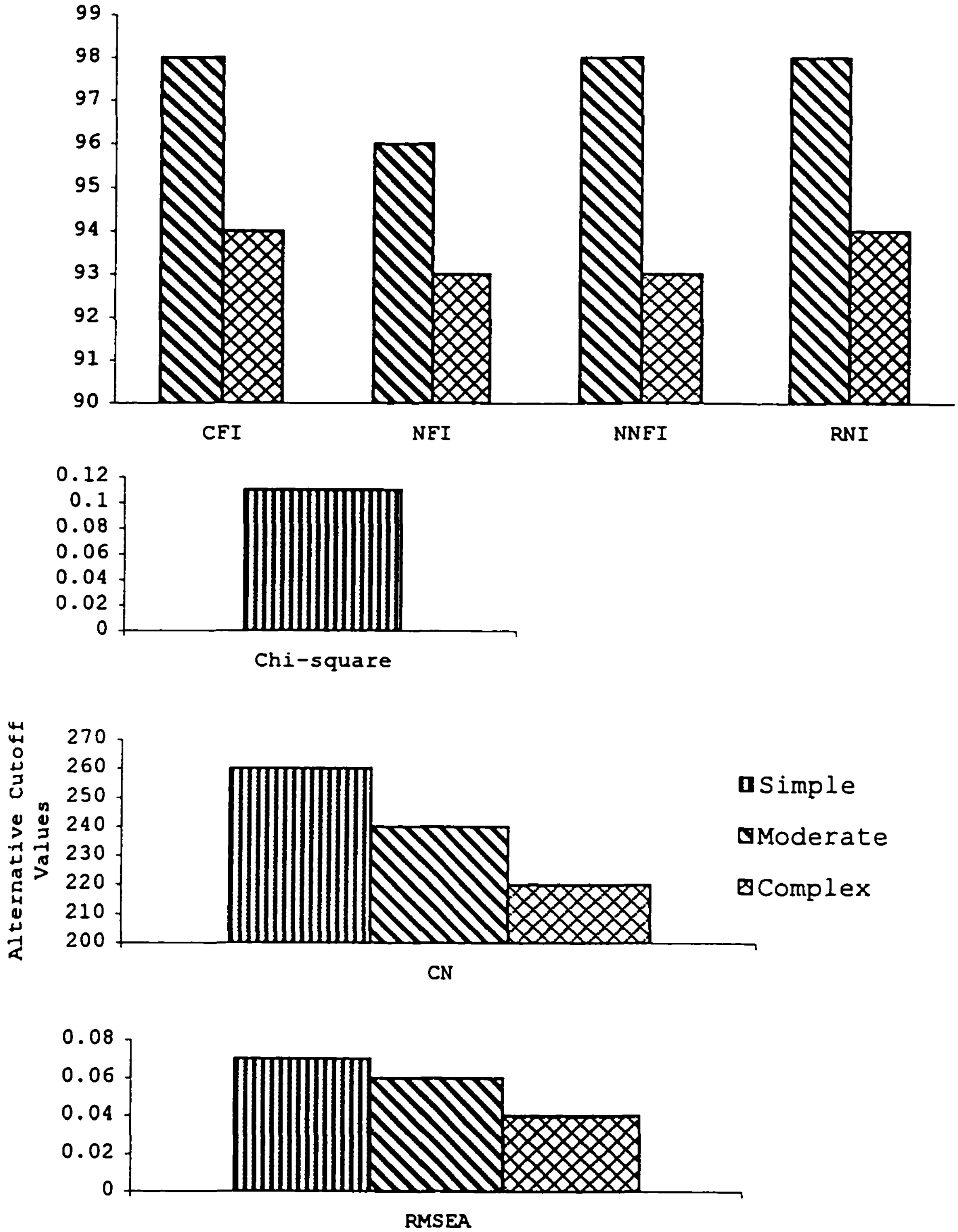


Figure 46. Alternative cutoff values for the fit indices as a function of model complexity.

variable were considered, alternative values were useful only for single versus multiple indicator models.

When the true and omission conditions were compared in the simple model, the ratio of model acceptance for the CFI, NFI, NNFI, and RNI, changed very little across alternative values. Thus, no alternative value minimized the percentage of model acceptance for misspecified solutions without also minimizing the percentage of model acceptance for true solutions. However, in the moderate multiple indicator models, an alternative cutoff value of .98 for the CFI, NNFI, and RNI resulted in over 90% acceptance for the true condition and 28% or less acceptance for the omission condition. An alternative value of .96 in the moderate multiple indicator models for the NFI resulted in 77% acceptance for the true condition and 38% acceptance for the omission condition.

However, for single indicator moderate models, an alternative value of .94 was suggested for the NFI. This value resulted in the NFI accepting 75% of the true condition and 10% of the omission condition.

In the complex multiple indicator models, the suggested alternative cutoff values for the CFI, NFI, NNFI, and RNI were less stringent than the suggested values in the moderate models. That is, the suggested values for the

CFI and RNI were .94, whereas the suggested values for the NFI and NNFI were .93. For the CFI, NNFI, and RNI, the suggested values accepted between 89% to 94% of the true conditions and between 38% to 39% of the omission conditions. As in the moderate multiple indicator models, the alternative value for the NFI was not as sensitive as the alternative values were for the CFI, NNFI, and RNI. That is, at a value of .93, 69% of the true conditions and 26% of the omission conditions yielded values suggesting acceptable fit. When the complex model specified one indicator, an alternative value of .92 for the NFI resulted in 69% acceptance for the true condition and 18% of the omission condition.

For the chi-square statistic, alternative values were suggested in the simple model for single and multiple indicators. No suggestions could be offered in the moderate or complex models. When the probability value of a nonsignificant chi-square was relaxed to .11, 73% of the true conditions were accepted, whereas only 19% of the omission conditions were accepted. However, if the simple model used single indicators, then an alternative value of .10 was suggested. An alternative value of .10 resulted in 80% acceptance of the true condition and 10% acceptance of the omission condition.

For the CN, the suggested alternative values for multiple indicator models decreased from the simple to moderate to complex models (i.e., simple = 260; moderate = 240; complex = 220). The alternative values for the CN were less able to discriminate between the true and omission conditions as the models became more complex. In the simple model, 100% of the true conditions and 45% of the omission conditions were accepted at a value of 260. However, the percentage of accepted true conditions decreased in the moderate (i.e., 85%) and complex (i.e., 65%) models. The percentage of accepted omission conditions in the moderate and complex models was approximately the same (i.e., 31% versus 30%, respectively).

For single indicator models, alternative values were suggested for the CN in the simple, moderate, and complex simulations. In the simple simulation, an alternative value of 250 resulted in 100% acceptance of the true condition and 28% acceptance of the omission condition. In the moderate simulation, an alternative value of 230 resulted in 75% acceptance of the true condition and 25% acceptance of the omission condition. In the complex simulation, an alternative value of 210 resulted in 60% acceptance of the true condition and 20% acceptance of the omission condition.

For the RMSEA, alternative values for multiple indicator models became more stringent as the model became more complex. That is, in the simple model, the suggested alternative value was .07, whereas the suggested alternative values in the moderate and complex models were .06 and .04, respectively. The percentage of model acceptance for the true condition increased as the model became more complex. When the suggested alternatives were used, the percentage of model acceptance for the true condition in the simple, moderate, and complex models was 38%, 79%, and 90%, respectively. The percentage of model acceptance for the omission conditions in the simple, moderate, and complex models was 7%, 35%, and 4%, respectively.

Discussion

Overview

The purposes of Study 2 were to: (a) Examine the performance of the goodness-of-fit indices under varying conditions of sample size, number of indicators per latent variable, model misspecifications, and model complexity, (b) evaluate the recommended cutoff values for adequacy and appropriateness, and (c) consider and suggest alternative cutoff values.

The discussion is presented in two sections. The first section describes and considers the results from the Monte Carlo simulations. The second section discusses the use of the recommended cutoff values. The latter part of this section reviews the alternative cutoff values and considers situations under which their use may be appropriate.

Findings from the Monte Carlo Simulations

The primary purpose of Study 2 was to examine the performance of the goodness-of-fit indices as a function of sample size, number of indicators per latent variable, and model misspecifications in three simulations that differed in model complexity. The simulation models were chosen from published research to reflect models that researchers examine in "typical" research applications. Overall, the results supported prior research findings regarding sample size, number of indicators per latent variable, and model misspecifications (e.g., Andersen & Gerbing, 1984; Boomsma, 1982; Ding et al., 1995; La Du & Tanaka, 1989; Mulaik et al., 1989). The following sections review the hypotheses generated for the simulations and the implications of the results.

Sample size. Sample size was hypothesized to influence values of the chi-square statistic, CN, GFI, NFI, and RMSEA. In comparison, no sample size effects were expected for the CFI, NNFI, and RNI. However, at a sample size of 100, the NNFI was expected to exhibit more variability in standard deviations than the CFI, GFI, NFI, and RNI. With the exception of the RMSEA, all sample size hypotheses were supported.

As expected, increases in sample size led to significant increases in chi-square values, suggesting poorer fit. This finding supports prior research demonstrating that as the sample size increases, the chi-square statistic is more likely to yield values suggesting unacceptable fit (e.g., Andersen & Gerbing, 1984; Bearden et al., 1982; Boomsma, 1982; Marsh et al., 1988; Mulaik et al., 1989).

For the GFI, and NFI, increases in sample size also led to increased values. However, for these indices, an increase in values suggested better rather than poorer fit. For the GFI, significant increases were noted in the simulations when the sample size increased from 100 to 500. In comparison, the NFI was slightly less affected in the simple and moderate simulations. That is, NFI values increased significantly when the sample size increased from 100 to 200 but were relatively stable across further increases in sample size. However, in the complex model, the NFI behaved similar to the GFI and exhibited significant increases when the sample size increased from 100 to 500.

In support of Hu and Bentler (1995), the CN was significantly affected by increases in sample size. For the CN, increases in sample size led to significantly larger values, suggesting better model fit. This finding is important because it demonstrates clearly that the CN is not independent of sample size. Therefore, the usefulness of the CN in model evaluation is in question.

In support of Ding et al. (1995), Marsh et al. (1988), and Mulaik et al. (1989), the CFI, NNFI, and RNI were relatively independent of sample size. Values for these indices were slightly lower when the sample size was 100, however, further increases in sample size had no effect on their values.

As hypothesized, when the sample size was 100, the NNFI exhibited more extreme variability in standard deviations than did the CFI, GFI, NFI, and RNI. This finding suggests that when the sample size is 100, the NNFI is not a precise index.

In contrast to Browne and Cudeck (1993) and the study hypotheses, no sample size effects were noted for the RMSEA. Browne and Cudeck showed that as the sample size increased, values for the RMSEA also tended to decrease, but generally not below .05. In the current research, RMSEA values decreased when the sample size increased from 100 to 200 in the moderate and complex simulations, whereas RMSEA values in the simple simulation remained the same or increased when the sample size increased. Two reasons may explain the discrepancy between Browne and Cudeck's (1993) results and those in the current research. First, Browne and Cudeck's largest sample size was significantly larger than the largest sample size in the current research. Specifically, they examined a sample size of 11,739, whereas the largest sample size in the current research was 5000.

If the current research had used a sample size larger than 5000, it seems unlikely that additional increases in sample size would have demonstrated sample size effects. Although RMSEA values decreased when the sample size increased from 100 to 200, no further decreases were noted. In comparison, Browne and Cudeck found continual decreases in RMSEA values with sample size increases.

The second difference between the current research and that of Browne and Cudeck (1993) may be more helpful in understanding the difference in results. That is, the current research used structural equation models, whereas

Browne and Cudeck used confirmatory factor analysis models. Perhaps the RMSEA is more sensitive to increases in sample size when examining a measurement model rather than a structural model. However, there does not appear to be any obvious reason why the RMSEA would be more sensitive to sample size in one type of application versus another. Future research should examine the performance of the RMSEA using confirmatory factor analysis models and structural equation models across a wide range of sample sizes (e.g., from 100 to 12,000) to clarify these findings.

In sum, the chi-square statistic, CN, GFI, and NFI were found to have sample size effects, whereas the CFI, NNFI, RMSEA, and RNI were relatively independent of sample size. With the exception of the chi-square statistic, all indices suggested better fit when the sample size was 200 or greater. The chi-square statistic had values suggesting better fit when the sample size was 100. In agreement with Bearden et al. (1982) and Boomsma (1982), it appears a minimum sample size of 200 would be prudent in most situations.

<u>Number of indicators per latent variable.</u> Significant effects from number of indicators per latent variable were found for all indices. In agreement with the study hypotheses, increases in the number of indicators per

latent variable resulted in values suggesting poorer model fit for the chi-square statistic and GFI. Moreover, interaction effects of sample size and number of indicators per latent variable were found for the chi-square statistic and GFI. Chi-square values increased significantly when the sample size was increased and the number of indicators increased. For the GFI, decreases in sample size coupled with increases in the number of indicators led to significantly lower values.

As hypothesized, increases in number of indicators generally resulted in values suggesting better model fit for the RMSEA. In particular, RMSEA values were greatest, suggesting poorer fit, when the model used one indicator. From two to five indicators, RMSEA values generally decreased, suggesting better fit. The hypothesized interaction of sample size by number of indicators was not supported for the RMSEA. That is, although increases in number of indicators resulted in decreased RMSEA values, increases in sample size did not lead to more pronounced decreases in RMSEA values.

Results partially supported the hypothesis that NFI values would decrease as the number of indicators increased. NFI values decreased in the simple simulation from two to five indicators, and in the moderate and complex simulations from three to five indicators. These results generally concur with Ding et al. (1995) who found that NFI values decreased when the number of indicators was increased from two to six.

However, in contrast to the study hypothesis, NFI values increased when the number of indicators increased from one to two or one to three. This finding suggests that the NFI is a more precise estimator of model fit when the model uses two or three indicators per latent variable.

Hypotheses regarding the CFI, NNFI, and RNI were also partially supported. That is, in the simulations, as the number of indicators increased between two and five, values for the CFI, NNFI, and RNI decreased, suggesting poorer fit. However, the average values for the CFI, NNFI, and RNI were quite similar when the model specified between two to five indicators. Thus, the same conclusion about model fit would be reached. In comparison, the CFI, NNFI, and RNI were significantly affected when the model specified one indicator. In every simulation, CFI, NNFI, and RNI values were significantly lower at one indicator than at 2, 3, 4, or 5 indicators.

In addition, only partial support was found for the hypothesis that the CFI, GFI, NFI, NNFI, and RNI would yield values suggesting poorer fit when the number of indicators increased but the sample size was maintained at 100. That is, GFI and NFI values suggested poorer fit as the number of indicators increased and the sample size was small. However, this effect occurred at sample sizes of 100, 200, and 500. In comparison, no effects were found for the CFI, NNFI, and RNI at a sample size of 100. In agreement with the interaction hypothesis, values for the CFI, NNFI, and RNI remained relatively stable when the sample size was 200 or greater and the number of indicators was increased.

No effect had been hypothesized for the CN and number of indicators per latent variable. However, across the simulations, increases in the number of indicators per latent variable resulted in significantly lower CN values, suggesting poorer model fit. In retrospect, this hypothesis might have been anticipated. Results from Study 1 demonstrated a negative correlation between the CN and number of estimated paths. Because an increase in number of indicators results in an increase in estimated paths, this result is expected.

In sum, number of indicators exerted a significant effect on the indices. For the chi-square statistic, CN, and GFI, increases in indicators resulted in values suggesting poorer model fit. In comparison, increases in indicators resulted in decreased RMSEA values, suggesting better fit. For the CFI, NFI, NNFI, and RNI, values were lowest at one indicator, and relatively stable from two to five indicators. When the simulation specified one indicator per latent variable, many of the indices (i.e., CFI, NFI, NNFI, RMSEA, and RNI) were poor estimators of model fit. Therefore, in agreement with Bullock et al. (1994), Cliff (1983), and Ding et al. (1995), researchers are cautioned against using one indicator per latent variable and are urged to use a minimum of two or three indicators per latent variable.

Model misspecifications. Three main hypotheses were generated for model misspecifications. First, the indices were expected to yield values suggesting acceptable model fit when the model was correctly specified. Second, the indices were hypothesized to reward inclusion conditions with approximately the same values as for the true conditions. Third, when the specification error included an omitted path (i.e., the omission and combination conditions) the indices were hypothesized to yield values suggesting a poorer fit than for the true or inclusion condition.

Overall, the first hypothesis was supported. When the model was correctly specified, the indices were more likely to yield values suggesting better model fit than when the misspecification included an omitted path. However, although the values for the true condition were greater than the values for the omission and combination condition, in some situations the magnitude of the values did not suggest acceptable fit. For example, when there were a greater number of indicators, the chi-square and GFI were less likely to produce values suggesting acceptable fit.

The second hypothesis was fully supported. As noted by La Du and Tanaka (1989), the fit indices rewarded the inclusion condition with values that suggested the same or slightly better fit than for the true condition. This finding raises issues regarding model evaluation. Some researchers might conclude that an inclusion was substantively important. In such a situation, researchers should consider whether: (a) The added parameter is theoretically appropriate; and (b) whether the change in the chi-square statistic when the parameter is added is statistically significant using a chi-square difference test. The theoretical appropriateness of the added parameter would be considered a necessary condition before the application of the chi-square difference test.

In the current research and in La Du and Tanaka's (1989) research, the inclusion condition was generated by adding a single incorrect structural path to the model. Results across both studies demonstrated that the fit indices were unable to detect the inclusion as a misspecification condition. Future research should examine inclusions more fully by comparing models with a single incorrect structural path to models that have multiple incorrect structural paths. Although the indices were unable to detect a single incorrect structural path, they may be able to detect multiple incorrect structural paths.

Another avenue of research regarding inclusions would be to compare differences in the values of the fit indices as a function of type of unnecessary inclusion path. For example, incorrect measurement paths may be detected more readily than incorrect structural paths or incorrect latent correlations.

The third hypothesis was generally supported in the moderate and complex simulations. That is, the indices were able to detect the omission and combination conditions. Values for the omission and combination conditions suggested significantly poorer fit in these simulations than for the true and inclusion conditions. However, although the difference in values was practically significant, results indicated that values on the fit indices often suggested acceptable model fit for omission and combination conditions. In particular, for most of the indices, when two or more indicators were used, there was little distinction in model acceptance across the misspecification conditions.

Another concern is that the indices (i.e., except for the CN) were unable to detect the omission and combination conditions in the simple model. This finding suggests that simple models yield favorable values primarily because they are parsimonious. In comparison, when a model has more parameters to estimate, the indices were better able to detect omitted paths.

Future research should examine whether this finding is specific to the model chosen for the simple simulation or could be expected for most simple models. A research design might compare simple confirmatory factor analyses to simple structural equation models. The number of latent variables and estimated parameters could be manipulated to gain additional insight into this behavior.

Interaction hypotheses including sample size and model misspecifications and number of indicators per latent variable and model misspecifications were also examined in the simulations. Three hypotheses regarding sample size and model misspecifications were proposed, however, none of the hypotheses were supported. That is, the chi-square statistic was expected to detect misspecifications more accurately when sample size decreased, and less accurately as sample size increased. However, the findings showed that as the sample size increased, values on the chi-square statistic became significantly more pronounced for omission and combination conditions. In other words, the chi-square statistic was more sensitive to omitted misspecifications with increases rather than decreases in sample size. Because smaller sample sizes are rewarded with chi-square values suggesting better fit, it appears that discrepancies between the hypothesized variance-covariance matrix and sample variance-covariance matrix are more noticeable as the sample size increases.

The hypotheses regarding the GFI and NFI also were not supported. These indices had been expected to detect misspecifications more accurately as the sample size increased, and less accurately as the sample size decreased. For the GFI and NFI, there was very little difference in detection of model misspecifications across levels of sample size. In fact, as the sample size increased, these indices rewarded all levels of misspecification with higher values. Moreover, the values for true versus omission conditions were generally within .02 to .05 of one another. This finding suggests that the

GFI and NFI have trouble discriminating between true and omitted conditions.

Although it was not hypothesized, an interaction for sample size and model misspecifications was noted for the CN. As the sample size increased, values for the true and inclusion condition increased in significantly larger increments than did values for the omission and combination conditions. Thus, similar to the chi-square statistic, the CN was more sensitive to misspecifications when the sample size increased rather than decreased.

Several interaction effects had been proposed for model misspecifications and number of indicators per latent variable. The chi-square statistic, GFI, and NFI were expected to detect misspecifications less accurately as the number of indicators increased, and more accurately as the number of indicators decreased. In comparison, the RMSEA was expected to detect misspecifications more accurately as the number of indicators increased, and less accurately as the number of indicators decreased. No interaction effects had been proposed for the CFI, CN, NNFI, and RNI.

Results failed to support the interaction hypotheses for the chi-square statistic and GFI. Overall, increases in the number of indicators led to substantially larger chi-square values across all levels of misspecifications.

Similarly, increases in the number of indicators led to substantially smaller GFI values across all levels of misspecifications. Examination of mean values for the chi-square and GFI in Appendices K, L, and M demonstrated that the differences in values for true and inclusion conditions versus omission and combinations were exhibited in relatively similar proportions across the simulations and number of indicators.

The interaction regarding the RMSEA also was not supported. That is, the RMSEA detected misspecifications more accurately as the number of indicators decreased, and less accurately as the number of indicators increased. In particular, at one indicator, the RMSEA exhibited the largest difference in values between true and inclusion conditions versus omission and combination conditions. In contrast, when two or more indicators were specified, the differences between RMSEA values were less pronounced. This finding suggests that as the number of indicators increase, the RMSEA is less accurate at detecting misspecifications.

Interaction effects were also noted for the CFI, NFI, NNFI, and RNI. For these indices, average values across two to five indicators remained relatively stable across levels of model misspecifications. However, when one indicator was specified, the average values for the true and inclusion conditions were significantly higher than for the omission and combination conditions.

These findings suggest that the CFI, NFI, NNFI, RMSEA, and RNI may be useful in detecting models with omitted paths in single indicator models. Although researchers are urged to use multiple indicator models, situations may arise in which single indicator models are the only possible choice. In such a situation, these indices may provide insight into the fit of the model.

Summary of Findings from the Monte Carlo Simulations

The findings from the simulations showed that the study conditions exerted significant effects on the indices. In particular, none of the indices were completely independent of sample size or number of indicators per latent variable. However, a review of the findings suggests that chi-square, CN, GFI, and NFI values were significantly affected by sample size and number of indicators. Thus, based on the results of the current research and prior findings (e.g., Andersen & Gerbing, 1984; Bearden et al., 1982; Boomsma, 1982; Marsh et al., 1988; Mulaik et al., 1989), these indices are not recommended for evaluating the fit of a model.

The one exception to this rule occurs when nested models are compared. In such a situation, the models can be compared through use of a chi-square difference test. If the more saturated model has a chi-square value that is not significantly different from the more restricted model, then it suggests that the extra parameter in the saturated model is not necessary.

Another reason that researchers may continue to provide chi-square values for model evaluation is to allow researchers the opportunity to calculate other indices. As was noted earlier, the indices selected in the current research and several others not selected use the chi-square value for the hypothesized and/or null model in their calculation.

The remaining indices (i.e., the CFI, NNFI, RMSEA, and RNI) performed better across the study conditions. That is, each of these indices was relatively independent of sample size. Moreover, when the model specified between two and five indicators, these indices were relatively stable. However, two caveats are noted. First, the NNFI exhibited extreme variability when the sample size was 100. Thus, in situations in which a small sample size is unavoidable, the NNFI should not be used. Second, the indices were less sensitive to omission and combination conditions when the model specified two or more indicators.

Thus, when a model receives values that suggest acceptable model fit, researchers should carefully review their models to examine whether there are paths included that are not substantively important (i.e., an inclusion) or whether there are paths that are substantively important but were not included (i.e., an omission).

Limitations of the Simulations

Although the findings from the Monte Carlo simulations generally replicated prior research (e.g., Andersen & Gerbing, 1984; Gerbing & Andersen, 1993) and extended information regarding single and multiple indicator models, the simulations were not without limitations.

The most obvious question is whether the choice of models selected to reflect the levels of model complexity are generalizable to published and unpublished research. The criteria to consider a study for model selection included: (a) successful reanalysis, (b) goodness-of-fit values that met or exceeded the recommended cutoff values, and (c) availability of a complete covariance matrix. Although the review in Study 1 was extensive and examined four journals over a 10 year period, only 20 (i.e., 6%) of 366 articles met the criteria.

Given that the journals chosen were cited in other reviews (i.e., Breckler, 1990; MacCallum et al., 1993;

Tremblay & Gardner, 1996) as most likely to publish structural equation models, it is unlikely that the addition of other journals would have contributed significantly to the articles available for model selection. Furthermore, given that so many articles were unable to meet the criteria for inclusion into the model selection sample, it seems likely that the same phenomena would be noted in other journals.

Another potential criticism of the models chosen for the simulations is that because they are based and generated from actual research applications, they are not "true" models. In other words, the models may contain some specification error.

Researchers who conduct Monte Carlo simulations have to decide whether to use models from substantive literature that contain some specification error or whether to utilize models that have limited generalizability but absolutely reflect the true population variance-covariance matrix. An examination of Monte Carlo simulations shows that both strategies are used. Early simulations tended to generate data that absolutely reflected a population variance-covariance matrix (e.g., Andersen & Gerbing, 1984; Bearden et al., 1984; Boomsma, 1982). More recent investigations have used models from the substantive literature (e.g., Gerbing & Andersen, 1993; Bandalos, 1993, 1997) or have used both strategies simultaneously (e.g., La Du & Tanaka, 1989; Mulaik et al., 1989).

The decision to use articles from the substantive literature in the current research was done to understand the performance of the fit indices under conditions encountered in "typical" research applications. As Tukey stated in an interview with Anscombe (1988, p. 143), "real problems deserve realistic attention. Which implies that it's better to have an approximate solution to the right problem than to have an exact solution to the wrong one." Of course, the entire issue of the models chosen may be moot because the findings from the current research are in agreement with prior findings that used substantive applications, specified models, or both.

A final question is whether the findings regarding model misspecifications are specific to those chosen in the simulations or would generalize to other misspecifications. For example, if different paths had been omitted in the models, then the fit indices might have detected the omissions more accurately. And, if other incorrect structural paths had been added, the inclusion condition might have been detected.

These are reasonable concerns that should be addressed. With respect to the omitted paths, one possibility is that the omitted paths did not account for enough of the variance in the structural equations to be detected. This possibility seems unlikely. For example, when La Du and Tanaka (1989) omitted a correct structural path, the structural equation for the dependent latent variable was reduced from .54 to .51 (i.e., a reduction of 6%). In the current research, the removal of the omitted paths accounted for approximately 25% of the variance in the respective structural equations. Therefore, the misspecifications in the current research were more extreme than La Du and Tanaka's and should have been detected readily.

Moreover, a comparison of the fit indices used in both studies (i.e., the GFI and NFI) demonstrates that the difference in values for true and omitted conditions was approximately the same. That is, the difference in GFI and NFI values for true versus omitted conditions was approximately .05 (e.g., for the NFI, .87 versus .82 for La Du and Tanaka, and .94 versus .89 in the complex simulation). Thus, for the GFI and NFI, the effect of an omission was similar in both studies even though the omissions differed significantly in the proportion of variance accounted for in their structural equations.

Similarly, the choice of incorrect added structural paths could explain why the misspecifications were not detected. In the current research, the squared multiple correlation for the structural equations increased approximately 4% when the incorrect structural paths were added, whereas La Du and Tanaka's (1989) inclusion did not increase or decrease the squared multiple correlation. However, the performance of the fit indices was similar across the investigations. Included paths were not detected as misspecifications and the fit indices yielded values suggesting the same or better fit than the true condition. Therefore, the argument is flawed that the fit indices in the current research were more likely to yield values suggesting better fit than the true condition because of the increase in the squared multiple correlation.

Findings Regarding Recommended and Alternative Cutoff Values

In agreement with Hu and Bentler (1995), the recommended cutoff values were often inappropriate and inadequate. For example, in the simple model, the recommended cutoff values provided little to no assistance in selecting the true condition versus the omission and combination condition. In fact, the best performance in the simple model using the recommended cutoff values occurred for the CN. Using a value of 200 as the recommended cutoff, the CN accepted almost 100% of the true conditions and accepted about 50% of the omission conditions. Although 50% acceptance of omission conditions may appear high, the CFI, GFI, NFI, NNFI, and RNI accepted 70% or more of the omission and combination conditions! Clearly, use of the recommended cutoff values in the simple simulation would lead to confusion regarding the merits of a model.

Use of the recommended cutoff values in the moderate and complex simulations resulted in better performance for the fit indices than in the simple simulation. However, the best performance in those simulations for multiple indicator models was not any better than the performance of the CN in the simple simulation. In other words, using the recommended cutoff values, the best performance that was demonstrated was 100% acceptance of true conditions and approximately 50% acceptance of omission and combination conditions. Clearly, these findings are unacceptable if researchers hope to have confidence in their conclusions.

In comparison, when the model specified a single indicator in the moderate and complex models, the recommended cutoff values were adequate for the CFI, NNFI, RMSEA, and RNI. That is, the recommended values resulted in almost complete acceptance of the true conditions and almost complete rejection of the omission conditions.

An examination of alternative values across the simulations found that the percentages of accepted solutions with omissions could be reduced for multiple indicator models in the moderate and complex simulations, but not in the simple simulation. As an example, for the CFI, NNFI, and RNI, an alternative value of .98 in the moderate simulation resulted in over 90% acceptance of the true condition and 28% or less acceptance of the omission condition. Use of this alternative value resulted in a slight decrease in model acceptance for the true condition (less than 10%) and a substantial decrease in the model acceptance for the omission condition (about 45%).

Alternative values were also recommended for the RMSEA in the simulations. However, in the simple and moderate simulations, the alternative values either rejected a substantial percentage of true conditions (i.e., 62% in the simple simulation) or accepted a relatively high percentage of omitted conditions (i.e., 35% in the moderate simulation). Use of alternative values for the RMSEA was most beneficial in the complex simulation. Using an alternative value of .04, the RMSEA accepted 90% of the true conditions and accepted 4% of the omission conditions.

Summary of Study 2

Results from Study 2 demonstrated that sample size, model complexity, model misspecifications, and number of indicators per latent variable influence the values of the fit indices. For example, the chi-square, CN, GFI, and NFI were strongly influenced by sample size and number of indicators per latent variable. Furthermore, these indices were not particularly sensitive to model misspecifications. And, percentages of model acceptance were strongly influenced by model complexity, sample size, and number of indicators per latent variable. Thus, researchers are cautioned not to choose these indices for model evaluation. This recommendation is in agreement with findings from Andersen and Gerbing (1984), Bearden et al. (1982), Ding et al. (1995), Hu and Bentler (1995), Marsh et al. (1988), and Mulaik et al. (1989) cautioning researchers not to use the chi-square, CN, GFI, and NFI.

However, because the chi-square statistic can provide information about nested models and because the chi-square value is useful for calculating other indices, researchers are encouraged to report chi-square values for the hypothesized and null models with their findings.

In addition, Study 2 results supported that the CFI, NNFI, RMSEA, and RNI were relatively independent of sample size, and yielded stable values from two to five indicators. Furthermore, these indices detected omission and combination conditions in the moderate and complex simulations. These findings are in agreement with Ding et al. (1995), Gerbing and Andersen (1993), and Mulaik et al. (1989). Therefore, the CFI, NNFI, RMSEA, and RNI are preferred for model evaluation.

The findings from the evaluation of recommended and alternative cutoff values demonstrate that use of recommended cutoff values may lead to inappropriate conclusions about the fit of a model. Unfortunately, although the use of alternative cutoff values improved the ratio of accepted true conditions versus accepted omitted conditions, additional research is needed.

CHAPTER IV

CONCLUSIONS

The results from Study 1 documented the widespread use of structural equation modeling procedures. Researchers are using these procedures to examine a variety of applications including confirmatory factor analyses, single and multiple indicator structural equation models, as well as structural equation techniques and Monte Carlo simulations.

The results from Study 1 also demonstrated a significant amount of variability in the characteristics of models examined by researchers. For example, sample sizes ranged from less than 100 to more than 40,000. There was also variability in the number of indicators per latent variable used. Although the majority of articles (74%) used multiple indicators, 26% used single indicators. This occurrence becomes more striking when structural equation models are considered on their own. Of the 149 articles examining structural equation models, 64% (N = 95) used single indicators. Given the additional demands of structural equation models (i.e., developing and assessing valid and reliable measurement and structural models), this finding is particularly troubling.

Furthermore, the results from Study 1 confirmed that researchers are using a variety of goodness-of-fit indices to evaluate their models. The results also showed that most researchers are reporting between two to four indices in the articles. As expected, the most commonly reported index was the chi-square statistic. Other indices that were reported often were the CFI, GFI, NFI, and NNFI.

The results from Study 2 demonstrated that aspects of structural equation models influence values on the fit indices. In particular, many of the indices were influenced by sample size, number of indicators per latent variable, model misspecifications, and model complexity. An ideal index should be independent of sample size, number of indicators per latent variable, and model complexity. Further, an ideal index should be able to detect model misspecifications (i.e., incorrect added structural paths and omitted correct structural paths) and yield values suggesting poorer model fit when these misspecifications are detected.

The results from Study 2 showed that none of the indices studied meet the criteria to be considered the ideal index. However, there were significant differences in their independence from sample size, number of indicators per latent variable, and model complexity. Moreover, there were significant differences in their ability to detect model misspecifications.

Recommendations

Researchers who develop and examine structural equation models should be mindful of the strategies and guidelines that enhance the development and testing of sound models and later interpretation of those models. First, there are specific strategies that will improve the development of sound models. Second, there are guidelines that will improve the interpretability of model results.

Model development. Brannick (1995), Gavin and Williams (1993), and Williams and James (1994) have argued that researchers should devote more attention and effort to model development prior to data collection. When researchers choose not to devote attention to model development, it is likely that later interpretations of the models will be compromised. Unfortunately, once the data have been collected, there is usually very little a researcher can do to correct these problems, short of revising the model and collecting data from a new sample.

Measurement model development and assessment. The careful development of measurement models is critical to later evaluations of structural models. Although a carefully developed measurement model does not guarantee confidence in structural model interpretations, a carefully developed measurement model is a necessary condition for a well-defined structural model. In other words, the measurement model(s) demonstrates the adequacy of the indicators to represent the latent variables reliably and validly. Without reliable and valid indicators, the structural model cannot explain hypothesized relationships among the latent variables.

Researchers should give careful consideration to the number of indicators that are specified per latent variable. When a single indicator is assigned to a latent variable, there is less empirical information available on the latent variable. Furthermore, a single indicator is not as reliable as multiple indicators. However, the optimum number of indicators per latent variable is unclear. Study 2 results demonstrated that the optimum number of indicators for the fit indices differed as a function of model misspecifications and model complexity. For the preferred indices (i.e., the CFI, NNFI, RMSEA, and RNI), between two and four indicators per latent variable appeared best. A further increase from four to five indicators did not seem to provide any additional benefits.

One recommendation in measurement model development is to generate a large number of indicators per latent variable (e.g., 9 or 10). After these indicators are examined for reliability and validity, the indicators can be grouped into subscales (e.g., in sets of three or four indicators per subscale). The choice of grouping indicators into subscales could be based on theoretical similarity and/or correlations among the indicators. The resulting subscales would then serve as subscale indicators for the latent variables. This process would increase the reliability of the latent variables and would result in two to four subscale indicators per latent variable.

Several examinations of the measurement models should be considered before proceeding to structural model assessment. Among these are evaluations of the latent variable weights, t-values, measurement error variances, and squared multiple correlations for the latent variables. Latent variable weights should demonstrate that the indicators adequately reflect the latent variable. Similarly, t-values should be statistically significant (i.e., greater than 1.96 in absolute value). Moreover, measurement error variances should be positive and small. Negative error variances suggest that there are problems with the data such as an ill-conditioned matrix. Finally, the squared multiple correlations for the latent variables should demonstrate that a significant portion of variance is accounted for in the latent variable when the indicators are assigned to it.

One further assessment of the latent variables in the measurement model would be to calculate the composite reliability for each of the latent variables. Latent variables with poor composite reliability should not be used.

Structural model development and assessment. Perhaps the most important consideration in structural model development is ensuring that there are no omitted variables or paths. The underidentification of variables results in an inability to obtain unique parameter estimates to represent the relationships of interest. When a model has no omitted variables, it is said to be self-contained (James & James, 1989). That is, in a self-contained model, there are no relevant variables (independent or dependent) that have been left out. A relevant variable is one that is related to a dependent variable(s) and correlated with other independent variables in the model. If a model is not self-contained, the parameter estimates for the variables included will be biased, threatening the validity of any ongoing conclusions.

James and James (1989) and Medsker et al. (1994) argued that few researchers attend to the self-containment condition. Self-containment is suggested theoretically by lack of covariation between the variables included in a structural equation and the residual term of that equation (Johnston, 1984). Unfortunately, it is impossible to know whether the omitted variable problem has ever been reasonably satisfied. In fact, many researchers believe that it is more reasonable to assume that the omitted variable problem is never satisfied (Gavin & Williams, 1993; Williams & James, 1994). The omitted variable problem is especially likely when there are multiple dependent variables. That is, when these dependent variables have some common predictors and not all of these predictors are included in the design, problems are likely to occur.

The choice of number of indicators per latent variable appears to mask the omitted variable problem. That is, when there are two or more indicators per latent variable, the fit indices tend to yield values that in most cases, still suggest acceptable model fit. Thus, the researcher might not recognize that there were structural paths omitted in the model. In comparison, when the model uses one indicator per latent variable and an omission or combination condition exists, the fit indices are more sensitive to the omission. In particular, for the CFI, NFI, NNFI, RMSEA, and RNI, when single indicators are used, omissions are more readily noted.

Thus, one strategy might be for researchers to develop valid and reliable measurement models that use multiple indicators or subscales. Then, to test whether the structural model has omissions, the indicators or subscales could be summed or averaged to single composite variables, yielding reliable single indicator models. These single indicator models could then evaluate the structural models by removing one latent variable or latent path at a time, and examining model fit as changes are made.

If the fit indices suggested a significant reduction in model fit when the latent variable or path was omitted, the researcher could have additional confidence in the importance of that latent variable or path. On the other hand, if there was little change in the fit values after a latent variable or path was removed, then the researcher might conclude that the latent variable or path was extraneous to the true model.

Choosing a Goodness-of-Fit Index

Evaluating structural equation models requires researchers to examine many aspects of their models. Testing fit is an important component in the model evaluation process. The purposes that fit indices can serve are to assess: (a) The overall fit of a model, and

(b) the relative gain in fit provided by a model when compared to an alternative model based on the same data.

Choosing a goodness-of-fit index from the myriad of choices available is but one aspect of the evaluation process. The choice of a goodness-of-fit index should take into account the size of the sample, number of indicators per latent variable, detection of model misspecifications, and model complexity. The results of the current studies provide some insight when making those choices.

Sample size. The findings of the effects of sample size replicated and extended previous studies (e.g., Andersen & Gerbing, 1984; Bearden et al., 1982; Boomsma, 1982; Marsh et al., 1988; Mulaik et al., 1989). None of the fit indices were totally independent of sample size. However, for the CFI, NNFI, RMSEA, and RNI, the effects were relatively small.

With the exception of the chi-square test statistic, larger sample sizes were associated with better (i.e., more acceptable) estimates of model fit. Furthermore, for all of the indices, larger sample sizes were associated with more precise estimates of fit (i.e., smaller standard deviations). Boomsma (1982) recommended that researchers use sample sizes of 200 or more. The results of the current research generally support Boomsma's contention.

However, for the CFI, NNFI, RMSEA, and RNI, sample sizes greater than 200 may be unnecessary. These indices appear to be relatively independent of sample size and behaved well even when the sample size was 200. In fact, if the model specified two or more indicators, these indices behaved well at a sample size of 100.

In contrast, sample sizes larger than 200 may be needed for the CN, GFI, and NFI. For the CN, GFI, and NFI, smaller sample sizes were associated with smaller values that sometimes suggested unacceptable model fit even under the true condition. For these indices, a minimum sample size of 500 may be necessary. Further increases in sample size may be required if the model becomes more complex.

Therefore, if the sample size is small (e.g., 100 or 200), the preferred indices are the CFI, RMSEA, and RNI. The NNFI is not recommended at a sample size of 100 because it displayed extreme variability in standard deviations at that sample size. However, once the sample size reaches 200, the NNFI is stable and can be recommended. If the sample size is 500 or greater, the CN, GFI, and NFI may be used, however, values suggesting acceptable model fit may result primarily from the size of the sample rather than the fit of the model.

Number of indicators per latent variable. The number of indicators per latent variable exerted a strong influence on the indices studied. With the exception of the chi-square statistic, CN, and GFI, models that specified single indicators yielded values on the fit indices suggesting significantly poorer fit than when a greater number of indicators were specified.

In agreement with Andersen and Gerbing (1984) and Ding et al. (1995), increases in the number of indicators per latent variable resulted in poorer fit for the CFI, NFI, NNFI, and RNI. However, the effects of number of indicators appeared to be moderated by the simulation model. That is, in the simple model, the optimum number of indicators per latent variable appeared to be two. Further increases in indicators generally resulted in decrements in the values for these indices. In comparison, the optimum number of indicators in the moderate model appeared to be three or four. In the complex model, the optimum number of indicators for the CFI, NFI, NNFI, and RNI once again appeared to be three. Therefore, based on the findings from the simulations and the recommendations from Andersen and Gerbing (1984) and Ding et al. (1995), it appears that a recommendation of two to four indicators per latent variable is prudent.

Therefore, if the model specifies between two and four indicators, the preferred indices are the CFI, NNFI, RMSEA, and RNI. The chi-square, CN, and GFI performed best when the model specified a single indicator. However, these indices were extremely dependent on sample size, so their conclusions should be considered with caution.

Detection of model misspecifications. Results from Study 2 demonstrated that in the simple model, the CN was the only index sensitive to omitted misspecifications. However, values on the CN were significantly influenced by sample size and number of indicators per latent variable. Thus, the CN is recommended for detecting model misspecifications in the simple model, albeit with caution. However, in the moderate and complex models, the CFI, NNFI, RMSEA, and RNI detected omitted misspecifications. Furthermore, when the model specified a single indicator, these indices were more sensitive to omitted misspecifications. In comparison, the GFI and NFI were not particularly sensitive to omitted paths in the moderate and complex models. Therefore, the preferred indices for detecting omitted misspecifications in the moderate and complex models are the CFI, NNFI, RMSEA, and RNI.

Model complexity. The majority of the indices (i.e., the chi-square statistic, CN, CFI, GFI, NFI, NNFI, and RNI) yielded the highest percentages of model acceptance when the model was simple. Although the percentages of model acceptance for the CFI, NNFI, and RNI were lower in the moderate and/or complex models, the difference in model acceptance was not substantial.

In contrast, the RMSEA yielded the highest percentage of model acceptance when the model was complex or moderate. The percentage of model acceptance was substantially lower for the RMSEA when the model was simple.

The chi-square statistic, GFI, and NFI had the highest percentage of model acceptance in the simple model and decreased substantially as the models increased in complexity.

Therefore, if a model is simple or moderate (i.e., four or fewer latent variables for a simple model versus five to eight latent variables for a moderate model), the preferred indices are the CFI, NNFI, or RNI. The NFI also performed relatively well in the simple model, however, it was substantially affected by sample size. These indices can also be used in the complex model, however, the percentage of model acceptance in the complex model will likely be lower. In addition, the RMSEA is recommended with a complex or moderate model. However, the RMSEA is not recommended with a simple model.

Summary

Several recommendations were made with reference to goodness-of-fit indices. Use of an index can assist researchers in the model evaluation process. However, researchers are cautioned against making interpretations of model fit that are based solely on fit indices. In agreement with Marsh et al. (1988), there is no single index that will meet the evaluation needs of all researchers. Therefore, evaluation of structural models should be based on multiple levels of evaluations. First, the measurement properties of a model should be considered. Second, the structural properties of a model should be examined. Assuming the measurement and structural properties of a model appear to be well-defined, the global fit of the model can be evaluated with goodness-of-fit indices. Ideally, researchers should consider values from two or three fit indices that provide complementary information about the model. For example, one of the relative fit indices could be used (i.e., the CFI, NNFI, or RNI) along with an index that provides information about the degree of error reflected in the model (i.e., the RMSEA). These indices appear promising as candidates for overall global fit indices, although further research would provide a more complete understanding of their properties.

Ultimately, researchers will need to look for consistency in the indices and across evaluations of the measurement and structural properties to have confidence in model results.

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APPENDIX A

Equations for Goodness-of-Fit Indices

Chi-square test statistic

$$\chi^2 = (n - 1)\ F_{ML} \tag{1}$$

Root mean square error of approximation

$$\text{RMSEA} = \sqrt{\frac{\chi^2_{\text{hypothesized}} - df_{\text{hypothesized}}}{(df_{\text{hypothesized}})(n-1)}} \tag{2}$$

Goodness-of-fit index

$$\text{GFI} = 1 - \frac{\text{tr}[(\hat{\Sigma}^{-1}\text{S} - \text{I})^2]}{\text{tr}[(\hat{\Sigma}^{-1}\text{S})^2]} \tag{3}$$

Critical N

$$\text{CN} = \frac{\text{critical}\ \chi^2}{\text{F}_{\text{ML}}} + 1 \tag{4}$$

Normed fit index

$$\text{NFI} = \frac{\chi^2_{\text{null}} - \chi^2_{\text{hypothesized}}}{\chi^2_{\text{null}}} \tag{5}$$

Nonnormed fit index

$$\text{NNFI} = \frac{\left(\dfrac{\chi^2_{\text{null}}}{\text{df}_{\text{null}}}\right) - \left(\dfrac{\chi^2_{\text{hypothesized}}}{\text{df}_{\text{hypothesized}}}\right)}{\left(\dfrac{\chi^2_{\text{null}}}{\text{df}_{\text{null}}}\right) - 1} \tag{6}$$

Comparative fit index

$$\text{CFI} = 1 - \frac{\text{maximum} \quad [[\chi_h^2 - df_k], \text{ or } 0]}{\text{maximum} \quad [[\chi_h^2 - df_k], [\chi_n^2 - df_n], \text{ or } 0]} \tag{7}$$

Relative noncentrality index

$$\text{RNI} = \frac{\left(\chi^2_{\text{null}} - \text{df}_{\text{null}}\right) - \left(\chi^2_{\text{hypothesized}} - \text{df}_{\text{hypothesized}}\right)}{\chi^2_{\text{null}} - \text{df}_{\text{null}}} \tag{8}$$

APPENDIX B

Coding Sheet for Study 1

Journal (year, vol): ______________________________

Article Title (pp): ______________________________

____

Authors: ______________________________

Number of Latent Independent (IV) & Dependent (DV) Variables : (total)________ (IV)_______ (DV)________

Number of Indicators per Latent Variable: (Harmonic Mean) (overall)______ (IV) _____ (DV)_________

Ratio of IV/DV : _________

Number of Estimated Paths: Overall _________
Measured ______ Latent ______ Correlated Residual______

Number of Models Tested: _________

Goodness-of-Fit Indices Evaluated: ______________
____
____

Sample Size: ______________

Type of Application: ______________________

Type of Model: _____Single Indicator _____Multiple Indicator

Matrix Used : Covariance _____Correlation_____

Reproducible : Reanalysis _____ Formula _____ No _____

Additional Notes : ______________________

APPENDIX C

Programs Used to Generate Goodness-of-Fit Indices

```
OPTIONS LS=70 PS=70 NODATE;
TITLE "GENERATING GFI INDICES FROM TABLED DATA";
PROC IML;
CHIH = (insert article value for hypothesized chi-square
test statistic);
DFH = (insert article value for hypothesized degrees of
freedom);
CHIN = (insert article value for null chi-square test
statistic);
DFN = (insert article value for null degrees of freedom);
SS = (insert sample size from article);
CFIN1 = (CHIH-DFH);
IF CFIN1<0 THEN CFIN1=0;
CFI = 1 - (CFIN1/(CHIN-DFN));
RMSEA = SQRT((CHIH-DFH)/((SS-1)*DFH));
NFI = (CHIN-CHIH)/CHIN;
NNFI = (((CHIN/DFN) - (CHIH-DFH))/((CHIN/DFN)-1));
RNI = (((CHIN-DFN) - (CHIH-DFH))/(CHIN-DFN));
CNN = (((SQRT((DFH*2)-1))));
CNT = ((((CNN + 2.326)*(CNN*2.326))))/2);
CNB = (CHIH/(SS-1);
CN = (CNT/CNB)+1;
PRINT CFI;
PRINT RMSEA;
PRINT NFI;
PRINT NNFI;
PRINT RNI;
PRINT CN;
RUN;
```

APPENDIX D

List of Articles from Study 1

The letters before articles signify how an article was coded in Study 1. Multiple letters indicate the article was coded more than once. The number(s) after the letter(s) denote the complexity of the article, where 1 = simple, 2 = moderate, and 3 = complex.

(a) = Reanalyzed using LISREL 8.14

(b) = Formula generated including GFI

(c) = Formula generated without GFI

(d) = Coded only

(d3) Abbey, A., Andrews, F. M., & Halman, L. J. (1995). Provision and receipt of social support and disregard: What is their impact on the marital life quality of infertile and fertile couples? Journal of Personality and Social Psychology, 68, 455-469.

(d1) Abedi, J., & Baker, E. L. (1995). A latent-variable modeling approach to assessing interrater reliability, topic generalizability, and validity of a content assessment scoring rubric. Educational and Psychological Measurement, 55, 701-715.

(d3) Adams, G. A., King, L. A., & King, D. W. (1996). Relationships of job and family involvement, family social support, and work-family conflict with job and life satisfaction. Journal of Personality and Social Psychology, 81, 411-420.

(d1) Anderson, J. X., & Gerbing, D. W. (1991). Predicting the performance of measures in a confirmatory factor analysis with a pretest assessment of their substantive validities. Journal of Applied Psychology, 76, 732-740.

(b3) Anderson, S. E., & Williams, L. J. (1996). Interpersonal, job, and individual factors related to helping processes at work. Journal of Applied Psychology, 81, 282-296.

(d1) Arthur, W., Jr., & Day, D. V. (1994). Development of a short form for the Raven advanced progressive matrices test. Educational and Psychological Measurement, 54, 394-403.

(d1) Arthur, W., Jr., & Woehr, D. J. (1993). A confirmatory factor analytic study examining the dimensionality of the Raven's advanced progressive matrices. Educational and Psychological Measurement, 53, 471-478.

(a1) Arvey, R. D., Landon, T. E., Nutting, S. N., & Maxwell, S. E. (1992). Development of physical ability tests for police officers: A construct validation approach. Journal of Applied Psychology, 77, 996-1009.

(d2) Asendorf, J. B., & Meier, G. H. (1993). Personality effects on children's speech in everyday life: Sociability-mediated exposure and shyness-mediated reactivity to social situations. Journal of Personality and Social Psychology, 64, 1072-1083.

(d2) Aspinwall, L. G., & Taylor, S. E. (1992). Modeling cognitive adaptation: A longitudinal investigation of the impact of individual differences and coping on college adjustment and performance. Journal of Personality and Social Psychology, 63, 989-1003.

(b1) Bachelor, P. A. (1989). Maximum likelihood confirmatory factor-analytic investigation of factors within Guilford's structure of intellect model. Journal of Applied Psychology, 74, 797-804.

(d1) Bachelor, P. A., & Bachelor, B. G. (1989). An investigation of the higher-order symbolic factors of cognition and convergent production within the structure of intellect model. Educational and Psychological Measurement, 49, 537-548.

(b1) Bachelor, P. A., Michael, W. B., & Kim, S. (1994). First-order and higher-order semantic and figural factors in structure-of-intellect divergent production measures. Educational and Psychological Measurement, 54, 608-619.

(d2) Bachman, J. G., & O'Malley, P. M. (1986). Self-concepts, self-esteem, and educational experiences: The frog pond revisited (again). Journal of Personality and Social Psychology, 50, 35-46.

(c1) Bagozzi, R. P. (1991). Further thoughts on the validity of measures of elation, gladness, and joy. Journal of Personality and Social Psychology, 61, 98-104.

(d1) Bagozzi, R. P. (1993). An examination of the psychometric properties of measures of negative affect in the PANAS-X scales. Journal of Personality and Social Psychology, 65, 836-851.

(d1) Bagozzi, R. P. (1994). Effects of arousal on organization of positive and negative affect and cognitions: Application to attitude theory. Structural Equation Modeling, 1, 222-252.

(c1) Bagozzi, R. P., & Heatherton, T. F. (1994). A general approach to representing multifaceted personality constructs: Application to state self-esteem. Structural Equation Modeling, 1, 35-67.

(c1) Bagozzi, R. P., & Yi, Y. (1990). Assessing method variance in multitrait-multimethod matrices: The case of self-reported affect and perceptions at work. Journal of Applied Psychology, 75, 547-560.

(d1) Bandalos, D., & Benson, J. (1990). Testing the factor structure invariance of a computer attitude scale over two grouping conditions. Educational and Psychological Measurement, 50, 49-60.

(d3) Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (1996). Mechanisms of moral disengagement in the exercise of moral agency. Journal of Personality and Social Psychology, 71, 364-374.

(a2) Barling, J., Kelloway, E. K., & Bremerman, E. H. (1991). Preemployment predictors of union attitudes: The role of family socialization and work beliefs. Journal of Applied Psychology, 76, 725-731.

(b2) Barrick, M. R., & Mount, M. K. (1996). Effects of impression management and self-deception on the predictive validity of personality constructs. Journal of Applied Psychology, 81, 261-272.

(a3) Barrick, M. R., Mount, M. K., & Strauss, J. P. (1993). Conscientiousness and performance of sales representatives: Test of the mediating effects of goal setting. Journal of Applied Psychology, 78, 715-722.

(d1) Barton, R. M., Andrew, M. D., & Schwab, R. L. (1994). Factorial validity and reliability of a survey to assess the teaching effectiveness of graduates of teacher education programs. Educational and Psychological Measurement, 54, 218-226.

(c3) Bauer, T. N., & Green, S. G. (1994). Effect of newcomer involvement in work-related activities: A longitudinal study of socialization. Journal of Applied Psychology, 79, 211-223.

(d1) Benson, J. (1987). Detecting item bias in affective scales. Educational and Psychological Measurement, 47, 55-67.

(a1) Benson, J., & El-Zahhar, N. (1994). Further refinement and validation of the revised test anxiety scale. Structural Equation Modeling, 1, 203-221.

(b1) Benson, J., & Renstsch, J. (1988). Testing the dimensionality of the Piers-Harris children's self-concept scale. Educational and Psychological Measurement, 48, 615-626.

(a2) Boldizar, J. P., Wilson, K. L., & Deemer, D. K. (1989). Gender, life experiences, and moral judgment development: A process-oriented approach. Journal of Personality and Social Psychology, 57, 229-238.

(d2) Boninger, D. S., Krosnick, J. A., & Berent, M. K. (1995). Origins of attitude importance: Self-interest, social identification, and value relevance. Journal of Personality and Social Psychology, 68, 61-80.

(a2) Borman, W. C., Hanson, M. A., Oppler, S. H., Pulakos, E. D., & White, L. A. (1993). Role of early supervisory experience in supervisor performance. Journal of Applied Psychology, 78, 443-449.

(a2a2)Borman, W. C., White, L. A., & Dorsey, D. W. (1995). Effects of ratee task performance and interpersonal factors on supervisor and peer performance ratings. Journal of Applied Psychology, 80, 168-177.

(d2) Borman, W. C., White, L. A., Pulakos, E. D., & Oppler, S. H. (1991). Models of supervisory job performance ratings. Journal of Applied Psychology, 76, 863-872.

(b1) Breaugh, J. A., & Colihan, J. P. (1994). Measuring facets of job ambiguity: Construct validity evidence. Journal of Applied Psychology, 79, 191-202.

(d1) Bretz, R. D., Jr., & Thomas, S. L. (1992). Perceived equity, motivation, and final-offer arbitration in major league baseball. Journal of Applied Psychology, 77, 280-287.

(d2) Brodnick, R. J., & Ree, M. J. (1995). A structural model of academic performance, socioeconomic status, and Spearman's g. Educational and Psychological Measurement, 55, 583-594.

(d1) Brooke, P. P., Russell, D. W., & Price, J. L. (1988). Discriminant validation of measures of job satisfaction, job involvement, and organizational commitment. Journal of Applied Psychology, 73, 139-145.

(d1) Brown, R., & Marcoulides, G. A. (1996). A cross-cultural comparison of the Brown locus of control scale. Educational and Psychological Measurement, 56, 858-863.

(a1) Brown, S. P., & Leigh, T. W. (1996). A new look at psychological climate and its relationship to job involvement, effort, and performance. Journal of Applied Psychology, 81, 358-368.

(b1) Buckley, M. R., Carraher, S. M., & Cote, J. A. (1992). Measurement issues concerning the use of inventories of job satisfaction. Educational and Psychological Measurement, 52, 529-542.

(d1) Burke, M. J., Brief, A. P., George, J. M., Roberson, L., & Webster, J. (1989). Measuring affect at work: Confirmatory analyses of competing mood structures with conceptual linkage to cortical regulatory systems. Journal of Personality and Social Psychology, 57, 1091-1102.

(d3) Burkholder, G. J., & Harlow, L. L. (1996). Using structural equation modeling techniques to evaluate HIV risk models. Structural Equation Modeling, 3, 348-368.

(a1) Bycio, P., Alvares, K. M., & Hahn, J. (1987). Situational specificity in assessment center ratings: A confirmatory factor analysis. Journal of Applied Psychology, 72, 463-474.

(c1) Byrne, B. M. (1988). The self description questionnaire III: Testing for equivalent factorial ability. Educational and Psychological Measurement, 48, 397-406.

(d1) Byrne, B. M., & Shavelson, R. J. (1996). On the structure of social self-concept for pre-, early, and late adolescents: A test of the Shavelson, Hubner, and Stanton (1976) model. Journal of Personality and Social Psychology, 70, 599-613.

(d1) Carey, L. M., Dedrick, R. F., Carey, J. O., & Kushner, S. N. (1994). Procedures for designing course evaluation instruments: Masked personality format versus transparent achievement format. Educational and Psychological Measurement, 54, 134-145.

(d1) Chang, L., & McBride-Chang, C. (1996). The factor structure of the Life Orientation Test. Educational and Psychological Measurement, 56, 325-329.

(b1) Chen, C., & Michael, W. B. (1993). Higher-order abilities conceptualized within Guilford's structure-of-intellect (SOI) model for a sample of United States Coast Guard Academy cadets: A reanalysis of an SOI data base. Educational and Psychological Measurement, 53, 941-950.

(b1) Chen, S. A., & Michael, W. B. (1993). First-order and higher-order factors of creative social intelligence within Guilford's structure-of-intellect model: A reanalysis of a Guilford data base. Educational and Psychological Measurement, 53, 619-641.

(d1) Chow, P., & Winzer, M. M. (1992). Reliability and validity of a scale measuring attitudes towards mainstreaming. Educational and Psychological Measurement, 52, 223-228.

(c1) Christiansen, N. D., Lovejoy, M. C., Szymanski, J., & Lang, A. (1996). Evaluating the structural validity of measures of hierarchical models: An illustrative example using the Social Problem-Solving Inventory. Educational and Psychological Measurement, 56, 600-625.

(b1) Church, A. T., & Burke, P. J. (1994). Exploratory and confirmatory tests of the Big 5 and Tellegen's three and four-dimensional models. Journal of Personality and Social Psychology, 66, 93-114.

(d1) Cohen, A. (1996). On the discriminant validity of the Meyer and Allen measure of organizational commitment: How does it fit with the work commitment construct? Educational and Psychological Measurement, 56, 494-503.

(a2) Cohen, S., Doyle, W. J., Skoner, D. P., Fireman, P., Gwaltney, J. M., & Newsom, J. T. (1995). State and trait negative affect as predictors of objective and subjective symptoms of respiratory viral infections. Journal of Personality and Social Psychology, 68, 159-169.

(d2) Collins, N. L. (1996). Working models of attachment: Implications for explanation, emotion, and behavior. Journal of Personality and Social Psychology, 71, 810-832.

(d3) Collins, N. L., Dunkel-Schetter, C., Lobel, M., & Scrimshaw, S. C. (1993). Social support in pregnancy: Psychosocial correlates of birth outcomes and postpartum depression. Journal of Personality and Social Psychology, 65, 1243-1258.

(b1) Conte, J. M., Landy, F. J., & Mathieu, J. E. (1995). Time urgency: Conceptual and construct development. Journal of Applied Psychology, 80, 178-185.

(d2) Cook, W. L. (1993). Interdependence and the interpersonal sense of control: An analysis of family relationships. Journal of Personality and Social Psychology, 64, 587-601.

(b1) Cooke, D. K., (1994). The factor structure and predictive validity of Burbach's university alienation scale. Educational and Psychological Measurement, 54, 973-982.

(a3a3)Cooper, M. L., Frone, M. R., Russell, M., & Muldar, P. (1995). Drinking to regulate positive and negative emotions: A motivational model of alcohol use. Journal of Personality and Social Psychology, 69, 990-1005.

(d2) Copeland, J. T. (1994). Prophecies of power: Motivational implications of social power for behavioral confirmation. Journal of Personality and Social Psychology, 67, 264-277.

(d1) Cordery, J. L., & Sevastos, P. P. (1993). Responses to the original and revised job diagnostic survey: Is education a factor in responses to negatively worded items? Journal of Applied Psychology, 78, 141-143.

(a2) Council, J. R., Kirsch, I., & Hafner, L. P. (1986). Expectancy versus absorption in the prediction of hypnotic responding. Journal of Personality and Social Psychology, 50, 182-189.

(b1) Crowder, B., & Michael, W. B. (1991). The development and validation of a short form of a multidimensional self-concept measure for high technology employees. Educational and Psychological Measurement, 51, 447-455.

(d2) Cutrona, C. E., Cole, V., Colangelo, N., Assouline, S. G., & Russell, D. W. (1994). Perceived parental support and academic achievement: An attachment theory perspective. Journal of Personality and Social Psychology, 66, 369-378.

(d3) Davis, M. H., & Franzoi, S. L. (1986). Adolescent loneliness, self-disclosure, and private self-consciousness: A longitudinal investigation. Journal of Personality and Social Psychology, 58, 595-608.

(c1) De Aquino-Villar, I., Michael, W. B., & Gribbons, B. (1995). The development and construct validation of a Portuguese version of an academic self-concept scale. Educational and Psychological Measurement, 55, 115-123.

(d1) DeConnick, J. B., Stilwell, C. D., & Brock, B. A. (1996). A construct validity analysis of scores on measures of distributive justice and pay satisfaction. Educational and Psychological Measurement, 56, 1026-1036.

(d2) de Jong-Geirveld, J. (1987). Developing and testing a model of loneliness. Journal of Personality and Social Psychology, 53, 119-128.

(d1) Diener, E., Smith, H., & Fujita, F. (1995). The personality structure of affect. Journal of Personality and Social Psychology, 69, 130-141.

(d1) Ding, L., Velicer, W. F., & Harlow, L. L. (1995). Effects of estimation method, number of indicators per factor, and improper solutions on structural equation modeling fit indices. Structural Equation Modeling, 2, 119-143.

(d2) Dovidio, J. F., Allen, J. L., & Schroeder, D. A. (1990). Specificity of empathy-induced helping: Evidence for altruistic motivation. Journal of Personality and Social Psychology, 59, 249-260.

(d1) Downey, G., Silver, R. C., & Wortman, C. B. (1990). Reconsidering the attribution-adjustment relation following a major negative event: Coping with the loss of a child. Journal of Personality and Social Psychology, 59, 925-940.

(d1) Dreger, R. M. (1991). The latent structure of the salvation questionnaire: A measure of religious attitudes in the American Christian tradition. Educational and Psychological Measurement, 51, 707-719.

(d1) Duncan, T. E., & Duncan, S. C. (1995). Modeling the processes of development via latent variable growth curve methodology. Structural Equation Modeling, 2, 187-213.

(d1) Duncan, S. C., & Duncan, T. E. (1996). A multivariate latent growth curve analysis of adolescent substance use. Structural Equation Modeling, 3, 323-347.

(c1) Dunham, R. B., Grube, J. A., & Castaneda, M. B. (1994). Organizational commitment: The utility of an integrative definition. Journal of Applied Psychology, 79, 370-380.

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APPENDIX E

Population Variance/Covariance Matrices

Symmetrical matrices are presented in block format to conserve space.

Simple model: One indicator

1.02010	.46359	.72250	.64832	.45654	1.71610
.14544	.12240	.12262	.51840		

Simple model: Two indicators

1.02010	.84840	1.0000	.46359	.47650	.72250
.45167	.46440	.62135	.73960	.59883	.61710
.42168	.43705	1.46410	.61610	.59780	.44591
.41968	1.29906	1.48840	.45440	.17280	.12140
.13003	.11326	.10541	.51840	.17210	.15620
.13277	.12212	.12866	.12127	.40385	.50410

Simple model: Three indicators

1.02010	.84840	1.00000	.85507	.86700	1.04040
.46359	.46750	.45951	.72250	.45167	.46440
.48246	.62135	.73960	.44965	.43680	.46267
.61404	.60682	.70560	.59883	.61710	.61710
.42168	.43705	.43705	1.46410	.61610	.59780
.63464	.44591	.41968	.43042	1.29906	1.48840
.61812	.60000	.58752	.42840	.44376	.41328
1.29928	1.27368	1.44000	.14544	.17280	.16157
.12240	.13003	.13306	.11326	.10541	.12096
.51840	.17210	.15620	.14484	.13277	.12212
.12524	.12886	.12127	.11076	.40385	.50410
.16221	.14600	.17870	.13030	.13812	.12264
.12366	.11578	.13140	.42048	.40427	.53290

Simple model: Four indicators

1.02010	.84840	1.00000	.85507	.86700	1.04040
.86708	.84840	.85507	1.02010	.46359	.46750
.45951	.44642	.72250	.45167	.46440	.48246
.46036	.62135	.73960	.44965	.43680	.46267
.46662	.61404	.60682	.70560	.47218	.45050
.45084	.46359	.60690	.62135	.61404	.72250
.59883	.61710	.61710	.58661	.43197	.42665
.43705	.42168	1.46410	.61610	.59870	.63464
.59146	.41480	.45116	.43042	.44591	1.29906
1.48840	.61812	.60000	.58752	.59388	.43860
.43344	.41328	.44880	1.29228	1.2736	1.44000

Simple model: Four indicators concluded

.58661	.58080	.60476	.62327	.45254	.41624
.42689	.44225	1.27377	1.29906	1.29228	1.46410
.14544	.17280	.16157	.16726	.12240	.13003
.13306	.14076	.11326	.10541	.12096	.13068
.51840	.17210	.15620	.14484	.15059	.13277
.12212	.12524	.13277	.12886	.12127	.11076
.10309	.40385	.50410	.16221	.14600	.17870
.16958	.13030	.13812	.12264	.13030	.12366
.11578	.10512	.13250	.42048	.40427	.53290
.15271	.16560	.16891	.14544	.14076	.13003
.13006	.12240	.10454	.13176	.12960	.12197
.40435	.40385	.42048	.51840		

Simple model: Five indicators

1.02010	.84840	1.00000	.85507	.86700	1.04040
.86708	.84840	.85507	1.02010	.84840	.83000
.86700	.84840	1.00000	.46359	.46750	.45951
.44642	.46750	.72250	.45167	.46440	.48246
.46036	.46440	.62135	.73960	.44965	.43680
.46267	.46662	.43680	.61404	.60682	.70560
.47218	.45050	.45084	.46359	.45050	.60690
.62135	.61404	.72250	.45167	.46440	.48246
.46036	.46440	.62135	.63606	.60682	.62135
.73960	.59883	.61710	.61710	.58661	.59290
.43197	.42665	.43705	.42168	.41624	1.46410
.61610	.59780	.63464	.59146	.61000	.41480
.45116	.43042	.44591	.46165	1.29906	1.48440
.61812	.60000	.58752	.59388	.61200	.43860
.43344	.41328	.44880	.41280	1.29228	1.27368
1.44000	.58661	.58080	.60476	.62327	.58080
.45254	.41624	.42689	.44225	.42665	1.27377
1.29906	1.29228	1.46410	.61610	.62220	.59731
.60378	.59780	.42517	.46165	.45091	.43554
.45116	1.29906	1.32468	1.27368	1.29906	1.48440
.14544	.17280	.16151	.16726	.15120	.12240
.13003	.13306	.14076	.13622	.11326	.10541
.12096	.13068	.11419	.51840	.17210	.15620
.14484	.15059	.16330	.13277	.12212	.12524
.13277	.12212	.12886	.12127	.11076	.10309
.12993	.40385	.50410	.16221	.14600	.17870
.16958	.15330	.13030	.13812	.12264	.13030
.14439	.12366	.11578	.10512	.13250	.12468
.42048	.40427	.53290	.15271	.16560	.16891
.14544	.17280	.14076	.13003	.13306	.12240
.13003	.10454	.13176	.12960	.12197	.11419
.40435	.40385	.42048	.51840	.16958	.15330
.16381	.17695	.16060	.12410	.13812	.12877

Simple model: Five Indicators concluded

.14271	.13812	.13250	.12468	.11388	.10600
.12468	.41522	.41464	.41566	.41522	.53290

Moderate model: One indicator

.24010	.18596	.62410	.09689	.30276	.57708
-.09632	-.29668	-.48029	1.13303	.06078	.10375
.05405	-.05894	.21181	.01071	.01827	.00952
-.29927	.02428	1.10201			

Moderate model: Two indicators

.27040	.20384	.24010	.19515	.18346	.62410
.19912	.18718	.57593	.65610	.10488	.09860
.30336	.30952	.57760	.09837	.09247	.28452
.29030	.48330	.54760	-.10247	-.09634	-.29139
-.29731	-.48739	-.45713	1.13325	-.10099	-.09494
-.28719	-.29302	-.48036	-.45053	1.11811	1.30842
.06646	.06247	.10890	.11111	.05853	.05489
-.06507	-.06413	.22090	.06082	.05717	.09966
.10168	.05356	.05023	-.05955	-.05869	.15446
.20250	.01327	.01247	.02174	.02218	.01168
.01096	-.31478	-.31024	.03369	.03083	1.02013
.01148	.01079	.01881	.01919	.01011	.00948
-.27237	-.26844	.02915	.02668	.87568	1.04046

Moderate model: Three indicators

.27040	.20366	.24010	.20776	.20449	.26010
.18371	.18081	.18446	.62410	.19596	.19287
.19676	.57552	.65610	.19007	.18707	.19084
.55822	.59546	.64000	.09607	.09456	.09647
.28216	.30098	.29194	.57760	.09663	.09511
.09703	.28381	.30274	.29364	.48322	.54760
.09659	.09507	.09699	.28369	.30261	.29351
.48301	.48583	.56250	-.09594	-.09443	-.09633
-.27692	-.29539	-.28651	-.46428	-.46699	-.46679
1.34217	-.09874	-.09718	-.09914	-.28499	-.30400
-.29486	-.47781	-.48060	-.48039	1.19185	1.32356
-.09807	-.09653	-.09848	-.28307	-.30195	-.29287
-.47459	-.47736	-.47716	1.18385	1.21832	1.34511
.06216	.06118	.06241	.10166	.10844	.10518
.05317	.05348	.05345	-.06026	-.06202	-.06160
.22090	.06245	.06146	.06270	.10214	.10895
.10568	.05342	.05373	.05370	-.06054	-.06230
-.06189	.15432	.20250	.06239	.06141	.06265
.10204	.10885	.10558	.05337	.05368	.05365
-.06049	-.06225	-.06183	.15417	.15490	.21160

Moderate model: Three indicators concluded

.01154	.01136	.01159	.01887	.02013	.01953
.00987	.00993	.00992	-.29768	-.30635	-.30429
.02852	.02865	.02862	1.02017	.01135	.01117
.01140	.01856	.01980	.01921	.00971	.00976
.00976	-.29279	-.30132	-.29929	.02805	.02818
.02815	.87549	1.04041	.01164	.01145	.01168
.01903	.02030	.01969	.00995	.01001	.01001
-.30017	-.30892	-.30684	.02875	.02889	.02886
.89756	.88282	1.04043			

Moderate model: Four indicators

.27040	.20254	.24010	.20993	.20370	.26010
.20822	.20204	.20941	.26010	.18600	.18047
.18706	.18554	.62410	.19581	.18999	.19693
.19533	.57253	.65610	.19285	.18712	.19395
.19237	.56387	.59362	.64000	.19111	.18544
.19221	.19064	.55880	.58828	.57938	.64000
.09750	.09460	.09806	.09726	.28509	.30013
.29559	.29293	.57760	.09719	.09431	.09775
.09695	.28418	.29917	.29465	.29200	.48072
.54760	.09833	.09541	.09889	.09808	.28750
.30267	.29809	.29541	.48633	.48479	.56250
.09759	.09469	.09815	.09735	.28535	.30041
.29586	.29321	.48270	.48117	.48679	.56250
-.09847	-.09554	-.09903	-.09823	-.28300	-.29793
-.29342	-.29078	-.47156	-.47007	-.47556	-.47201
1.34678	-.10013	-.09716	-.10070	-.09988	-.28777
-.30295	-.29837	-.29569	-.47952	-.47800	-.48358
-.47997	1.18997	1.32654	-.10084	-.09785	-.10142
-.10060	-.28983	-.30511	-.30050	-.29780	-.48294
-.48141	-.48703	-.48339	1.19842	1.21863	1.35016
-.09908	-.09613	-.09964	-.09883	-.28474	-.29976
-.29523	-.29257	-.47447	-.47297	-.47849	-.47492
1.17747	1.19733	1.20586	1.32504	.06336	.06147
.06372	.06320	.10273	.10815	.10651	.10556
.05385	.05368	.05431	.05390	-.06155	-.06259
-.06304	-.06193	.22090	.06261	.06075	.06297
.06246	.10152	.10688	.10526	.10431	.05322
.05305	.05367	.05327	-.06083	-.06185	-.06229
-.06120	.15331	.20250	.06372	.06183	.06409
.06356	.10332	.10877	.10713	.10616	.05416
.05399	.05462	.05421	-.06191	-.06295	-.06340
-.06229	.15603	.15420	.21160	.06317	.06129
.06353	.06301	.10242	.10783	.10620	.10524
.05369	.05352	.05415	.05374	-.06137	-.06240
-.06285	-.06175	.15468	.15286	.15557	.21160
.01145	.01111	.01152	.01142	.01857	.01955

Moderate model: Four indicators concluded

.01925	.01908	.00973	.00970	.00982	.00974
-.29718	-.30219	-.30435	-.29901	.02804	.02771
.02820	.02796	1.02014	.01147	.01113	.01154
.01144	.01860	.01958	.01928	.01911	.00975
.00972	.00983	.00976	-.29766	-.30268	-.30484
-.29949	.02809	.02776	.02825	.02800	.87351
1.04042	.01170	.01135	.01176	.01167	.01897
.01997	.01967	.01949	.00994	.00991	.01003
.00995	-.30355	-.30867	-.31087	-.30542	.02864
.02831	.02881	.02856	.89081	.89225	1.04043
.01151	.01116	.01157	.01148	.01866	.01964
.01934	.01917	.00978	.00975	.00986	.00979
-.29857	-.30361	-.30577	-.30041	.02817	.02784
.02834	.02809	.87620	.87761	.89499	1.02013

Moderate model: Five indicators

.27040	.20107	.24010	.21057	.20402	.26010
.20356	.19723	.20654	.25000	.21062	.20407
.21370	.20659	.26010	.18618	.18039	.18891
.18262	.18895	.62410	.19560	.18951	.19847
.19186	.19851	.57274	.65610	.19217	.18619
.19499	.18850	.19503	.56270	.59118	.64000
.18934	.18344	.19211	.18571	.19216	.55439
.58245	.57224	.62410	.19182	.18585	.19463
.18815	.19468	.56167	.59009	.57975	.57119
.64000	.09753	.09449	.09896	.09566	.09898
.28557	.30003	.29477	.29042	.29423	.57760
.09849	.09542	.09993	.09660	.09995	.28837
.30296	.29765	.29326	.29711	.48736	.56250
.09672	.09371	.09814	.09487	.09816	.28321
.29754	.29232	.28801	.29179	.47863	.48332
.54760	.09788	.09484	.09932	.09601	.09934
.28661	.30111	.29584	.29147	.29529	.48438
.48912	.48036	.56250	.09919	.09610	.10064
.09729	.10066	.29042	.30512	.29977	.29534
.29922	.49082	.49562	.48675	.49260	.57760
-.09898	-.09590	-.10043	-.09709	-.10046	-.28465
-.29906	-.29381	-.28948	-.29328	-.47336	-.47799
-.46944	-.47507	-.48139	1.34865	-.10085	-.09771
-.10233	-.09892	-.10235	-.29003	-.30471	-.29937
-.29495	-.29882	-.48231	-.48703	-.47831	-.48405
-.49049	1.19451	1.32889	-.10095	-.09781	-.10243
-.09902	-.10245	-.29030	-.30500	-.29965	-.29523
-.29910	-.48276	-.48749	-.47876	-.48451	-.49095
1.19562	1.21829	1.35153	-.09885	-.09577	-.10029
-.09696	-.10032	-.28426	-.29865	-.29341	-.28908
-.29288	-.47271	-.47734	-.46879	-.47443	-.48073

Moderate model: Five indicators concluded

1.17077	1.19281	1.19398	1.30366	-.09919	-.09610
-.10064	-.09729	-.10066	-.28523	-.29967	-.29442
-.29007	-.29388	-.47433	-.47897	-.47040	-.47605
-.48238	1.17477	1.19692	1.19806	1.17319	1.32642
.06282	.06086	.06374	.06162	.06375	.10317
.10839	.10649	.10492	.10630	.05405	.05457
.05360	.05424	.05496	-.06257	-.06375	-.06381
-.06248	-.06270	.22090	.06339	.06142	.06432
.06218	.06434	.10411	.10938	.10746	.10588
.10727	.05454	.05507	.05409	.05474	.05546
-.06314	-.06433	-.06439	-.06305	-.06327	.15666
.21160	.06212	.06018	.06302	.06093	.06304
.10201	.10718	.10530	.10374	.10511	.05344
.05396	.05300	.05363	.05435	-.06187	-.06304
-.06310	-.06178	-.06199	.15350	.15490	.20250
.06231	.06037	.06322	.06111	.06323	.10233
.10750	.10562	.10406	.10543	.05360	.05413
.05316	.05380	.05451	-.06206	-.06323	-.06329
-.06197	-.06218	.15397	.15538	.15224	.21160
.06424	.06224	.06518	.06301	.06520	.10550
.11084	.10890	.10729	.10870	.05527	.05581
.05481	.05547	.05620	-.06398	-.06519	-.06525
-.06390	-.06411	.15875	.16020	.15697	.15745
.22090	.01208	.01170	.01226	.01185	.01226
.01984	.02084	.02048	.02018	.02044	.01039
.01050	.01031	.01043	.01057	-.29882	-.30446
-.30475	-.29841	-.29943	.02985	.03013	.02952
.02961	.03053	1.02018	1.23030	1.19207	.01248
.01207	.01249	.02021	.02123	.02086	.02055
.02082	.01058	.01069	.01050	.01062	.01076
-.30431	-.31006	-.31036	-.30390	-.30494	.03040
.03068	.03006	.03015	.03109	.88219	1.06094
.01239	.01200	.01257	.01215	.01257	.02035
.02138	.02100	.02069	.02096	.01066	.01076
.01057	.01070	.01084	-.30645	-.31224	-.31254
-.30603	-.30708	.03062	.03090	.03027	.03037
.03131	.88839	.90473	1.04049	.01205	.01167
.01223	.01182	.01223	.01979	.02079	.02043
.02012	.02039	.01037	.01047	.01028	.01040
.01054	-.29804	-.30368	-.30396	-.29763	-.29865
.02978	.03005	.02944	.02953	.03045	.86401
.87990	.88609	1.00007	.01231	.01193	.01249
.01208	.01249	.02022	.02124	.02087	.02056
.02083	.01059	.01070	.01050	.01063	.01077
-.30450	-.31026	-.31055	-.30408	-.30512	.03042
.03070	.03008	.03017	.03111	.88273	.89897
.90529	.88044	1.02013			

Complex model: One indicator

.58565	.31290	1.00683	.23451	.44193	.71772
.16856	.16685	.21981	.30107	.70545	.46685
.41831	.26714	1.96137	.45216	.66116	.42394
.21535	1.06222	1.71510	.18908	.06866	.08781
.06472	.28242	.16911	.51842	.10337	.05761
.05665	.03783	.16387	.13059	.12313	.20250
.04405	.14497	.07598	.03080	.11064	.12228
-.00409	.01444	.51833			

Complex model: Two indicators

.58751	.48159	.60289	.33397	.33772	1.02507
.34388	.34773	.85079	1.00510	.25185	.25467
.46267	.47639	.72198	.24757	.25034	.45480
.46829	.62159	.73910	.17339	.17533	.19995
.20588	.22842	.22454	.32402	.18629	.18838
.21482	.22120	.24542	.24124	.26473	.34708
.67459	.68215	.43647	.44942	.33906	.33329
.24076	.25867	1.69003	.67367	.68122	.43588
.44881	.33860	.33284	.24043	.25832	1.44362
1.66414	.42952	.43434	.61795	.63628	.38017
.37371	.19830	.21305	.91430	.91305	1.46413
.42630	.43108	.61331	.63151	.37732	.37090
.19681	.21145	.90743	.90620	1.29856	1.48841
.19759	.19980	.06822	.07024	.07050	.06931
.06263	.06729	.26002	.25967	.15611	.15494
.51840	.19660	.19880	.06788	.06989	.07015
.06896	.06231	.06695	.25872	.25837	.15533
.15416	.42431	.50410	.10888	.11010	.06007
.06185	.04971	.04886	.03749	.04027	.15250
.15229	.12473	.12379	.12470	.12408	.20250
.10941	.11063	.06036	.06215	.04995	.04910
.03767	.04047	.15323	.15302	.12533	.12439
.12530	.12468	.16353	.21160	.04398	.04447
.15313	.15768	.08234	.08094	.03220	.03460
.10182	.10169	.11871	.11782	-.00829	-.00826
.01603	.01610	.51840	.04373	.04422	.15226
.15678	.08187	.08048	.03201	.03439	.10124
.10110	.11803	.11714	-.00825	-.00821	.01594
.01601	.40384	.50410			

Complex model: Three indicators

.58698	.48097	.60251	.47213	.47084	.57193
.33779	.33687	.33068	1.02404	.34211	.34118
.33491	.85117	1.00403	.34514	.34420	.33787
.85870	.86968	1.04454	.25453	.25383	.24917
.46244	.46836	.47250	.72135	.25173	.25104

Complex model: Three indicators continued

.24643	.45734	.46320	.46729	.62106	.73847
.24833	.24765	.24310	.45117	.45695	.46099
.61268	.60593	.70450	.17941	.17892	.17563
.20582	.20845	.21030	.23394	.23136	.22824
.32380	.18278	.18228	.17893	.20969	.21237
.21425	.23834	.23571	.23253	.26451	.34696
.18121	.18071	.17739	.20788	.21054	.21241
.23629	.23368	.23053	.26224	.26716	.33527
.68424	.68237	.66983	.44409	.44978	.45376
.34457	.34078	.33618	.24987	.25457	.25237
1.69002	.66739	.66557	.65334	.43316	.43870
.44259	.33609	.33239	.32790	.24372	.24830
.24616	1.44253	1.66416	.68395	.68208	.66955
.44391	.44959	.45357	.34443	.34063	.33604
.24977	.25446	.25227	1.47825	1.44181	1.71615
.43252	.43134	.42341	.62399	.63198	.63757
.37936	.37518	.37012	.20352	.20734	.20556
.92609	.90329	.92570	1.46416	.42755	.42638
.41855	.61683	.62472	.63024	.37500	.37087
.36587	.20118	.20496	.20320	.91545	.89291
.91507	1.29882	1.48841	.42481	.42364	.41586
.61287	.62071	.62620	.37260	.36849	.36352
.19989	.20365	.20189	.90957	.88718	.90919
1.29053	1.27571	1.44008	.20124	.20069	.19700
.07029	.07119	.07182	.07295	.07215	.07117
.06548	.06671	.06614	.26702	.26045	.26691
.15984	.15801	.15699	.51840	.19385	.19332
.18977	.06771	.06857	.06918	.07027	.06950
.06856	.06308	.06426	.06371	.25722	.25089
.25711	.15397	.15221	.15123	.42442	.50410
.20157	.20101	.19732	.07040	.07130	.07193
.07307	.07227	.07129	.06559	.06682	.06624
.26746	.26087	.26735	.16010	.15827	.15725
.44132	.42512	.53290	.11281	.11251	.11044
.06127	.06205	.06260	.05119	.05062	.04994
.03961	.04036	.04001	.15507	.15125	.15500
.12653	.12507	.12427	.12593	.12131	.12614
.20250	.11247	.11216	.11010	.06108	.06186
.06241	.05103	.05047	.04979	.03949	.04023
.03988	.15459	.15078	.15453	.12614	.12469
.12389	.12554	.12094	.12575	.16349	.21160
.10897	.10867	.10668	.05918	.05994	.06047
.04944	.04890	.04824	.03826	.03898	.03864
.14978	.14610	.14972	.12221	.12081	.12004
.12164	.11718	.12184	.15840	.15792	.19360
.04502	.04490	.04407	.15029	.15221	.15356
.07965	.07877	.07771	.03251	.03312	.03284
.10469	.10211	.10465	.12162	.12022	.11945

Complex model: Three indicators concluded

-.01005	-.00969	-.01007	.01692	.01687	.01634
.51840	.04328	.04316	.04237	.14448	.14633
.14762	.07657	.07573	.07471	.03126	.03184
.03157	.10064	.09817	.10060	.11692	.11557
.11483	-.00966	-.00931	-.00968	.01626	.01621
.01571	.40387	.50410	.04506	.04494	.04411
.15043	.15235	.15370	.07972	.07884	.07778
.03254	.03315	.03287	.10479	.10221	.10474
.12173	.12033	.11955	-.01006	-.00969	-.01008
.01693	.01688	.01636	.42048	.40423	.53290

Complex model: Four indicators

.58522	.47913	.60052	.46636	.47213	.57014
.47312	.47897	.46621	.58522	.33459	.33873
.32971	.33448	1.02407	.33310	.33722	.32824
.33299	.85597	1.00394	.33647	.34064	.33156
.33636	.86463	.86077	1.04434	.33451	.33865
.32963	.33440	.85960	.85577	.86442	1.02406
.24947	.25256	.24583	.24939	.46051	.45845
.46309	.46040	.72039	.25079	.25390	.24713
.25071	.46295	.46089	.46555	.46284	.61556
.73746	.24796	.25103	.24433	.24788	.45771
.45567	.46028	.45761	.60860	.61183	.70351
.24950	.25259	.24586	.24942	.46056	.45851
.46315	.46045	.61239	.61564	.60868	.72039
.17556	.17773	.17300	.17550	.20536	.20445
.20651	.20531	.23002	.23124	.22863	.23005
.32336	.18089	.18313	.17825	.18083	.21160
.21065	.21278	.21155	.23700	.23826	.23557
.23703	.26233	.34646	.17991	.18214	.17729
.17985	.21045	.20952	.21164	.21040	.23573
.23698	.23430	.23575	.26091	.26883	.33478
.17585	.17802	.17328	.17579	.20570	.20478
.20685	.20565	.23040	.23162	.22900	.23043
.25501	.26275	.26134	.32335	.67358	.68192
.66374	.67336	.44178	.43981	.44426	.44168
.33936	.34116	.33730	.33940	.24538	.25282
.25146	.24578	1.69003	.66479	.67301	.65508
.66457	.43601	.43407	.43846	.43591	.33493
.33671	.33290	.33497	.24217	.24952	.24818
.24257	1.43509	1.66419	.68191	.69035	.67195
.68168	.44724	.44525	.44975	.44714	.34355
.34538	.34147	.34360	.24841	.25595	.25457
.24882	1.47204	1.45286	1.71614	.67383	.68217
.66399	.67361	.44195	.43998	.44443	.44184
.33949	.34129	.33743	.33953	.24547	.25292
.25155	.24587	1.45454	1.43556	1.47259	1.69003

Complex model: Four indicators continued

.42565	.43092	.41944	.42551	.61918	.61642
.62265	.61903	.36946	.37142	.36722	.36950
.19938	.20543	.20432	.19971	.91153	.89963
.92280	.91187	1.46418	.42661	.43189	.42038
.42647	.62057	.61781	.62406	.62043	.37029
.37225	.36804	.37033	.19983	.20590	.20479
.20016	.91359	.90166	.92488	.91393	1.29212
1.48841	.42431	.42957	.41812	.42418	.61723
.61448	.62070	.61708	.36829	.37025	.36606
.36834	.19875	.20479	.20368	.19908	.90867
.89680	.91990	.90901	1.28512	1.28809	1.44003
.42542	.43069	.41921	.42528	.61884	.61608
.62232	.61870	.36926	.37122	.36702	.36930
.19927	.20532	.20421	.19960	.91104	.89915
.92230	.91138	1.28854	1.29141	1.28446	1.46412
.19685	.19928	.19397	.19678	.06932	.06901
.06971	.06931	.07192	.07230	.07148	.07193
.06392	.06586	.06550	.06402	.26345	.26001
.26671	.26355	.15591	.15626	.15542	.15583
.51840	.19397	.19638	.19114	.19391	.06831
.06801	.06870	.06829	.07087	.07125	.07044
.07088	.06298	.06490	.06455	.06309	.25961
.25622	.26282	.25971	.15364	.15399	.15316
.15356	.42450	.50410	.19938	.20185	.19647
.07323	.07240	.07286	.06474	.06670	.06634
.06485	.26685	.26337	.27015	.26695	.15792
.15828	.15743	.15784	.43634	.42997	.53290
.19671	.19915	.19384	.19665	.06928	.06897
.06966	.06926	.07187	.07225	.07143	.07188
.06387	.06581	.06546	.06398	.26328	.25984
.26653	.26338	.15581	.15616	.15532	.15572
.43049	.42421	.43604	.51840	.11023	.11159
.10862	.11019	.06044	.06017	.06078	.06042
.05013	.05040	.04983	.05014	.03861	.03978
.03957	.03867	.15282	.15083	.15471	.15288
.12346	.12374	.12307	.12339	.12316	.12136
.12475	.12308	.20250	.11197	.11335	.11033
.11193	.06139	.06112	.06174	.06138	.05092
.05119	.05061	.05093	.03922	.04041	.04019
.03928	.15524	.15321	.15716	.15530	.12541
.12569	.12502	.12534	.12510	.12328	.12672
.12502	.16256	.21160	.10845	.10979	.10686
.10841	.05946	.05920	.05980	.05945	.04932
.04958	.04902	.04933	.03799	.03914	.03893
.03805	.15036	.14840	.15222	.15041	.12147
.12174	.12109	.12140	.12117	.11940	.12273
.12109	.15745	.15993	.19360	.11016	.11153
.10855	.11013	.06040	.06013	.06074	.06039

Complex model: Four indicators concluded

.05010	.05037	.04980	.05011	.03859	.03976
.03954	.03865	.15274	.15074	.15462	.15279
.12339	.12367	.12300	.12332	.12309	.12129
.12467	.12300	.15994	.16246	.15736	.20250
.04356	.04410	.04293	.04355	.14933	.14867
.15017	.14930	.07700	.07741	.07654	.07701
.03161	.03257	.03240	.03166	.10111	.09979
.10236	.10114	.11867	.11893	.11829	.11860
-.00966	-.00952	-.00978	-.00965	.01630	.01656
.01603	.01629	.51840	.04267	.04319	.04204
.04265	.14626	.14561	.14708	.14623	.07542
.07582	.07496	.07543	.03096	.03190	.03173
.03101	.09903	.09773	.10025	.09906	.11623
.11649	.11586	.11616	-.00946	-.00932	-.00958
-.00945	.01596	.01621	.01570	.01595	.40115
.50410	.04446	.04501	.04381	.04445	.15242
.15174	.15327	.15238	.07859	.07901	.07812
.07860	.03226	.03324	.03306	.03232	.10320
.10185	.10447	.10323	.12112	.12139	.12074
.12105	-.00986	-.00972	-.00999	-.00986	.01663
.01690	.01637	.01662	.41804	.40944	.53290
.04356	.04410	.04292	.04354	.14932	.14865
.15015	.14928	.07699	.07740	.07653	.07700
.03161	.03257	.03239	.03166	.10109	.09978
.10234	.10113	.11865	.11892	.11828	.11859
-.00966	-.00952	-.00978	-.00965	.01630	.01655
.01603	.01629	.40953	.40111	.41799	.51840

Complex model: Five indicators

.58513	.48054	.60050	.46635	.47039	.57016
.47428	.47839	.46426	.58520	.46881	.47287
.45890	.46671	.57008	.33605	.33896	.32895
.33455	.33068	1.02483	.33294	.33583	.32590
.33145	.32762	.85298	1.00467	.33953	.34248
.33236	.33802	.33411	.86987	.86183	1.04523
.33605	.33896	.32895	.33455	.33068	.86095
.85299	.86988	1.02482	.33264	.33552	.32561
.33115	.32733	.85221	.84433	.86105	.85222
1.00461	.25125	.25343	.24594	.25013	.24724
.46091	.45665	.46569	.46091	.45623	.72057
.25419	.25639	.24881	.25305	.25013	.46629
.46198	.47112	.46629	.46156	.61956	.73763
.24822	.25038	.24298	.24711	.24426	.45535
.45114	.46008	.45535	.45073	.60503	.61210
.70372	.25127	.25345	.24596	.25015	.24726
.46094	.45668	.46572	.46094	.45626	.61246
.61961	.60507	.72057	.25416	.25636	.24879

Complex model: Five indicators continued

.25302	.25010	.46623	.46192	.47107	.46624
.46151	.61950	.62673	.61203	.61954	.73763
.17646	.17799	.17273	.17567	.17364	.20525
.20336	.20738	.20526	.20317	.22973	.23241
.22696	.22974	.23238	.32339	.18271	.18429
.17885	.18189	.17979	.21252	.21056	.21473
.21252	.21036	.23786	.24064	.23499	.23788
.24061	.26415	.34648	.17956	.18112	.17576
.17876	.17669	.20886	.20693	.21103	.20886
.20674	.23376	.23649	.23094	.23378	.23646
.25960	.26879	.33483	.17649	.17802	.17276
.17570	.17367	.20528	.20339	.20741	.20529
.20320	.22976	.23244	.22699	.22978	.23242
.25516	.26419	.25964	.32338	.17334	.17485
.16968	.17257	.17058	.20163	.19976	.20372
.20163	.19958	.22567	.22830	.22295	.22569
.22828	.25061	.25949	.25502	.25065	.31214
.68070	.68660	.66632	.67766	.66983	.44421
.44010	.44882	.44421	.43970	.34265	.34665
.33852	.34268	.34661	.24747	.25624	.25182
.24751	.24310	1.69007	.66885	.67464	.65471
.66586	.65817	.43647	.43243	.44100	.43647
.43204	.33668	.34061	.33262	.33671	.34057
.24316	.25177	.24743	.24320	.23887	1.43923
1.66415	.68592	.69186	.67142	.68285	.67496
.44761	.44347	.45225	.44761	.44307	.34528
.34931	.34111	.34530	.34927	.24937	.25820
.25375	.24941	.24497	1.47594	1.45020	1.71617
.67631	.68217	.66202	.67329	.66551	.44134
.43726	.44592	.44134	.43686	.34044	.34441
.33634	.34046	.34437	.24588	.25458	.25019
.24591	.24153	1.45526	1.42993	1.46640	1.69002
.67181	.67763	.65761	.66880	.66108	.43840
.43435	.44295	.43840	.43395	.33817	.34212
.33410	.33820	.34208	.24424	.25289	.24853
.24427	.23993	1.44555	1.42039	1.45667	1.43620
1.66415	.42826	.43198	.41921	.42635	.42143
.61990	.61416	.62633	.61990	.61361	.37036
.37469	.36590	.37039	.37465	.19978	.20685
.20329	.19981	.19625	.91526	.89931	.92227
.90935	.90329	1.46419	.43192	.43567	.42280
.42999	.42503	.62519	.61941	.63168	.62520
.61885	.37353	.37789	.36903	.37355	.37785
.20148	.20862	.20502	.20151	.19793	.92308
.90700	.93014	.91712	.91101	1.29931	1.48844
.42474	.42842	.41576	.42284	.41796	.61479
.60911	.62117	.61480	.60855	.36731	.37160
.36289	.36734	.37156	.19813	.20515	.20161

Complex model: Five indicators continued

.19816	.19463	.90772	.89191	.91467	.90186
.89585	1.27774	1.28861	1.44002	.42824	.43195
.41919	.42632	.42140	.61985	.61412	.62629
.61986	.61357	.37034	.37466	.36588	.37036
.37462	.19976	.20684	.20327	.19979	.19624
.91520	.89925	.92220	.90929	.90323	1.28826
1.29924	1.27766	1.46413	.43172	.43546	.42259
.42979	.42482	.62489	.61912	.63138	.62490
.61855	.37335	.37771	.36885	.37338	.37767
.20139	.20852	.20492	.20142	.19783	.92264
.90656	.92970	.91668	.91058	1.29871	1.30985
1.28809	1.29862	1.48847	.19924	.20097	.19503
.19835	.19606	.06958	.06893	.07030	.06958
.06887	.07281	.07366	.07193	.07282	.07365
.06461	.06690	.06574	.06462	.06347	.26508
.26047	.26711	.26337	.26162	.15608	.15742
.15480	.15607	.15734	.51840	.19560	.19730
.19147	.19473	.19248	.06831	.06767	.06902
.06831	.06761	.07148	.07232	.07062	.07149
.07231	.06343	.06568	.06454	.06344	.06231
.26024	.25571	.26224	.25856	.25684	.15323
.15454	.15197	.15322	.15447	.42605	.50410
.20033	.20206	.19610	.19943	.19713	.06996
.06931	.07068	.07000	.06925	.07321	.07406
.07233	.07321	.07406	.06496	.06726	.06610
.06497	.06381	.26653	.26189	.26857	.26481
.26305	.15693	.15827	.15564	.15692	.15820
.43634	.42837	.53290	.19826	.19998	.19407
.19737	.19509	.06923	.06859	.06995	.06923
.06853	.07245	.07330	.07158	.07246	.07329
.06429	.06657	.06542	.06430	.06316	.26377
.25918	.26579	.26207	.26033	.15531	.15664
.15403	.15530	.15656	.43183	.42394	.43418
.51840	.20127	.20301	.19702	.20037	.19806
.07028	.06963	.07101	.07029	.06957	.07355
.07441	.07267	.07356	.07440	.06527	.06758
.06641	.06528	.06411	.26778	.26312	.26983
.26605	.26428	.15767	.15902	.15637	.15766
.15894	.43839	.43038	.44078	.43622	.53290
.11021	.11117	.10789	.10972	.10845	.06045
.05989	.06107	.06045	.05983	.05026	.05085
.04966	.05026	.05084	.03858	.03995	.03926
.03859	.03790	.15417	.15148	.15535	.15317
.15215	.12314	.12419	.12213	.12313	.12413
.12390	.12164	.12458	.12329	.12516	.20250
.11264	.11362	.11026	.11214	.11084	.06178
.06121	.06242	.06178	.06115	.05137	.05197
.05075	.05137	.05196	.03943	.04083	.04013

Complex model: Five indicators continued

.03944	.03874	.15756	.15481	.15877	.15654
.15550	.12585	.12693	.12482	.12584	.12687
.12663	.12432	.12732	.12600	.12792	.16350
.21160	.10778	.10871	.10550	.10730	.10606
.05911	.05856	.05972	.05911	.05851	.04915
.04972	.04856	.04915	.04972	.03773	.03907
.03839	.03774	.03706	.15076	.14813	.15191
.14979	.14879	.12042	.12145	.11943	.12041
.12139	.12116	.11895	.12182	.12057	.12240
.15644	.15989	.19360	.11023	.11118	.10790
.10973	.10847	.06045	.05989	.06108	.06045
.05984	.05027	.05085	.04966	.05027	.05085
.03859	.03996	.03927	.03859	.03791	.15418
.15150	.15536	.15319	.15217	.12316	.12421
.12214	.12315	.12415	.12392	.12165	.12459
.12330	.12518	.16000	.16352	.15646	.20250
.10776	.10869	.10548	.10727	.10604	.05910
.05855	.05971	.05910	.05850	.04914	.04971
.04855	.04914	.04971	.03772	.03906	.03839
.03773	.03706	.15073	.14810	.15188	.14975
.14876	.12040	.12142	.11940	.12039	.12137
.12114	.11893	.12180	.12054	.12237	.15641
.15985	.15295	.15643	.19360	.04355	.04393
.04263	.04335	.04285	.14880	.14742	.15034
.14880	.14729	.07666	.07755	.07573	.07666
.07754	.03142	.03253	.03197	.03142	.03087
.10100	.09924	.10178	.10035	.09968	.11882
.11983	.11784	.11881	.11977	-.00964	-.00947
-.00969	-.00959	-.00974	.01655	.01691	.01618
.01655	.01618	.51840	.04294	.04331	.04203
.04275	.04226	.14673	.14537	.14825	.14673
.14524	.07559	.07647	.07468	.07559	.07646
.03098	.03208	.03153	.03099	.03044	.09960
.09786	.10036	.09895	.09829	.11716	.11816
.11620	.11715	.11811	-.00951	-.00933	-.00956
-.00946	-.00960	.01632	.01668	.01596	.01632
.01595	.40382	.50410	.04415	.04453	.04322
.04395	.04345	.15086	.14947	.15243	.15086
.14933	.07772	.07863	.07678	.07773	.07862
.03186	.03298	.03241	.03186	.03129	.10240
.10062	.10319	.10174	.10106	.12046	.12149
.11947	.12046	.12143	-.00977	-.00960	-.00983
-.00973	-.00987	.01678	.01715	.01641	.01678
.01640	.41520	.40942	.53290	.04355	.04393
.04263	.04336	.04286	.14881	.14743	.15035
.14881	.14730	.07666	.07756	.07574	.07667
.07755	.03142	.03253	.03197	.03143	.03087
.10101	.09925	.10178	.10036	.09969	.11882

Complex model: Five indicators concluded

.11984	.11785	.11882	.11978	-.00964	-.00947
-.00969	-.00959	-.00974	.01655	.01691	.01618
.01655	.01618	.40955	.40385	.41523	.51840
.04416	.04454	.04322	.04396	.04345	.15088
.14948	.15244	.15088	.14935	.07773	.07863
.07679	.07773	.07863	.03186	.03299	.03241
.03186	.03130	.10241	.10063	.10320	.10175
.10107	.12048	.12150	.11948	.12047	.12145
-.00978	-.00960	-.00983	-.00973	-.00988	.01678
.01715	.01641	.01678	.01640	.41524	.40946
.42099	.41527	.53290			

APPENDIX F

Sample LISREL 8.14 Program to Calculate T from a Specified Input Matrix

```
Fitting T*T to SIGMA
DA NI=8 NO=100000
CM=SIM2.COV
MO NX=8 NK=8 PH=ID TD=ZE
PA LX
1 0 0 0 0 0 0 0
1 1 0 0 0 0 0 0
1 1 1 0 0 0 0 0
1 1 1 1 0 0 0 0
1 1 1 1 1 0 0 0
1 1 1 1 1 1 0 0
1 1 1 1 1 1 1 0
1 1 1 1 1 1 1 1
MA LX
1 0 0 0 0 0 0 0
1 1 0 0 0 0 0 0
1 1 1 0 0 0 0 0
1 1 1 1 0 0 0 0
1 1 1 1 1 0 0 0
1 1 1 1 1 1 0 0
1 1 1 1 1 1 1 0
1 1 1 1 1 1 1 1
OU ND=6
```

Note. This program was used for the two indicator simple model.

APPENDIX G

Sample PRELIS 2.14 Program to Generate Multivariate Normal Variables with a Specified Covariance Matrix

```
DA NO=200
NE V1=NRAND
NE V2=NRAND
NE V3=NRAND
NE V4=NRAND
NE V5=NRAND
NE V6=NRAND
NE V7=NRAND
NE V8=NRAND
NE X1=V1
NE X2= .378*V1+.925806*V2
NE X3=  .72*V1+.068956*V2 +.690540*V3
NE X4= .324*V1+.321372*V2 +.047151*V3+ .88855*V4
NE X5=  .27*V1+ .26781*V2 +.039292*V3+.140229*V4 +.913329*V5
NE V6=  .27*V1+.025858*V2 +.063453*V3+.010374*V4 +.006818*V5
        +.960339*V6
NE V7=  .47*V1+ .11654*V2 +.338792*V3+.278664*V4 +.003189*V5
        +.010146*V6 + .885304*V7
NE V8=  .46*V1+ .13405*V2 +.363089*V3+.291443*V4 +.006790*V5
        +.012675*V6 + .496053*V7 + .682731*V8
CO ALL
SD V1-V8
OU CM=SIM2TR.DAT ND=5 XM IX=123456 RP=200
```

Note. This program is an example for generating 200 sets of variance-covariance matrices for the two indicator, true specification of the simple model.

APPENDIX H

Fortran Program to Generate Random Seeds

```
FUNCTION RAN1(IDUM)
DIMENSION R(97)
PARAMETER (M1=259200, IA1=7141, IC1=54773, RM1=1./M1)
PARAMETER (M2=134456, IA2=8121, IC2=28411, RM2=1./M2)
PARAMETER (M3=243000, IA3=4562, IC3=51349)
DATA IFF /0/
IF (IDUM.LT.0.OR.IFF.EQ.0) THEN
IFF=1
IX1=MOD(IC1-IDUM,M1)
IX1=MOD(IA1*IX1+IC1,M1)
IX2=MOD(IX1,M2)
IX1=MOD(IA1*IX1+IC1,M1)
IX3=MOD(IX1,M3)
DO 11 J=1.97
     IX1=MOD(IA1*IX1+IC1,M1)
     IX2=MOD(IA2*IX2+IC2,M2)
     R(J)=(FLOAT(IX1)+FLOAT(IX2)*RM2)*RM1
   11 CONTINUE
 IDUM=1
ENDIF
IX1=MOD(IA1*IX1+IC1,M1)
IX2=MOD(IA2*IX2+IC2,M2)
IX3=MOD(IA3*IX3+IC3M3)
J=1+(97*IX3)/M3
IF(J.GT.97.OR.J.LT.1)PAUSE
RAN1=R(J)
R(J)=(FLOAT(IX1)+FLOAT(IX2)*RM2)*RM1
RETURN
END
```

APPENDIX I

Sample LISREL 8.14 Program to Generate Goodness-of-Fit Indices

```
GENERATING 200 SETS OF FIT MEASURES FROM S2TR100.DAT
**(note = S2TR100 represents (a)S = Simple complexity; (b)
   2 = Two indicator; (c) TR = True specification; and (d)
   100 = Sample size of 100.)
DA NI=8 NO=100 RP=200
LA
DE1 DE2 AU1 AU2 SE1 SE2 SO1 SO2
CM=S2TR100.DAT
MO NY=2 NK=2 BE=FU GA=FI
LE
DRINKE ALCUSE
LK
SENSEEK SOCIO
FI LY 1 1 LY 3 2
FI LX 1 1 LX 3 2
FR LY 2 1 LY 4 2
FR LX 2 1 LX 4 2
VA 1.0 LY 1 1 LY 3 2 LX1 1 LX3 2
FR BE 2 1
FR GA 2 1 GA 2 2
OU ND=5 XM IT=100 GF=S2TR100.GFM
```

APPENDIX J

Expected Mean Squares Table for the Monte Carlo Simulations

Indicators (I) = (fixed)=0
Model Misspecifications (M) = (fixed) = 0
Sample Size (S)= (fixed) = 0
Replications (R) (Sample Size) = (random) = 1

Source	i	J	k	l	m	Expected Mean Square	Error Term
I_I	0	Q	r	s	1	$\sigma e^2+\sigma^2 IR(S)$	$\sigma^2 IR(S)$
M_j	p	0	r	s	1	$\sigma e^2+\sigma^2 MR(S)$	$\sigma^2 MR(S)$
S_k	p	Q	0	s	1	$\sigma e^2+\sigma^2 R(S)+\sigma^2 S$	$\sigma^2 R(S)$
IM_{ij}	0	0	r	s	1	$\sigma e^2+\sigma^2 IMR(S)$	$\sigma^2 IMR(S)$
IS_{ik}	0	q	0	s	1	$\sigma e^2+\sigma^2 IR(S)$	$\sigma^2 IR(S)$
MS_{jk}	p	0	0	s	1	$\sigma e^2+\sigma^2 MR(S)$	$\sigma^2 MR(S)$
$R(S)_{l(k)}$	p	q	1	1	1	$\sigma e^2+\sigma^2 R(S)$	No test
IMS_{ijk}	0	0	0	s	1	$\sigma e^2+\sigma^2 IMR(S)+\sigma^2 IMS$	$\sigma^2 IMR(S)$
$IR(S)_{il(k)}$	0	q	1	1	1	$\sigma e^2+\sigma^2 IR(S)$	No test
$MR(S)_{jl(k)}$	p	0	1	1	1	$\sigma e^2+\sigma^2 MR(S)$	No test
$IMR(S)_{ijl(k)}$	0	0	1	1	1	$\sigma e^2+\sigma^2 IMR(S)$	No test
E_{ijklm}	1	1	1	1	1	σe^2	--

Note. The following abbreviations have been used: I = Indicators per latent variable; M = Model misspecifications; R = Replications; S = Sample size.
All simulations examined the same conditions. Therefore, all analyses of variance specified the same error terms regardless of the simulation model. Three main effects were calculated: Indicators per latent variable; Model misspecifications; and Sample Size. Three two-way interactions were calculated: Indicators by Model misspecifications; Indicators by Sample size; and Model misspecifications by Sample size. One three-way interaction was calculated: Indicators by Model misspecifications by Sample size. The remaining sources of variance were not estimated because error terms were not available.

APPENDIX K

Descriptive Statistics for the Simple Model

Table K.01

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	5.4532	5.1014	0.5785	31.2600
16	2	26.9962	8.2394	10.0380	50.3410
50	3	82.4489	14.2418	34.3180	117.8700
100	4	175.1080	21.6553	132.2600	223.9100
166	5	287.0069	29.3178	223.1500	384.0400
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	2.1033	2.9417	0.0001	14.6630
15	2	24.2961	7.9440	8.4951	47.6820
49	3	80.7678	15.5493	45.5380	138.3300
99	4	172.0907	22.6193	122.2600	223.2800
165	5	285.9589	26.7933	221.8900	338.3600
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	8.5527	4.9801	0.6367	24.5510
17	2	32.4532	8.5666	14.7730	48.8160
51	3	87.2587	14.4834	53.5870	127.5400
101	4	182.3494	19.9483	130.7400	238.7600
167	5	299.8293	27.7931	244.7700	405.0000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	7.3551	5.2053	0.0761	27.5930
16	2	29.2334	9.8584	12.3690	53.9400
50	3	85.8460	15.8877	51.4280	127.1000
100	4	174.5298	19.7274	138.5300	238.1300
166	5	287.7052	26.2674	216.3800	357.9200

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.02

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	7.3657	4.8327	0.0055	21.2300
16	2	37.2771	11.4025	14.2120	69.8300
50	3	106.6925	17.0096	74.6920	152.3800
100	4	243.4651	25.0778	192.3200	308.4500
166	5	390.2788	31.5858	314.5800	475.9300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	5.0479	3.3271	0.0258	19.9330
15	2	34.5165	11.0466	14.9720	71.5180
49	3	108.4564	18.3057	68.1320	165.1500
99	4	234.7543	25.2335	175.3500	306.6400
165	5	390.0683	32.6111	299.7300	489.0100
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	13.5707	5.7794	4.2394	29.9130
17	2	47.2531	12.7768	18.1080	76.7350
51	3	122.0541	16.2751	84.2930	159.0800
101	4	256.3591	28.9492	178.7300	324.1800
167	5	397.4405	36.5307	312.9000	479.6100
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	9.7511	4.2308	1.5286	19.5490
16	2	29.2334	9.8584	12.6790	71.8430
50	3	113.9278	19.7717	71.9360	162.4700
100	4	248.0792	23.3269	194.2100	321.0100
166	5	393.5619	35.9204	315.9600	487.8200

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.03

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	18.9820	8.9968	4.7562	44.6620
16	2	68.8545	14.3005	36.2020	126.4400
50	3	192.7362	24.2110	141.8900	248.5300
100	4	447.2011	39.4391	364.6900	576.2700
166	5	706.4783	38.7573	600.3100	828.4300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	11.2626	7.7014	1.5195	31.7730
15	2	61.3630	14.7414	30.8320	112.0600
49	3	194.6755	23.2694	145.0200	278.0500
99	4	437.4809	32.2560	361.7400	518.7600
165	5	709.0403	47.1329	605.6800	832.4900
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	31.2677	9.0094	8.5479	62.8600
17	2	88.7497	16.1476	45.5180	120.7900
51	3	217.3129	26.2061	156.9800	276.3400
101	4	469.7034	41.6774	329.3700	585.7500
167	5	734.6380	44.1285	613.0600	876.3100
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	24.1762	8.4946	7.4588	42.3170
16	2	81.8890	17.9702	42.4390	135.7000
50	3	207.0727	27.3152	145.4800	285.6300
100	4	458.1070	34.2575	324.4600	533.1400
166	5	726.6928	46.7322	596.2100	846.5700

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.04

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	31.6910	11.1389	11.129	64.8750
16	2	116.0613	22.4461	61.3120	187.0400
50	3	339.7706	33.6911	250.7100	414.4100
100	4	792.9733	54.6199	658.8400	928.1800
166	5	1249.1300	62.3617	1073.0000	1432.2000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	21.9858	8.7977	6.7003	46.2190
15	2	107.7331	20.5081	63.6630	168.1600
49	3	327.7025	33.8550	236.2200	428.5700
99	4	783.3929	51.1195	664.7400	949.7300
165	5	1230.2200	66.5902	952.6900	1409.1000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	63.1710	13.7259	33.9060	105.9200
17	2	159.4303	23.3786	91.7040	213.9800
51	3	386.1542	37.9163	299.4100	491.9300
101	4	840.0986	51.4373	703.0800	991.1600
167	5	1295.2200	61.4032	1168.5000	1456.4000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	43.8604	12.8674	17.0640	85.3150
16	2	147.4381	26.1329	71.2770	223.3500
50	3	376.0933	41.8563	281.8100	470.5000
100	4	816.6047	52.8354	661.2700	946.6500
166	5	1285.1800	66.7624	1096.1000	1518.5000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.05

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	69.8245	14.9977	30.3900	110.7050
16	2	220.2224	32.7681	144.9400	299.4500
50	3	628.8460	49.1669	479.2000	753.2900
100	4	1493.6400	79.4248	1212.0000	1677.1000
166	5	2332.4700	89.7223	2128.1000	2573.5000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	44.9400	13.9955	20.3230	96.9930
15	2	200.7395	28.8932	140.7000	304.9000
49	3	617.2977	48.1723	511.8700	776.3100
99	4	1465.9200	69.5138	1290.9000	1619.3000
165	5	2301.6000	90.7709	2034.3000	2544.9000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	116.0935	19.9285	63.1000	157.5400
17	2	300.9707	29.8699	232.5400	383.5000
51	3	718.6212	53.0165	584.5300	859.0000
101	4	1575.0800	78.8962	1395.3000	1806.2000
167	5	2432.9300	91.3947	2235.9000	2646.4000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	89.9327	20.1684	53.5720	126.0500
16	2	280.5897	36.1500	192.2400	400.6500
50	3	697.8970	52.6622	541.0400	867.1700
100	4	1543.1100	76.4609	1369.4000	1716.0000
166	5	2384.5000	82.4715	2212.1000	2588.8000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.06

Descriptive Statistics for the Chi-Square Test Statistic from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	157.7981	25.9586	103.1300	226.4900
16	2	524.9826	43.4908	418.8600	635.5700
50	3	1511.9200	69.6334	1305.9000	1683.0000
100	4	3577.0500	110.5321	3266.4000	3899.7000
166	5	5594.4900	128.2373	5246.7000	5968.5000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	114.3466	22.4521	63.1310	167.4000
15	2	486.4326	49.1305	381.7700	656.8700
49	3	1460.2500	75.1190	1253.3000	1721.6000
99	4	3518.7100	123.7864	3242.7000	3835.4000
165	5	5540.6600	131.9686	5183.5000	6038.1000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	286.0332	34.2707	217.6200	391.3100
17	2	731.9223	49.1631	611.3200	851.0200
51	3	1739.3600	71.3909	1549.5000	1926.1000
101	4	3790.2200	118.5355	3526.0000	4264.8000
167	5	5817.7400	131.0648	5514.5000	6390.8000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	220.2242	30.5566	132.7200	301.1900
16	2	679.6093	53.8805	545.7700	812.4200
50	3	1652.2900	77.8118	1445.1000	1866.9000
100	4	3718.0900	122.8179	3421.1000	4049.4000
166	5	5734.5200	151.2402	5306.8000	6303.6000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.07

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9458	0.0647	0.6857	1.0000
16	2	0.9804	0.0141	0.9387	1.0000
50	3	0.9731	0.0110	0.9453	1.0000
100	4	0.9602	0.0120	0.9313	0.9833
166	5	0.9527	0.0118	0.9192	0.9762
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9784	0.0341	0.8512	1.0000
15	2	0.9832	0.0122	0.9424	1.0000
49	3	0.9733	0.0127	0.9296	1.0000
99	4	0.9606	0.0127	0.9286	0.9872
165	5	0.9530	0.0107	0.9255	0.9792
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9229	0.0626	0.6677	1.0000
17	2	0.9733	0.0149	0.9409	1.0000
51	3	0.9701	0.0118	0.9393	0.9980
101	4	0.9559	0.0111	0.9224	0.9839
167	5	0.9484	0.0103	0.9155	0.9718
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9249	0.0673	0.6871	1.0000
16	2	0.9779	0.0164	0.9285	1.0000
50	3	0.9704	0.0128	0.9335	0.9988
100	4	0.9597	0.0112	0.9226	0.9802
166	5	0.9523	0.0103	0.9218	0.9805

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.08

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9609	0.0340	0.8795	1.0000
16	2	0.9819	0.0097	0.9543	1.0000
50	3	0.9763	0.0068	0.9580	0.9905
100	4	0.9615	0.0069	0.9448	0.9747
166	5	0.9566	0.0063	0.9363	0.9694
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9701	0.0249	0.8555	1.0000
15	2	0.9833	0.0093	0.9521	1.0000
49	3	0.9754	0.0077	0.9505	0.9920
99	4	0.9636	0.0067	0.9471	0.9795
165	5	0.9564	0.0063	0.9386	0.9746
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9281	0.0364	0.8234	0.9933
17	2	0.9743	0.0109	0.9480	0.9992
51	3	0.9708	0.0067	0.9530	0.9848
101	4	0.9583	0.0077	0.9396	0.9763
167	5	0.9554	0.0072	0.9387	0.9741
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9394	0.0350	0.8295	1.0000
16	2	0.9784	0.0099	0.9541	1.0000
50	3	0.9736	0.0081	0.9505	0.9906
100	4	0.9602	0.0064	0.9407	0.9747
166	5	0.9556	0.0069	0.9350	0.9706

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.09

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9511	0.0265	0.8769	0.9920
16	2	0.9822	0.0047	0.9651	0.9935
50	3	0.9764	0.0039	0.9679	0.9854
100	4	0.9628	0.0044	0.9495	0.9721
166	5	0.9597	0.0031	0.9476	0.9669
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9707	0.0212	0.9165	0.9983
15	2	0.9844	0.0050	0.9686	0.9942
49	3	0.9759	0.0039	0.9628	0.9844
99	4	0.9640	0.0035	0.9538	0.9721
165	5	0.9578	0.0038	0.9496	0.9665
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9180	0.0274	0.8458	0.9819
17	2	0.9756	0.0055	0.9638	0.9899
51	3	0.9725	0.0043	0.9623	0.9819
101	4	0.9606	0.0042	0.9495	0.9745
167	5	0.9558	0.0035	0.9439	0.9648
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9368	0.0238	0.8859	0.9826
16	2	0.9776	0.0062	0.9590	0.9906
50	3	0.9741	0.0045	0.9603	0.9832
100	4	0.9619	0.0036	0.9540	0.9760
166	5	0.9562	0.0039	0.9441	0.9670

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.10

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9578	0.0167	0.8988	0.9863
16	2	0.9831	0.0038	0.9709	0.9923
50	3	0.9761	0.0028	0.9698	0.9834
100	4	0.9631	0.0029	0.9558	0.9694
166	5	0.9579	0.0026	0.9507	0.9650
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9707	0.0121	0.9395	0.9917
15	2	0.9843	0.0034	0.9737	0.9917
49	3	0.9770	0.0028	0.9688	0.9844
99	4	0.9635	0.0028	0.9546	0.9697
165	5	0.9585	0.0026	0.9513	0.9700
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9163	0.0191	0.8529	0.9523
17	2	0.9758	0.0039	0.9662	0.9869
51	3	0.9723	0.0030	0.9637	0.9783
101	4	0.9606	0.0027	0.9536	0.9675
167	5	0.9561	0.0025	0.9495	0.9616
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9418	0.0174	0.8870	0.9792
16	2	0.9777	0.0044	0.9638	0.9901
50	3	0.9731	0.0035	0.9648	0.9806
100	4	0.9618	0.0028	0.9555	0.9697
166	5	0.9565	0.0027	0.9478	0.9642

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.11

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9518	0.0111	0.9219	0.9803
16	2	0.9827	0.0028	0.9749	0.9893
50	3	0.9761	0.0021	0.9707	0.9822
100	4	0.9629	0.0022	0.9577	0.9707
166	5	0.9580	0.0018	0.9527	0.9620
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9689	0.0099	0.9342	0.9872
15	2	0.9843	0.0024	0.9756	0.9892
49	3	0.9766	0.0020	0.9695	0.9811
99	4	0.9636	0.0019	0.9591	0.9684
165	5	0.9585	0.0018	0.9533	0.9637
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9207	0.0135	0.8849	0.9573
17	2	0.9759	0.0025	0.9692	0.9819
51	3	0.9725	0.0022	0.9670	0.9781
101	4	0.9607	0.0021	0.9548	0.9656
167	5	0.9560	0.0018	0.9516	0.9598
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9377	0.0145	0.9072	0.9676
16	2	0.9776	0.0030	0.9684	0.9850
50	3	0.9733	0.0021	0.9664	0.9794
100	4	0.9616	0.0020	0.9570	0.9667
166	5	0.9569	0.0016	0.9521	0.9608

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.12

Descriptive Statistics for the Comparative Fit Index from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9562	0.0071	0.9376	0.9725
16	2	0.9828	0.0015	0.9792	0.9864
50	3	0.9759	0.0011	0.9729	0.9792
100	4	0.9630	0.0012	0.9599	0.9666
166	5	0.9579	0.0010	0.9545	0.9607
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9684	0.0065	0.9535	0.9829
15	2	0.9841	0.0016	0.9782	0.9876
49	3	0.9768	0.0013	0.9723	0.9804
99	4	0.9636	0.0013	0.9598	0.9664
165	5	0.9583	0.0010	0.9548	0.9614
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9209	0.0096	0.8933	0.9340
17	2	0.9758	0.0017	0.9714	0.9804
51	3	0.9722	0.0012	0.9690	0.9751
101	4	0.9607	0.0012	0.9554	0.9637
167	5	0.9561	0.0010	0.9519	0.9585
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9389	0.0084	0.9172	0.9616
16	2	0.9775	0.0018	0.9727	0.9818
50	3	0.9736	0.0013	0.9703	0.9775
100	4	0.9615	0.0014	0.9573	0.9649
166	5	0.9568	0.0012	0.9525	0.9601

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.13

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	401.0421	394.3500	30.1720	1577.3000
16	2	169.1757	44.0060	63.9310	416.6100
50	3	143.0367	19.5242	64.9640	220.7000
100	4	138.8264	9.6661	61.0480	185.2500
166	5	115.4050	7.4891	55.4720	146.9300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	488.8799	472.7466	45.8880	1730.0934
15	2	200.3509	48.7977	64.4930	399.5000
49	3	167.5511	19.6938	54.6170	248.9500
99	4	143.2950	10.5569	60.7010	197.0430
165	5	121.3000	7.7157	62.4960	151.0000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	242.4576	360.0195	46.7570	1765.4000
17	2	110.9386	32.3931	68.7580	224.9000
51	3	91.2779	15.3501	61.0740	143.9800
101	4	76.2782	8.4820	57.7960	104.7200
167	5	71.7234	6.3265	52.9300	86.9210
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	262.6238	382.5090	34.0490	1435.0108
16	2	121.7328	39.6141	59.7320	257.1200
50	3	91.8536	16.9936	60.3200	147.6000
100	4	78.9823	8.4862	57.4630	98.0570
166	5	74.3298	6.8692	59.4480	97.6810

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.14

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	693.0000	422.0000	87.3390	1645.8900
16	2	409.1517	70.2260	92.1930	713.5200
50	3	388.0060	22.4056	100.4600	562.0310
100	4	335.2994	11.3764	88.6200	401.9502
166	5	219.0473	8.9208	89.3540	293.4300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	703.0596	499.0000	67.2390	1720.0930
15	2	452.3121	62.4914	86.0920	740.9512
49	3	390.5289	24.2924	91.2760	602.4400
99	4	348.6015	12.3300	88.3810	459.0703
165	5	260.1719	9.0577	86.5310	311.0088
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	202.7696	95.3271	76.4860	533.6400
17	2	153.2638	46.2357	87.6470	368.1800
51	3	129.5015	17.7502	97.8110	183.7100
101	4	108.7268	12.6174	85.0850	153.5100
167	5	108.2804	10.0283	89.1450	136.1100
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	259.2160	209.8211	94.7670	1200.1000
16	2	170.5872	63.9179	89.6370	503.2400
50	3	138.3052	25.3760	94.2830	211.6800
100	4	110.9072	10.3719	85.1920	140.1600
166	5	108.7296	9.7682	87.2000	134.0900

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.15

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	805.1606	196.6957	103.9100	1746.9398
16	2	749.3432	51.3164	127.2900	1295.3321
50	3	692.6613	25.4271	153.9100	1010.1500
100	4	657.9096	13.3331	118.6000	983.7912
166	5	401.8123	8.2463	128.2800	470.0000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	866.3694	448.4847	105.2100	1923.8500
15	2	769.9287	69.0462	137.1800	1330.4213
49	3	712.0056	22.8417	135.4500	1087.6600
99	4	689.2842	11.7235	130.5200	965.3200
165	5	459.9176	9.8049	126.9800	508.0086
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	202.7181	81.3805	91.0750	663.4000
17	2	195.7743	39.6924	139.0300	367.2800
51	3	181.3582	22.3726	140.7500	247.0000
101	4	147.6864	13.3910	117.6900	208.5200
167	5	145.8168	8.7189	121.9700	173.9100
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	222.2572	100.7965	109.6200	617.2400
16	2	205.4986	45.5893	118.6700	377.2600
50	3	187.7834	25.2939	134.0500	262.2200
100	4	149.8172	12.0025	128.1100	209.8700
166	5	145.6999	9.4033	125.5500	177.8600

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.16

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	1199.0700	133.0746	142.8400	2011.3900
16	2	1024.8677	57.7479	171.9200	1745.0470
50	3	973.3500	22.9302	184.5900	1517.2200
100	4	735.2002	11.8187	147.1700	1223.6900
166	5	511.9933	8.5049	149.3200	596.2300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	1237.1937	168.2146	144.4100	2047.7820
15	2	1084.7280	58.2294	182.6800	1848.4800
49	3	953.3284	24.7329	175.6400	1634.1700
99	4	756.9542	11.1597	142.6300	1320.5300
165	5	538.2111	9.4289	150.0100	602.7900
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	189.0770	42.1198	108.0200	335.3200
17	2	215.2320	34.2747	156.9800	364.9700
51	3	203.0967	19.4775	158.1600	259.2200
101	4	164.5001	10.1385	139.0600	195.6300
167	5	165.2203	7.8065	146.7200	182.6300
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	231.7628	78.5748	108.8600	540.2600
16	2	225.0744	42.6623	144.1300	449.5000
50	3	205.7603	22.4685	162.7000	270.9700
100	4	167.8540	11.0366	144.3200	206.1700
166	5	165.6988	8.6063	140.0200	193.6000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.17

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	1228.0190	86.4566	167.3300	1999.3900
16	2	1059.9800	46.9058	214.6100	1743.1800
50	3	905.6024	19.5633	203.1000	1482.0610
100	4	838.9115	9.9988	162.8800	1116.5500
166	5	607.3886	7.0189	165.1400	693.1400
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	1291.3211	121.6819	137.7500	2004.6500
15	2	1096.4683	43.8724	201.5000	1909.4430
49	3	936.0595	18.7311	193.9200	1775.2390
99	4	850.5288	8.8257	167.2200	1252.9000
165	5	643.0500	7.2301	166.0900	702.4500
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	202.6248	37.6934	144.9800	360.4700
17	2	225.0844	22.2088	175.1600	288.2200
51	3	217.4608	16.1729	181.1000	265.6700
101	4	175.2780	8.7587	152.5900	197.2400
167	5	175.7930	6.5403	161.4700	190.9300
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	217.3760	53.3621	147.0700	344.7100
16	2	232.8642	30.8885	160.6600	333.7500
50	3	220.3773	16.6031	176.5600	282.3800
100	4	177.3679	8.8120	159.2100	199.2500
166	5	178.3580	6.1137	164.1700	191.9500

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.18

Descriptive Statistics for the Critical N from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	1300.3839	50.6126	204.3000	1732.5900
16	2	1270.0514	25.8753	252.6900	1690.3085
50	3	1132.0085	11.6728	227.2000	1584.6600
100	4	916.0718	5.8591	175.1000	1238.1110
166	5	654.3639	4.3285	177.9800	699.4300
INCLUSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
1	1	1395.0398	68.0610	199.1400	1755.0200
15	2	1285.1352	30.5918	233.7300	1704.3700
49	3	1150.5277	13.1565	218.5500	1600.9900
99	4	927.4153	6.7574	176.4900	1244.8500
165	5	689.0533	4.5312	175.0100	707.2000
OMISSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
3	1	202.1481	24.0879	145.9600	261.6500
17	2	230.2322	15.5496	197.2600	274.2100
51	3	223.7977	9.1295	201.8600	250.6700
101	4	181.8358	5.6275	161.5600	195.2000
167	5	183.6326	4.0832	167.1700	193.5800
COMBINATION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
2	1	214.2941	31.0792	153.8800	347.9400
16	2	237.8544	18.7789	197.9000	294.1100
50	3	231.9254	10.9220	204.9300	264.4500
100	4	183.7968	6.0032	168.6600	199.4500
166	5	185.3331	4.8421	168.5800	200.0500

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.19

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9746	0.0216	0.8779	0.9971
16	2	0.9394	0.0170	0.8886	0.9759
50	3	0.8868	0.0173	0.8396	0.9457
100	4	0.8350	0.0167	0.8019	0.8660
166	5	0.7959	0.0171	0.7587	0.8331
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9899	0.0135	0.9345	1.0000
15	2	0.9450	0.0150	0.8929	0.9797
49	3	0.8892	0.0180	0.8302	0.9315
99	4	0.8385	0.0181	0.7907	0.8790
165	5	0.7959	0.0145	0.7603	0.8365
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9618	0.0201	0.9053	0.9968
17	2	0.9294	0.0166	0.8926	0.9669
51	3	0.8813	0.0170	0.8402	0.9235
101	4	0.8304	0.0155	0.7819	0.8698
167	5	0.7885	0.0179	0.7249	0.8199
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9652	0.0226	0.8852	0.9996
16	2	0.9353	0.0198	0.8911	0.9708
50	3	0.8822	0.0181	0.8398	0.9279
100	4	0.8350	0.0137	0.7914	0.8645
166	5	0.7947	0.0162	0.7539	0.8366

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.20

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9822	0.0113	0.9508	0.9999
16	2	0.9572	0.0118	0.9257	0.9822
50	3	0.9228	0.0104	0.8969	0.9429
100	4	0.8781	0.0108	0.8485	0.9009
166	5	0.8504	0.0110	0.8147	0.8766
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9876	0.0079	0.9539	0.9999
15	2	0.9591	0.0128	0.9205	0.9822
49	3	0.9212	0.0120	0.8831	0.9491
99	4	0.8827	0.0108	0.8529	0.9051
165	5	0.8501	0.0105	0.8183	0.8743
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9688	0.0130	0.9288	0.9896
17	2	0.9472	0.0131	0.9167	0.9783
51	3	0.9127	0.0110	0.8845	0.9344
101	4	0.8731	0.0125	0.8441	0.9076
167	5	0.8479	0.0124	0.8215	0.8772
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9762	0.0101	0.9532	0.9962
16	2	0.9520	0.0132	0.9241	0.9842
50	3	0.9179	0.0135	0.8828	0.9475
100	4	0.8759	0.0101	0.8488	0.9038
166	5	0.8483	0.0128	0.8179	0.8725

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.21

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9816	0.0084	0.9584	0.9953
16	2	0.9673	0.0068	0.9377	0.9825
50	3	0.9424	0.0068	0.9263	0.9569
100	4	0.9086	0.0072	0.8871	0.9239
166	5	0.8874	0.0063	0.8661	0.9023
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9890	0.0074	0.9696	0.9985
15	2	0.9706	0.0068	0.9498	0.9850
49	3	0.9421	0.0067	0.9153	0.9559
99	4	0.9103	0.0058	0.8946	0.9237
165	5	0.8874	0.0072	0.8686	0.9028
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9713	0.0078	0.9461	0.9917
17	2	0.9591	0.0070	0.9444	0.9787
51	3	0.9365	0.0070	0.9184	0.9529
101	4	0.9046	0.0077	0.8825	0.9306
167	5	0.8837	0.0065	0.8655	0.9032
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9763	0.0081	0.9590	0.9925
16	2	0.9613	0.0082	0.9352	0.9795
50	3	0.9384	0.0077	0.9169	0.9571
100	4	0.9058	0.0066	0.8909	0.9326
166	5	0.8848	0.0072	0.8625	0.9032

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.22

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9845	0.0053	0.9691	0.9945
16	2	0.9722	0.0053	0.9549	0.9850
50	3	0.9491	0.0048	0.9380	0.9603
100	4	0.9184	0.0051	0.9054	0.9303
166	5	0.9002	0.0047	0.8883	0.9147
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9892	0.0043	0.9777	0.9967
15	2	0.9740	0.0049	0.9597	0.9847
49	3	0.9507	0.0049	0.9361	0.9639
99	4	0.9196	0.0048	0.9041	0.9295
165	5	0.9015	0.0049	0.8873	0.9217
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9712	0.0058	0.9533	0.9841
17	2	0.9630	0.0052	0.9507	0.9778
51	3	0.9430	0.0052	0.9278	0.9541
101	4	0.9142	0.0048	0.9012	0.9277
167	5	0.8970	0.0044	0.8847	0.9077
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9784	0.0062	0.9592	0.9915
16	2	0.9649	0.0060	0.9480	0.9826
50	3	0.9437	0.0056	0.9293	0.9568
100	4	0.9160	0.0052	0.9027	0.9321
166	5	0.8972	0.0050	0.8788	0.9113

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.23

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9830	0.0036	0.9734	0.9925
16	2	0.9735	0.0039	0.9638	0.9828
50	3	0.9528	0.0035	0.9433	0.9635
100	4	0.9232	0.0037	0.9136	0.9365
166	5	0.9067	0.0035	0.8956	0.9150
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9889	0.0034	0.9766	0.9949
15	2	0.9757	0.0035	0.9639	0.9829
49	3	0.9537	0.0035	0.9435	0.9622
99	4	0.9246	0.0032	0.9176	0.9338
165	5	0.9078	0.0036	0.8979	0.9191
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9734	0.0043	0.9646	0.9849
17	2	0.9650	0.0033	0.9558	0.9731
51	3	0.9469	0.0037	0.9378	0.9561
101	4	0.9195	0.0036	0.9105	0.9282
167	5	0.9033	0.0035	0.8947	0.9118
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9778	0.0049	0.9691	0.9867
16	2	0.9663	0.0042	0.9524	0.9768
50	3	0.9476	0.0038	0.9359	0.9585
100	4	0.9206	0.0035	0.9124	0.9286
166	5	0.9043	0.0034	0.8958	0.9119

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.24

Descriptive Statistics for the Goodness of Fit Index from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9845	0.0025	0.9781	0.9898
16	2	0.9747	0.0021	0.9694	0.9799
50	3	0.9546	0.0020	0.9490	0.9610
100	4	0.9264	0.0022	0.9201	0.8324
166	5	0.9105	0.0020	0.9047	0.9159
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9887	0.0022	0.9836	0.9937
15	2	0.9765	0.0023	0.9685	0.9814
49	3	0.9562	0.0022	0.9491	0.9618
99	4	0.9276	0.0024	0.9213	0.9335
165	5	0.9113	0.0020	0.9038	0.9168
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9738	0.0030	0.9644	0.9798
17	2	0.9659	0.0022	0.9606	0.9715
51	3	0.9485	0.0020	0.9434	0.9540
101	4	0.9225	0.0023	0.9132	0.9280
167	5	0.9074	0.0020	0.8991	0.9113
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9782	0.0029	0.9703	0.9868
16	2	0.9763	0.0025	0.9610	0.9736
50	3	0.9503	0.0023	0.9444	0.9563
100	4	0.9233	0.0023	0.9170	0.9293
166	5	0.9083	0.0023	0.9002	0.9143

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.25

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9258	0.0636	0.6846	0.9943
16	2	0.9547	0.0141	0.9144	0.9851
50	3	0.9354	0.0109	0.9085	0.9713
100	4	0.9128	0.0123	0.8814	0.9354
166	5	0.8955	0.0119	0.8612	0.9189
INCLUSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
1	1	0.9702	0.0354	0.8501	1.0000
15	2	0.9593	0.0129	0.9200	0.9850
49	3	0.9355	0.0120	0.8964	0.9607
99	4	0.9129	0.0129	0.8780	0.9369
165	5	0.8966	0.0111	0.8631	0.9249
OMISSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
3	1	0.8909	0.0603	0.6533	0.9922
17	2	0.9465	0.0145	0.9118	0.9762
51	3	0.9318	0.0116	0.9021	0.9602
101	4	0.9072	0.0112	0.8741	0.9334
167	5	0.8914	0.0101	0.8649	0.9170
COMBINATION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
2	1	0.9062	0.0644	0.6857	0.9989
16	2	0.9535	0.0159	0.9035	0.9803
50	3	0.9325	0.0123	0.8963	0.9621
100	4	0.9114	0.0116	0.8704	0.9340
166	5	0.8950	0.0104	0.8647	0.9221

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.26

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9497	0.0340	0.8710	0.9999
16	2	0.9691	0.0096	0.9421	0.9862
50	3	0.9565	0.0066	0.9392	0.9707
100	4	0.9367	0.0070	0.9202	0.9505
166	5	0.9272	0.0063	0.9058	0.9402
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9646	0.0242	0.8546	0.9999
15	2	0.9712	0.0091	0.9408	0.9890
49	3	0.9563	0.0076	0.9315	0.9723
99	4	0.9390	0.0067	0.9211	0.9544
165	5	0.9272	0.0063	0.9105	0.9454
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9109	0.0353	0.8054	0.9777
17	2	0.9608	0.0107	0.9348	0.9864
51	3	0.9512	0.0067	0.9328	0.9640
101	4	0.9334	0.0075	0.9149	0.9500
167	5	0.9258	0.0072	0.9084	0.9463
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9273	0.0340	0.8202	0.9917
16	2	0.9657	0.0097	0.9423	0.9903
50	3	0.9541	0.0079	0.9305	0.9700
100	4	0.9355	0.0065	0.9166	0.9498
166	5	0.9260	0.0070	0.9051	0.9403

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.27

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9463	0.0261	0.8733	0.9865
16	2	0.9770	0.0047	0.9603	0.9884
50	3	0.9685	0.0039	0.9601	0.9779
100	4	0.9527	0.0044	0.9391	0.9621
166	5	0.9458	0.0032	0.9355	0.9554
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9683	0.0209	0.9152	0.9953
15	2	0.9795	0.0049	0.9641	0.9888
49	3	0.9682	0.0039	0.9553	0.9767
99	4	0.9541	0.0035	0.9437	0.9626
165	5	0.9458	0.0039	0.9375	0.9546
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9108	0.0271	0.8405	0.9726
17	2	0.9701	0.0055	0.9581	0.9840
51	3	0.9645	0.0043	0.9540	0.9735
101	4	0.9505	0.0041	0.9386	0.9637
167	5	0.9436	0.0035	0.9317	0.9524
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9323	0.0234	0.8823	0.9774
16	2	0.9725	0.0061	0.9538	0.9851
50	3	0.9662	0.0044	0.9524	0.9754
100	4	0.9519	0.0036	0.9439	0.9658
166	5	0.9441	0.0040	0.9315	0.9549

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.28

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9554	0.0166	0.8966	0.9838
16	2	0.9805	0.0038	0.9683	0.9896
50	3	0.9722	0.0028	0.9658	0.9794
100	4	0.9580	0.0029	0.9507	0.9642
166	5	0.9518	0.0023	0.9446	0.9589
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9695	0.0120	0.9386	0.9903
15	2	0.9818	0.0034	0.9712	0.9891
49	3	0.9731	0.0028	0.9650	0.9804
99	4	0.9585	0.0028	0.9496	0.9649
165	5	0.9524	0.0025	0.9453	0.9640
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9129	0.0190	0.8497	0.9485
17	2	0.9731	0.0039	0.9635	0.9840
51	3	0.9683	0.0030	0.9597	0.9740
101	4	0.9555	0.0027	0.9487	0.9624
167	5	0.9500	0.0025	0.9433	0.9555
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9395	0.0173	0.8852	0.9766
16	2	0.9751	0.0044	0.9612	0.9874
50	3	0.9692	0.0035	0.9609	0.9765
100	4	0.9567	0.0028	0.9506	0.9645
166	5	0.9504	0.0027	0.9418	0.9581

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.29

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9506	0.0111	0.9208	0.9790
16	2	0.9814	0.0028	0.9735	0.9880
50	3	0.9741	0.0021	0.9687	0.9802
100	4	0.9604	0.0022	0.9552	0.9681
166	5	0.9549	0.0018	0.9496	0.9589
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9683	0.0099	0.9338	0.9866
15	2	0.9830	0.0024	0.9744	0.9880
49	3	0.9746	0.0020	0.9675	0.9792
99	4	0.9611	0.0019	0.9566	0.9659
165	5	0.9554	0.0018	0.9503	0.9607
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9189	0.0135	0.8832	0.9554
17	2	0.9746	0.0025	0.9679	0.9805
51	3	0.9705	0.0021	0.9649	0.9760
101	4	0.9581	0.0021	0.9522	0.9631
167	5	0.9529	0.0018	0.9485	0.9567
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9365	0.0145	0.9061	0.9664
16	2	0.9763	0.0029	0.9672	0.9837
50	3	0.9713	0.0021	0.9645	0.9774
100	4	0.9591	0.0020	0.9545	0.9642
166	5	0.9539	0.0016	0.9490	0.9578

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.30

Descriptive Statistics for the Normed Fit Index from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9557	0.0071	0.9372	0.9720
16	2	0.9823	0.0015	0.9786	0.9859
50	3	0.9751	0.0011	0.9721	0.9784
100	4	0.9620	0.0012	0.9589	0.9656
166	5	0.9566	0.0010	0.9532	0.9595
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9681	0.0064	0.9533	0.9827
15	2	0.9836	0.0016	0.9777	0.9871
49	3	0.9760	0.0013	0.9715	0.9796
99	4	0.9626	0.0013	0.9587	0.9654
165	5	0.9571	0.0011	0.9536	0.9602
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9202	0.0096	0.8926	0.9392
17	2	0.9753	0.0017	0.9708	0.9799
51	3	0.9714	0.0012	0.9681	0.9743
101	4	0.9597	0.0012	0.9544	0.9627
167	5	0.9549	0.0010	0.9507	0.9573
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9384	0.0084	0.9167	0.9611
16	2	0.9770	0.0018	0.9722	0.9812
50	3	0.9728	0.0013	0.9695	0.9767
100	4	0.9605	0.0014	0.9563	0.9639
166	5	0.9555	0.0012	0.9513	0.9589

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.31

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8480	0.2039	0.0572	1.0679
16	2	0.9663	0.0256	0.8927	1.0162
50	3	0.9647	0.0151	0.9278	1.0184
100	4	0.9128	0.0144	0.9175	0.9799
166	5	0.9458	0.0135	0.9076	0.9727
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9135	0.2390	0.1069	1.3101
15	2	0.9693	0.0239	0.8925	1.0237
49	3	0.9641	0.0173	0.9052	1.0044
99	4	0.9522	0.0154	0.9135	0.9845
165	5	0.9459	0.0123	0.9142	0.9761
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.8497	0.1309	0.3349	1.0847
17	2	0.9562	0.0247	0.9026	1.0062
51	3	0.9614	0.0152	0.9214	0.9974
101	4	0.9476	0.0132	0.9079	0.9808
167	5	0.9413	0.0117	0.9038	0.9679
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.7800	0.2088	0.0614	1.0902
16	2	0.9616	0.0290	0.8749	1.0106
50	3	0.9609	0.0169	0.9122	0.9984
100	4	0.9516	0.0135	0.9071	0.9763
166	5	0.9454	0.0112	0.9105	0.9777

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.32

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8855	0.1055	0.6384	1.0548
16	2	0.9684	0.0172	0.9200	1.0031
50	3	0.9687	0.0090	0.9446	0.9869
100	4	0.9538	0.0082	0.9337	0.9696
166	5	0.9503	0.0072	0.9271	0.9649
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.8223	0.1512	0.1332	1.0460
15	2	0.9689	0.0172	0.9106	1.0000
49	3	0.9668	0.0103	0.9333	0.9892
99	4	0.9559	0.0081	0.9358	0.9751
165	5	0.9498	0.0072	0.9293	0.9708
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.8563	0.0727	0.6468	0.9866
17	2	0.9577	0.0179	0.9144	0.9986
51	3	0.9622	0.0087	0.9392	0.9803
101	4	0.9505	0.0091	0.9283	0.9719
167	5	0.9493	0.0082	0.9303	0.9705
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8185	0.1055	0.4885	1.0113
16	2	0.9623	0.0174	0.9196	1.0045
50	3	0.9651	0.0107	0.9346	0.9876
100	4	0.9523	0.0077	0.9289	0.9696
166	5	0.9492	0.0080	0.9256	0.9663

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.33

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8560	0.0796	0.6306	0.9951
16	2	0.9688	0.0082	0.9388	0.9886
50	3	0.9689	0.0052	0.9576	0.9808
100	4	0.9554	0.0053	0.9394	0.9665
166	5	0.9518	0.0036	0.9401	0.9621
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.8242	0.1274	0.4992	0.9897
15	2	0.9708	0.0092	0.9414	0.9891
49	3	0.9676	0.0052	0.9499	0.9790
99	4	0.9564	0.0042	0.9441	0.9661
165	5	0.9514	0.0044	0.9420	0.9614
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.8360	0.0548	0.6915	0.9637
17	2	0.9598	0.0091	0.9404	0.9833
51	3	0.9644	0.0056	0.9512	0.9766
101	4	0.9532	0.0050	0.9300	0.9697
167	5	0.9497	0.0040	0.9362	0.9600
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8105	0.0714	0.6578	0.9479
16	2	0.9609	0.0108	0.9282	0.9836
50	3	0.9658	0.0059	0.9476	0.9778
100	4	0.9543	0.0043	0.9448	0.9712
166	5	0.9499	0.0045	0.9360	0.9622

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.34

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8734	0.0501	0.6964	0.9588
16	2	0.9705	0.0067	0.9490	0.9865
50	3	0.9685	0.0036	0.9602	0.9781
100	4	0.9557	0.0035	0.9470	0.9633
166	5	0.9518	0.0029	0.9436	0.9600
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.8241	0.0724	0.6367	0.9499
15	2	0.9707	0.0064	0.9508	0.9844
49	3	0.9690	0.0038	0.9580	0.9790
99	4	0.9558	0.0034	0.9449	0.9633
165	5	0.9522	0.0029	0.9440	0.9655
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.8326	0.0382	0.7058	0.9046
17	2	0.9602	0.0065	0.9444	0.9784
51	3	0.9642	0.0039	0.9530	0.9719
101	4	0.9532	0.0033	0.9449	0.9614
167	5	0.9501	0.0028	0.9425	0.9563
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8253	0.0523	0.6609	0.9375
16	2	0.9609	0.0077	0.9367	0.9828
50	3	0.9645	0.0046	0.9535	0.9743
100	4	0.9541	0.0034	0.9466	0.9636
166	5	0.9502	0.0031	0.9403	0.9590

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.35

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8553	0.0333	0.7657	0.9409
16	2	0.9697	0.0050	0.9561	0.9813
50	3	0.9685	0.0027	0.9613	0.9766
100	4	0.9555	0.0026	0.9492	0.9648
166	5	0.9519	0.0021	0.9459	0.9565
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.8135	0.0595	0.6050	0.9231
15	2	0.9706	0.0045	0.9545	0.9799
49	3	0.9684	0.0027	0.9589	0.9745
99	4	0.9559	0.0023	0.9505	0.9617
165	5	0.9522	0.0021	0.9462	0.9582
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.8413	0.0271	0.7699	0.9147
17	2	0.9604	0.0041	0.9493	0.9702
51	3	0.9645	0.0028	0.9572	0.9716
101	4	0.9533	0.0025	0.9462	0.9592
167	5	0.9500	0.0020	0.9450	0.9542
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8130	0.0436	0.7215	0.9027
16	2	0.9608	0.0052	0.9448	0.9737
50	3	0.9647	0.0028	0.9557	0.9728
100	4	0.9540	0.0024	0.9484	0.9600
166	5	0.9507	0.0019	0.9452	0.9552

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.36

Descriptive Statistics for the Nonnormed Fit Index from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.8687	0.0213	0.8128	0.9174
16	2	0.9699	0.0026	0.9635	0.9763
50	3	0.9681	0.0015	0.9642	0.9726
100	4	0.9556	0.0014	0.9519	0.9599
166	5	0.9518	0.0012	0.9479	0.9551
INCLUSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
1	1	0.8101	0.0387	0.7208	0.8976
15	2	0.9703	0.0031	0.9593	0.9768
49	3	0.9687	0.0017	0.9626	0.9736
99	4	0.9559	0.0016	0.9512	0.9593
165	5	0.9520	0.0012	0.9479	0.9556
OMISSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
3	1	0.8417	0.0193	0.7865	0.8799
17	2	0.9602	0.0028	0.9528	0.9678
51	3	0.9640	0.0015	0.9598	0.9678
101	4	0.9534	0.0015	0.9470	0.9569
167	5	0.9501	0.0012	0.9453	0.9528
COMBINATION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
2	1	0.8166	0.0253	0.7515	0.8849
16	2	0.9607	0.0031	0.9522	0.9681
50	3	0.9651	0.0017	0.9607	0.9703
100	4	0.9538	0.0016	0.9488	0.9578
166	5	0.9505	0.0014	0.9456	0.9543

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.37

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1029	0.0904	0.0000	0.3844
16	2	0.0763	0.0353	0.0000	0.1472
50	3	0.0790	0.0188	0.0000	0.1171
100	4	0.0862	0.0127	0.0571	0.1118
166	5	0.0852	0.0104	0.0590	0.1152
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.0759	0.0953	0.0000	0.3711
15	2	0.0722	0.0346	0.0000	0.1484
49	3	0.0776	0.0233	0.0000	0.1357
99	4	0.0853	0.0137	0.0487	0.1126
165	5	0.0855	0.0098	0.0590	0.1030
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1238	0.0621	0.0000	0.2694
17	2	0.0910	0.0305	0.0000	0.1375
51	3	0.0829	0.0178	0.0226	0.1231
101	4	0.0895	0.0113	0.0545	0.1174
167	5	0.0892	0.0092	0.0686	0.1200
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1451	0.0812	0.0000	0.3595
16	2	0.0842	0.0362	0.0000	0.1548
50	3	0.0827	0.0199	0.0170	0.1248
100	4	0.0860	0.0113	0.0624	0.1181
166	5	0.0855	0.0095	0.0554	0.1081

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.38

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1020	0.0584	0.0000	0.2198
16	2	0.0778	0.0254	0.0000	0.1300
50	3	0.0747	0.0112	0.0498	0.1014
100	4	0.0846	0.0074	0.0681	0.1024
166	5	0.0822	0.0058	0.0671	0.0969
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.1288	0.0627	0.0000	0.3085
15	2	0.0772	0.0241	0.0000	0.1376
49	3	0.0771	0.0122	0.0443	0.1091
99	4	0.0827	0.0077	0.0623	0.1027
165	5	0.0826	0.0060	0.0641	0.0993
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1278	0.0371	0.0456	0.2123
17	2	0.0922	0.0210	0.0181	0.1329
51	3	0.0831	0.0098	0.0573	0.1032
101	4	0.0875	0.0083	0.0622	0.1054
167	5	0.0830	0.0067	0.0663	0.0970
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1318	0.0464	0.0000	0.2100
16	2	0.0866	0.0237	0.0000	0.1324
50	3	0.0791	0.0128	0.0470	0.1063
100	4	0.0860	0.0068	0.0688	0.1054
166	5	0.0827	0.0065	0.0674	0.0987

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.39

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1258	0.0346	0.0526	0.2068
16	2	0.0806	0.0109	0.0503	0.1176
50	3	0.0753	0.0064	0.0607	0.0892
100	4	0.0833	0.0047	0.0728	0.0977
166	5	0.0807	0.0029	0.0724	0.0894
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.1332	0.0532	0.0323	0.2483
15	2	0.0777	0.0127	0.0460	0.1139
49	3	0.0769	0.0061	0.0627	0.0968
99	4	0.0827	0.0040	0.0729	0.0922
165	5	0.0812	0.0035	0.0732	0.0900
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1355	0.0106	0.0580	0.1106
17	2	0.0913	0.0305	0.0000	0.1375
51	3	0.0806	0.0064	0.0645	0.0941
101	4	0.0854	0.0049	0.0673	0.0981
167	5	0.0825	0.0032	0.0732	0.0932
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1461	0.0297	0.0740	0.2010
16	2	0.0900	0.0123	0.0575	0.1224
50	3	0.0790	0.0069	0.0619	0.0972
100	4	0.0846	0.0041	0.0671	0.0932
166	5	0.0822	0.0034	0.0721	0.0906

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.40

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1197	0.0232	0.0676	0.1774
16	2	0.0786	0.0089	0.0532	0.1034
50	3	0.0760	0.0044	0.0634	0.0854
100	4	0.0832	0.0033	0.0748	0.0911
166	5	0.0808	0.0023	0.0740	0.0871
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.1417	0.0307	0.0755	0.2128
15	2	0.0782	0.0087	0.0570	0.1011
49	3	0.0753	0.0046	0.0618	0.0881
99	4	0.0831	0.0031	0.0756	0.0927
165	5	0.0803	0.0025	0.0691	0.0869
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1408	0.0160	0.1012	0.1853
17	2	0.0913	0.0076	0.0663	0.1077
51	3	0.0810	0.0045	0.0698	0.0930
101	4	0.0855	0.0030	0.0772	0.0939
167	5	0.0822	0.0022	0.0775	0.0879
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1430	0.0225	0.0868	0.2042
16	2	0.0902	0.0091	0.0588	0.1139
50	3	0.0806	0.0052	0.0681	0.0918
100	4	0.0846	0.0031	0.0750	0.0921
166	5	0.0821	0.0025	0.0749	0.0903

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.41

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1293	0.0154	0.0843	0.1649
16	2	0.0796	0.0065	0.0635	0.0941
50	3	0.0760	0.0032	0.0655	0.0839
100	4	0.0835	0.0024	0.0746	0.0888
166	5	0.0808	0.0017	0.0769	0.0852
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.1463	0.0240	0.0983	0.2191
15	2	0.0785	0.0060	0.0647	0.0983
49	3	0.0761	0.0032	0.0687	0.0862
99	4	0.0831	0.0021	0.0776	0.0876
165	5	0.0805	0.0017	0.0753	0.0849
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1368	0.0123	0.1001	0.1605
17	2	0.0913	0.0048	0.0796	0.1309
51	3	0.0809	0.0032	0.0723	0.0890
101	4	0.0854	0.0023	0.0801	0.0919
167	5	0.0824	0.0017	0.0787	0.0862
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1473	0.0174	0.1136	0.1762
16	2	0.0907	0.0062	0.0742	0.1097
50	3	0.0804	0.0033	0.0701	0.0904
100	4	0.0849	0.0023	0.0797	0.0899
166	5	0.0818	0.0015	0.0785	0.0854

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.42

Descriptive Statistics for the Root Mean Square Error of Approximation from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1244	0.0104	0.1006	0.1499
16	2	0.0797	0.0034	0.0710	0.0880
50	3	0.0765	0.0018	0.0709	0.0808
100	4	0.0833	0.0013	0.0796	0.0872
166	5	0.0809	0.0010	0.0782	0.0836
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.1498	0.0153	0.1115	0.1824
15	2	0.0792	0.0041	0.0699	0.0925
49	3	0.0759	0.0020	0.0701	0.0826
99	4	0.0831	0.0015	0.0797	0.0869
165	5	0.0807	0.0010	0.0780	0.0844
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.1371	0.0829	0.1196	0.1609
17	2	0.0917	0.0032	0.0836	0.0991
51	3	0.0814	0.0017	0.0767	0.0858
101	4	0.0855	0.0014	0.0824	0.0908
167	5	0.0823	0.0010	0.0800	0.0863
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.1474	0.0104	0.1144	0.1730
16	2	0.0910	0.0037	0.0814	0.0999
50	3	0.0800	0.0019	0.0747	0.0853
100	4	0.0851	0.0014	0.0815	0.0889
166	5	0.0819	0.0011	0.0787	0.0860

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.43

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9493	0.0680	0.6857	1.0226
16	2	0.9907	0.0146	0.9387	1.0092
50	3	0.9733	0.0115	0.9453	1.0139
100	4	0.9602	0.0120	0.9313	0.9833
166	5	0.9527	0.0118	0.9192	0.9762
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9885	0.0537	0.8512	1.3534
15	2	0.9836	0.0128	0.9424	1.0127
49	3	0.9734	0.0128	0.9296	1.0032
99	4	0.9606	0.0127	0.9286	0.9872
165	5	0.9530	0.0107	0.9255	0.9792
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9249	0.0655	0.6674	1.0423
17	2	0.9734	0.0150	0.9409	1.0038
51	3	0.9701	0.0118	0.9393	0.9980
101	4	0.9559	0.0111	0.9224	0.9839
167	5	0.9484	0.0103	0.9155	0.9718
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9267	0.0696	0.6871	1.0301
16	2	0.9781	0.0166	0.9285	1.0060
50	3	0.9704	0.0128	0.9335	0.9988
100	4	0.9597	0.0112	0.9226	0.9802
166	5	0.9523	0.0103	0.9218	0.9805

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.44

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9619	0.0352	0.8795	1.0183
16	2	0.9820	0.0098	0.9543	1.0018
50	3	0.9763	0.0068	0.9580	0.9901
100	4	0.9615	0.0069	0.9448	0.9747
166	5	0.9567	0.0063	0.9363	0.9694
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9704	0.0252	0.8555	1.0077
15	2	0.9833	0.0093	0.9521	1.0000
49	3	0.9754	0.0077	0.9505	0.9920
99	4	0.9636	0.0067	0.9471	0.9795
165	5	0.9564	0.0063	0.9386	0.9746
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9282	0.0364	0.8234	0.9933
17	2	0.9743	0.0109	0.9480	0.9991
51	3	0.9708	0.0067	0.9530	0.9848
101	4	0.9583	0.0077	0.9396	0.9763
167	5	0.9554	0.0072	0.9387	0.9741
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9395	0.0352	0.8295	1.0038
16	2	0.9784	0.0100	0.9541	1.0026
50	3	0.9736	0.0081	0.9505	0.9906
100	4	0.9602	0.0064	0.9407	0.9747
166	5	0.9556	0.0069	0.9350	0.9706

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.45

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9511	0.0265	0.8769	0.9920
16	2	0.9822	0.0047	0.9651	0.9935
50	3	0.9764	0.0039	0.9679	0.9854
100	4	0.9628	0.0044	0.9495	0.9721
166	5	0.9579	0.0031	0.9476	0.9669
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9707	0.0212	0.9165	0.9983
15	2	0.9844	0.0050	0.9686	0.9942
49	3	0.9759	0.0039	0.9628	0.9844
99	4	0.9639	0.0035	0.9538	0.9721
165	5	0.9578	0.0038	0.9496	0.9665
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9180	0.0274	0.8457	0.9819
17	2	0.9756	0.0055	0.9638	0.9899
51	3	0.9725	0.0043	0.9623	0.9819
101	4	0.9606	0.0042	0.9495	0.9745
167	5	0.9558	0.0035	0.9439	0.9648
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9368	0.0238	0.8859	0.9826
16	2	0.9776	0.0062	0.9590	0.9906
50	3	0.9741	0.0045	0.9603	0.9832
100	4	0.9619	0.0036	0.9540	0.9760
166	5	0.9562	0.0039	0.9441	0.9669

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.46

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9578	0.0167	0.8988	0.9863
16	2	0.9831	0.0038	0.9709	0.9923
50	3	0.9761	0.0028	0.9698	0.9834
100	4	0.9631	0.0029	0.9558	0.9694
166	5	0.9579	0.0026	0.9507	0.9650
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9707	0.0121	0.9395	0.9917
15	2	0.9843	0.0034	0.9737	0.9916
49	3	0.9770	0.0028	0.9688	0.9844
99	4	0.9635	0.0028	0.9545	0.9697
165	5	0.9585	0.0026	0.9513	0.9700
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9163	0.0191	0.8529	0.9523
17	2	0.9758	0.0039	0.9662	0.9869
51	3	0.9723	0.0030	0.9636	0.9783
101	4	0.9606	0.0027	0.9536	0.9675
167	5	0.9561	0.0025	0.9495	0.9616
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9418	0.0174	0.8870	0.9792
16	2	0.9777	0.0044	0.9638	0.9901
50	3	0.9731	0.0035	0.9648	0.9806
100	4	0.9618	0.0028	0.9555	0.9697
166	5	0.9565	0.0027	0.9478	0.9641

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.47

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9518	0.0111	0.9219	0.9803
16	2	0.9828	0.0028	0.9749	0.9893
50	3	0.9761	0.0021	0.9707	0.9822
100	4	0.9629	0.0022	0.9577	0.9707
166	5	0.9579	0.0018	0.9527	0.9619
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9689	0.0099	0.9342	0.9872
15	2	0.9843	0.0024	0.9756	0.9892
49	3	0.9766	0.0020	0.9695	0.9811
99	4	0.9636	0.0019	0.9591	0.9684
165	5	0.9585	0.0018	0.9533	0.9637
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9207	0.0135	0.8849	0.9573
17	2	0.9759	0.0025	0.9692	0.9819
51	3	0.9725	0.0021	0.9670	0.9781
101	4	0.9607	0.0021	0.9548	0.9656
167	5	0.9560	0.0018	0.9516	0.9598
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9377	0.0145	0.9072	0.9676
16	2	0.9776	0.0030	0.9684	0.9850
50	3	0.9733	0.0021	0.9664	0.9794
100	4	0.9616	0.0020	0.9570	0.9667
166	5	0.9569	0.0016	0.9521	0.9608

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table K.48

Descriptive Statistics for the Relative Noncentrality Index from the Simple Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9562	0.0071	0.9376	0.9725
16	2	0.9828	0.0015	0.9792	0.9864
50	3	0.9759	0.0011	0.9729	0.9792
100	4	0.9630	0.0012	0.9599	0.9666
166	5	0.9579	0.0010	0.9545	0.9607
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
1	1	0.9684	0.0064	0.9535	0.9829
15	2	0.9841	0.0016	0.9782	0.9876
49	3	0.9768	0.0013	0.9723	0.9804
99	4	0.9636	0.0013	0.9598	0.9664
165	5	0.9583	0.0010	0.9548	0.9614
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
3	1	0.9209	0.0096	0.8933	0.9400
17	2	0.9758	0.0017	0.9713	0.9804
51	3	0.9722	0.0012	0.9690	0.9751
101	4	0.9607	0.0012	0.9554	0.9637
167	5	0.9561	0.0010	0.9519	0.9830
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
2	1	0.9389	0.0084	0.9172	0.9616
16	2	0.9775	0.0018	0.9727	0.9817
50	3	0.9736	0.0013	0.9703	0.9775
100	4	0.9615	0.0014	0.9573	0.9649
166	5	0.9568	0.0012	0.9525	0.9601

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

APPENDIX L

Descriptive Statistics for the Moderate Model

Table L.01

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	7.8778	4.0600	1.7462	17.0470
47	2	50.5527	10.0533	44.7320	73.2960
128	3	140.3326	17.7983	100.6800	191.5000
245	4	275.4802	27.7449	201.8400	349.0900
398	5	519.4846	36.4761	431.4000	653.8400
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	7.4702	3.4245	1.8754	15.2110
46	2	47.8464	11.6382	24.1740	101.6700
127	3	137.2531	17.4267	97.6880	201.6400
244	4	271.1759	24.9029	198.4200	339.2900
397	5	523.9949	39.4478	436.8800	611.5000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	49.0328	13.4271	24.1570	89.8170
48	2	90.0483	14.1480	56.3940	130.3500
129	3	189.1112	24.9143	140.7200	257.5700
246	4	322.8717	28.6605	250.9900	394.9800
399	5	539.7608	37.1636	434.8500	663.1600
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	45.2474	12.8179	11.7500	93.3660
47	2	94.3582	15.3185	60.1320	136.6600
128	3	185.1495	19.1800	145.7300	245.2400
245	4	320.8211	26.3553	257.6700	392.6700
398	5	536.3518	36.7017	436.4500	636.1900

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.02

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	7.7112	4.2363	1.1082	28.1900
47	2	48.6543	9.5857	26.6820	78.8610
128	3	133.0963	16.1328	100.9500	186.1200
245	4	257.3267	25.0097	185.6900	344.4000
398	5	563.5933	37.6452	470.7500	673.2200
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	6.7267	3.2366	0.6462	17.4650
46	2	47.3579	10.2450	26.1750	74.3060
127	3	129.7316	17.1381	87.0450	177.0700
244	4	253.0249	21.6689	207.8400	308.9300
397	5	559.7545	38.6763	465.8500	661.1100
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	85.8421	18.8148	52.2560	141.5700
48	2	137.1790	20.3226	96.5470	192.5900
129	3	228.9103	23.6892	174.3700	302.7300
246	4	358.5898	24.8277	278.8300	439.1700
399	5	597.3948	38.4261	515.8000	706.0600
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	82.9794	16.3699	54.8760	125.0600
47	2	142.3966	21.2689	81.1990	195.7600
128	3	224.0241	22.5105	164.2000	272.6700
245	4	358.9777	29.1305	296.9900	425.0000
398	5	595.5059	38.6051	525.4700	733.2300

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.03

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	8.7782	4.6914	2.2136	23.0250
47	2	47.7286	10.0879	23.3510	103.9100
128	3	133.2831	16.3011	89.3760	173.6300
245	4	250.5377	22.3409	178.8100	321.1800
398	5	751.4145	47.1146	638.9000	864.1200
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	6.7172	3.9912	0.4541	20.3640
46	2	46.9546	9.6028	23.5700	79.7580
127	3	125.6547	15.7877	89.9620	173.9600
244	4	248.2537	22.6695	192.9000	310.3800
397	5	757.0588	43.3742	638.0200	919.1000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	208.8315	28.8783	156.0800	268.6100
48	2	272.2151	30.3522	208.8800	354.1400
129	3	370.8237	30.7472	284.8600	468.8200
246	4	502.5726	32.8822	413.4200	590.0500
399	5	838.2677	48.5726	671.7400	982.4100
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	206.9361	25.1248	152.3700	275.3000
47	2	273.4549	30.9022	215.6400	356.0600
128	3	366.9693	32.2536	282.8700	450.2300
245	4	500.1133	36.0058	408.9300	601.3700
398	5	839.1565	48.7636	705.9900	956.0100

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.04

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	8.8546	4.3347	1.7217	24.1940
47	2	48.6049	10.2193	27.5780	78.6320
128	3	128.4265	15.1877	88.9720	174.3700
245	4	246.9919	22.1593	193.7300	307.6000
398	5	1104.9700	59.1147	936.3700	1232.4000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	7.3388	4.1225	0.3778	23.1560
46	2	44.8905	9.1576	26.9320	78.9970
127	3	128.8564	17.2154	95.3550	184.8700
244	4	248.4819	21.3584	199.0000	304.8000
397	5	1100.9900	63.8523	959.7300	1329.7000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	396.7047	31.4900	331.1700	488.6400
48	2	503.6164	38.3308	395.3000	611.2900
129	3	608.9249	39.7206	490.4700	699.6900
246	4	752.2279	43.1785	630.9500	855.0500
399	5	1269.5400	60.4515	1126.3000	1515.9000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	388.9056	31.3101	321.4300	488.2100
47	2	494.3449	35.9689	399.9300	573.5800
128	3	607.7536	43.9497	519.0700	740.3500
245	4	748.8939	39.4783	643.3400	876.5000
398	5	1267.2500	55.6235	1112.3000	1472.2000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.05

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	8.7504	3.6479	2.2315	18.0960
47	2	48.4151	10.6796	22.1430	76.3680
128	3	130.2648	18.3357	88.0640	192.1400
245	4	248.3074	19.3605	197.7800	312.4200
398	5	1804.1200	73.9388	1566.4000	2007.3000
INCLUSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
7	1	7.0680	3.3560	1.2291	16.6550
46	2	47.3313	9.7493	24.5720	76.7700
127	3	129.3658	15.9050	91.4100	179.1300
244	4	245.3923	22.4798	186.2500	308.1000
397	5	1799.3300	83.5703	1627.6000	2104.2000
OMISSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
9	1	779.2475	52.2843	674.4600	914.0000
48	2	940.7132	59.2854	790.2500	1090.5000
129	3	1092.8700	58.5174	956.4300	1254.4000
246	4	1256.4900	56.7885	1109.2000	1418.4000
399	5	2126.4200	85.8546	1900.1000	2429.9000
COMBINATION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
8	1	778.8414	51.2345	602.6200	919.9800
47	2	941.2614	61.9609	803.5400	1095.0000
128	3	1089.8300	57.0034	939.4600	1273.9000
245	4	1257.1600	59.0726	1080.6000	1453.3000
398	5	2117.6700	82.1890	1905.5000	2336.9000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.06

Descriptive Statistics for the Chi-Square Test Statistic from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	8.3027	4.2816	1.0401	26.2330
47	2	49.7878	10.2709	30.7330	74.5230
128	3	129.3465	16.9423	92.0700	176.3400
245	4	243.2747	22.3170	158.7200	296.7700
398	5	3909.6400	129.1422	3588.2000	4548.4000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	7.3121	3.9434	0.6765	20.5110
46	2	48.7728	9.9682	27.1750	84.5690
127	3	128.7852	15.5559	85.6230	170.1700
244	4	245.1572	22.4747	195.8700	312.8200
397	5	3902.0500	106.7269	3661.4000	4251.8000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	1942.0600	73.3855	1720.7000	2111.2000
48	2	2276.9300	81.1952	2039.7000	2533.0000
129	3	2530.2400	95.5177	2277.0000	2783.6000
246	4	2762.8300	88.7666	2543.1000	3021.6000
399	5	4703.1600	132.6740	4309.4000	5148.0000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1942.8900	78.9727	1743.7000	2188.7000
47	2	2297.9700	83.8559	2049.0000	2522.7000
128	3	2516.5200	83.6835	2233.0000	2746.7000
245	4	2749.1500	89.5880	2554.6000	3010.8000
398	5	4686.1400	125.8931	4292.4000	5010.4000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.07

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9859	0.0238	0.8979	1.0000
47	2	0.9931	0.0081	0.9713	1.0000
128	3	0.9920	0.0078	0.9681	1.0000
245	4	0.9886	0.0091	0.9620	1.0000
398	5	0.9730	0.0079	0.9460	0.9921
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9852	0.0216	0.9164	1.0000
46	2	0.9944	0.0099	0.9418	1.0000
127	3	0.9930	0.0076	0.9563	1.0000
244	4	0.9898	0.0077	0.9671	1.0000
397	5	0.9716	0.0087	0.9522	0.9910
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6443	0.0962	0.4337	0.8115
48	2	0.9521	0.0150	0.9163	0.9899
129	3	0.9672	0.0132	0.9290	0.9934
246	4	0.9727	0.0100	0.9482	0.9981
399	5	0.9687	0.0081	0.9422	0.9917
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6479	0.1100	0.2989	0.9219
47	2	0.9470	0.0166	0.8992	0.9843
128	3	0.9686	0.0101	0.9377	0.9903
245	4	0.9730	0.0090	0.9471	0.9953
398	5	0.9693	0.0079	0.9479	0.9918

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.08

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9937	0.0121	0.9240	1.0000
47	2	0.9975	0.0039	0.9814	1.0000
128	3	0.9975	0.0032	0.9848	1.0000
245	4	0.9970	0.0034	0.9832	1.0000
398	5	0.9815	0.0041	0.9695	0.9920
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9950	0.0089	0.9595	1.0000
46	2	0.9973	0.0036	0.9847	1.0000
127	3	0.9977	0.0030	0.9865	1.0000
244	4	0.9976	0.0039	0.9889	1.0000
397	5	0.9818	0.0043	0.9699	0.9920
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6630	0.0594	0.5384	0.7932
48	2	0.9506	0.0104	0.9208	0.9721
129	3	0.9728	0.0061	0.9564	0.9865
246	4	0.9799	0.0043	0.9652	0.9941
399	5	0.9779	0.0042	0.9656	0.9870
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6668	0.0616	0.5402	0.7809
47	2	0.9475	0.0108	0.9198	0.9769
128	3	0.9738	0.0059	0.9586	0.9894
245	4	0.9797	0.0050	0.9665	0.9907
398	5	0.9780	0.0042	0.9633	0.9856

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.09

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9961	0.0063	0.9737	1.0000
47	2	0.9991	0.0015	0.9877	1.0000
128	3	0.9990	0.0013	0.9951	1.0000
245	4	0.9992	0.0011	0.9947	1.0000
398	5	0.9842	0.0021	0.9793	0.9890
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9926	0.0707	0.0000	1.0000
46	2	0.9990	0.0015	0.9927	1.0000
127	3	0.9994	0.0011	0.9949	1.0000
244	4	0.9992	0.0011	0.9953	1.0000
397	5	0.9839	0.0019	0.9771	0.9890
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6397	0.0414	0.5571	0.7282
48	2	0.9499	0.0062	0.9333	0.9635
129	3	0.9736	0.0031	0.9642	0.9823
246	4	0.9817	0.0022	0.9763	0.9878
399	5	0.9804	0.0021	0.9746	0.9874
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6465	0.0360	0.5744	0.7430
47	2	0.9494	0.0063	0.9293	0.9628
128	3	0.9740	0.0033	0.9658	0.9825
245	4	0.9819	0.0025	0.9748	0.9883
398	5	0.9803	0.0021	0.9747	0.9862

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.10

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9981	0.0029	0.9840	1.0000
47	2	0.9995	0.0008	0.9964	1.0000
128	3	0.9997	0.0005	0.9974	1.0000
245	4	0.9997	0.0005	0.9978	1.0000
398	5	0.9842	0.0013	0.9815	0.9883
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9936	0.0707	0.0000	1.0000
46	2	0.9997	0.0006	0.9964	1.0000
127	3	0.9996	0.0006	0.9968	1.0000
244	4	0.9996	0.0005	0.9978	1.0000
397	5	0.9842	0.0014	0.9793	0.9874
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6563	0.0237	0.5730	0.7049
48	2	0.9494	0.0038	0.9377	0.9612
129	3	0.9739	0.0021	0.9687	0.9803
246	4	0.9820	0.0015	0.9788	0.9860
399	5	0.9806	0.0013	0.9757	0.9841
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6549	0.0241	0.6010	0.7180
47	2	0.9501	0.0037	0.9401	0.9609
128	3	0.9739	0.0022	0.9665	0.9784
245	4	0.9821	0.0013	0.9778	0.9857
398	5	0.9807	0.0012	0.9760	0.9841

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.11

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9992	0.0012	0.9949	1.0000
47	2	0.9997	0.0004	0.9984	1.0000
128	3	0.9998	0.0003	0.9982	1.0000
245	4	0.9998	0.0002	0.9988	1.0000
398	5	0.9843	0.0008	0.9821	0.9871
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9994	0.0010	0.9957	1.0000
46	2	0.9998	0.0004	0.9983	1.0000
127	3	0.9998	0.0003	0.9986	1.0000
244	4	0.9998	0.0002	0.9989	1.0000
397	5	0.9844	0.0009	0.9810	0.9864
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6561	0.0209	0.6201	0.7044
48	2	0.9502	0.0031	0.9422	0.9585
129	3	0.9738	0.0015	0.9695	0.9773
246	4	0.9821	0.0010	0.9794	0.9845
399	5	0.9807	0.0009	0.9774	0.9833
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6551	0.0171	0.6182	0.7012
47	2	0.9502	0.0032	0.9430	0.9573
128	3	0.9738	0.0015	0.9693	0.9776
245	4	0.9820	0.0010	0.9788	0.9851
398	5	0.9808	0.0009	0.9784	0.9832

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.12

Descriptive Statistics for the Comparative Fit Index from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9997	0.0006	0.9968	1.0000
47	2	0.9999	0.0002	0.9994	1.0000
128	3	0.9999	0.0001	0.9995	1.0000
245	4	0.9999	0.0001	0.9996	1.0000
398	5	0.9843	0.0006	0.9818	0.9859
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9997	0.0005	0.9976	1.0000
46	2	0.9999	0.0002	0.9992	1.0000
127	3	0.9999	0.0001	0.9995	1.0000
244	4	0.9999	0.0001	0.9995	1.0000
397	5	0.9844	0.0005	0.9829	0.9855
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6565	0.0104	0.6263	0.6758
48	2	0.9503	0.0017	0.9452	0.9557
129	3	0.9739	0.0010	0.9710	0.9763
246	4	0.9821	0.0006	0.9803	0.9878
399	5	0.9808	0.0006	0.9788	0.9823
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6558	0.0113	0.6146	0.6906
47	2	0.9499	0.0017	0.9454	0.9549
128	3	0.9740	0.0009	0.9717	0.9769
245	4	0.9822	0.0006	0.9804	0.9837
398	5	0.9809	0.0005	0.9794	0.9826

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.13

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	349.7114	234.1276	117.6800	1140.1000
47	2	148.6673	30.0377	98.8490	252.0900
128	3	121.3949	14.7893	87.9220	166.3300
245	4	109.6957	11.0159	85.9130	147.8600
398	5	90.3449	6.1970	71.6440	108.0700
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	320.2838	190.0069	121.2500	976.3000
46	2	156.1604	34.9464	70.3340	292.5900
127	3	123.3636	15.4583	82.9860	170.2300
244	4	110.8464	10.4204	88.0430	149.8400
397	5	89.4467	6.7326	76.3600	106.4800
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	93.8715	13.8943	70.8120	130.3500
48	2	91.1272	13.5562	59.9290	120.0900
129	3	87.1821	11.6930	66.0650	119.5400
246	4	84.0706	8.2628	76.3240	107.4700
399	5	48.2830	6.0062	24.8820	89.7950
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	94.0244	20.8994	22.3040	170.2900
47	2	91.8246	12.5396	53.4800	120.2700
128	3	87.5228	9.2176	68.8740	115.2200
245	4	78.9789	7.7361	76.4890	116.0400
398	5	49.5733	5.9703	73.6030	106.8300

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.14

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	432.4366	274.6474	142.8300	1109.0000
47	2	308.3630	58.6403	183.8100	503.6200
128	3	256.0374	30.6885	180.7700	332.4200
245	4	234.7289	22.7871	174.0100	321.8800
398	5	166.4747	11.1195	138.9100	198.2300
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	569.9853	300.5307	211.5100	1468.3200
46	2	315.4818	73.7799	191.6900	542.3300
127	3	261.7673	35.6451	188.6700	382.7600
244	4	237.3174	20.0554	193.1600	286.6300
397	5	167.2759	11.5773	141.1100	199.8400
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	168.5719	11.6642	137.1700	215.4800
48	2	157.4142	16.3737	132.8000	181.4200
129	3	149.7242	15.3354	112.2800	194.1900
246	4	110.2553	11.6262	77.1370	152.8700
399	5	53.6995	9.9718	31.4550	83.5090
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	168.0832	10.1341	141.2000	201.6200
47	2	157.5385	15.5570	127.6300	177.6900
128	3	151.9255	15.8582	123.7100	204.7700
245	4	104.5010	13.6970	74.6420	178.5400
398	5	51.1284	9.7724	32.9720	73.8600

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.15

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	731.3100	295.7748	436.4300	1530.2000
47	2	692.3134	171.3019	348.9100	1149.1000
128	3	640.0705	79.9743	484.2100	939.7100
245	4	602.1650	54.8141	466.1900	836.5600
398	5	312.0685	19.8484	270.4200	365.4000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	939.7100	304.5000	453.7300	1765.8800
46	2	789.9609	165.6810	446.4700	1208.4000
127	3	674.2682	82.3841	480.0000	927.2400
244	4	605.5978	55.2157	480.6000	772.6800
397	5	308.8015	17.4350	253.7200	365.0500
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	300.6602	19.6320	255.1500	363.7300
48	2	280.3246	19.2320	238.5300	348.3900
129	3	230.3635	16.5211	181.1800	297.5300
246	4	137.7355	15.1808	104.8200	177.0200
399	5	53.7849	7.4436	41.2500	70.2680
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	301.3145	21.9266	249.4500	366.3700
47	2	279.3823	20.6220	244.5300	330.7700
128	3	231.4159	16.3687	187.3500	297.6000
245	4	134.3145	15.2040	102.5300	168.6400
398	5	50.1964	6.2638	37.4180	66.8000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.16

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	991.5000	326.8200	630.6200	1959.7000
47	2	856.2900	288.7932	521.3800	1625.2000
128	3	727.1600	157.7199	464.2900	1388.8000
245	4	621.8400	110.4949	373.4400	1145.0000
398	5	424.0351	22.9820	379.2100	498.7700
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	1151.6900	366.3600	798.1000	2098.4000
46	2	1071.3400	257.4016	701.4300	1742.1000
127	3	918.1800	172.1592	643.3900	1550.5000
244	4	809.1100	103.0964	578.7400	1398.6000
397	5	424.7454	24.1023	350.7100	485.5300
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	401.4458	4.3163	45.2960	66.3590
48	2	369.8080	11.4419	121.4200	187.2100
129	3	279.9334	18.8045	242.6900	345.7900
246	4	148.0235	23.4789	352.1100	476.8200
399	5	55.9010	17.3706	309.1900	415.7900
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	401.5256	21.2899	342.2700	465.9500
47	2	369.4964	19.9534	317.5900	420.0500
128	3	278.7996	15.9677	227.8700	324.5900
245	4	148.1942	11.0323	127.1700	181.9600
398	5	52.9410	4.1478	42.1130	63.4460

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.17

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1161.2300	330.9600	700.5000	2250.0000
47	2	951.5200	263.5845	647.3000	1740.6000
128	3	831.5900	166.8475	580.3000	1317.1000
245	4	726.0700	129.6220	516.8000	1027.9000
398	5	518.8301	21.3569	465.6300	596.7000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	1315.6600	350.2500	808.6000	2311.5000
46	2	1142.1300	284.4518	755.0000	1893.2000
127	3	920.8300	187.3138	634.5000	1452.0000
244	4	751.9000	140.2796	556.5000	1102.3000
397	5	519.2183	23.5869	443.2000	572.7000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	480.0868	21.7501	424.5300	542.6000
48	2	441.3337	17.7251	385.7200	492.9700
129	3	311.5193	16.6747	270.7500	354.8000
246	4	158.2070	10.0996	136.0700	187.3900
399	5	56.8295	3.7321	48.3870	65.2160
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	478.1619	22.7725	412.8400	554.8800
47	2	442.0791	17.2037	400.1100	490.4500
128	3	301.2386	16.2690	264.8400	358.7600
245	4	155.5285	10.3517	133.2600	181.2200
398	5	52.8032	3.6178	44.6570	67.6490

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.18

Descriptive Statistics for the Critical N from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1314.0000	347.9000	799.1000	2362.8000
47	2	1184.2000	303.2200	680.7000	1835.2000
128	3	911.3100	274.5116	632.8000	1541.6700
245	4	776.8900	109.4378	531.7000	1373.5000
398	5	598.2007	19.4861	513.7800	651.0100
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	1583.7700	367.8963	861.2900	2555.4800
46	2	1332.1100	316.3055	759.5060	1927.6000
127	3	1028.4900	298.6377	708.9000	1602.9100
244	4	843.3167	145.0986	599.2250	1427.0000
397	5	597.7775	16.3387	548.2800	636.5300
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	545.3157	17.4641	498.1800	591.7300
48	2	498.4526	14.0065	455.1100	543.4700
129	3	335.9240	12.7758	305.0000	372.6300
246	4	162.9777	5.8299	146.4200	181.5900
399	5	56.8515	2.1375	52.3030	63.9460
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	546.0295	17.7256	498.1300	586.9100
47	2	499.0688	13.4501	466.5000	544.1100
128	3	335.3645	11.2774	307.0000	377.4000
245	4	158.8038	5.7662	144.5600	177.7400
398	5	52.7794	2.0733	46.8910	58.6020

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.19

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9750	0.0122	0.9487	0.9942
47	2	0.9258	0.0134	0.8917	0.9571
128	3	0.8730	0.0129	0.8391	0.9081
245	4	0.8271	0.0141	0.7896	0.8653
398	5	0.7659	0.0118	0.7350	0.7960
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9761	0.0106	0.9550	0.9938
46	2	0.9295	0.0146	0.8657	0.9618
127	3	0.8759	0.0129	0.8250	0.9027
244	4	0.8295	0.0131	0.7981	0.8661
397	5	0.7638	0.0125	0.7355	0.7906
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.8813	0.0236	0.8276	0.9350
48	2	0.8858	0.0131	0.8516	0.9219
129	3	0.8448	0.0155	0.8018	0.8758
246	4	0.8088	0.0135	0.7717	0.8417
399	5	0.7605	0.0128	0.7272	0.7996
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.8888	0.0234	0.8048	0.9614
47	2	0.8825	0.0144	0.8445	0.9168
128	3	0.8458	0.0120	0.8099	0.8712
245	4	0.8092	0.0116	0.7814	0.8387
398	5	0.7612	0.0127	0.7282	0.7972

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.20

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9875	0.0066	0.9560	0.9981
47	2	0.9619	0.0073	0.9382	0.9765
128	3	0.9334	0.0073	0.9107	0.9479
245	4	0.9070	0.0082	0.8807	0.9304
398	5	0.8506	0.0086	0.8268	0.8710
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9889	0.0052	0.9724	0.9989
46	2	0.9628	0.0075	0.9430	0.9793
127	3	0.9349	0.0080	0.9129	0.9556
244	4	0.9085	0.0067	0.8887	0.9251
397	5	0.8517	0.0089	0.8265	0.8732
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.8938	0.0168	0.8522	0.9277
48	2	0.9128	0.0091	0.8891	0.9324
129	3	0.8997	0.0080	0.8777	0.9199
246	4	0.8818	0.0068	0.8621	0.9041
399	5	0.8461	0.0078	0.8257	0.8636
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.8968	0.0148	0.8639	0.9223
47	2	0.9098	0.0099	0.8882	0.9424
128	3	0.9009	0.0085	0.8843	0.9221
245	4	0.8821	0.0077	0.8649	0.8993
398	5	0.8465	0.0084	0.8184	0.8631

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.21

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9942	0.0030	0.9852	0.9985
47	2	0.9845	0.0032	0.9661	0.9924
128	3	0.9717	0.0033	0.9639	0.9808
245	4	0.9606	0.0033	0.9502	0.9715
398	5	0.9131	0.0047	0.9016	0.9259
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9906	0.0704	0.0000	0.9999
46	2	0.9847	0.0030	0.9748	0.9922
127	3	0.9732	0.0033	0.9653	0.9803
244	4	0.9609	0.0035	0.9506	0.9699
397	5	0.9125	0.0045	0.8977	0.9246
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.8969	0.0105	0.8764	0.9173
48	2	0.9303	0.0060	0.9155	0.9439
129	3	0.9345	0.0045	0.9200	0.9476
246	4	0.9316	0.0037	0.9222	0.9416
399	5	0.9074	0.0047	0.8934	0.9229
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.8978	0.0092	0.8755	0.9186
47	2	0.9301	0.0059	0.9164	0.9429
128	3	0.9350	0.0046	0.9229	0.9464
245	4	0.9321	0.0040	0.9205	0.9430
398	5	0.9074	0.0049	0.8948	0.9216

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.22

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9971	0.0014	0.9920	1.0000
47	2	0.9920	0.0017	0.9874	0.9955
128	3	0.9860	0.0016	0.9809	0.9902
245	4	0.9800	0.0017	0.9755	0.9842
398	5	0.9347	0.0034	0.9265	0.9435
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9926	0.0706	0.0000	0.9997
46	2	0.9926	0.0015	0.9867	0.9956
127	3	0.9860	0.0018	0.9804	0.9895
244	4	0.9799	0.0017	0.9758	0.9840
397	5	0.9350	0.0035	0.9242	0.9426
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.9012	0.0057	0.8846	0.9138
48	2	0.9359	0.0037	0.9255	0.9474
129	3	0.9467	0.0027	0.9409	0.9545
246	4	0.9496	0.0023	0.9440	0.9561
399	5	0.9293	0.0031	0.9189	0.9363
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9026	0.0059	0.8858	0.9160
47	2	0.9368	0.0035	0.9298	0.9467
128	3	0.9469	0.0030	0.9388	0.9534
245	4	0.9498	0.0021	0.9435	0.9553
398	5	0.9296	0.0029	0.9210	0.9383

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.23

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9985	0.0006	0.9970	0.9996
47	2	0.9960	0.0009	0.9937	0.9982
128	3	0.9928	0.0010	0.9895	0.9951
245	4	0.9898	0.0008	0.9872	0.9918
398	5	0.9465	0.0020	0.9410	0.9532
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9988	0.0015	0.9972	0.9998
46	2	0.9961	0.0008	0.9937	0.9980
127	3	0.9929	0.0009	0.9901	0.9949
244	4	0.9899	0.0009	0.9873	0.9923
397	5	0.9466	0.0021	0.9397	0.9512
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.9027	0.0048	0.8910	0.9126
48	2	0.9400	0.0029	0.9334	0.9476
129	3	0.9529	0.0019	0.9477	0.9575
246	4	0.9587	0.0015	0.9546	0.9625
399	5	0.9411	0.0022	0.9334	0.9467
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9029	0.0048	0.8902	0.9201
47	2	0.9400	0.0030	0.9330	0.9471
128	3	0.9530	0.0019	0.9472	0.9583
245	4	0.9587	0.0015	0.9533	0.9634
398	5	0.9413	0.0022	0.9346	0.9473

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.24

Descriptive Statistics for the Goodness of Fit Index from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9994	0.0003	0.9983	0.9999
47	2	0.9983	0.0003	0.9975	0.9990
128	3	0.9971	0.0004	0.9961	0.9980
245	4	0.9960	0.0005	0.9951	1.0000
398	5	0.9535	0.0013	0.9491	0.9573
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9995	0.0003	0.9986	0.9999
46	2	0.9984	0.0003	0.9972	0.9991
127	3	0.9971	0.0003	0.9962	0.9981
244	4	0.9959	0.0004	0.9948	0.9968
397	5	0.9536	0.0012	0.9493	0.9566
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.9030	0.0027	0.8968	0.9115
48	2	0.9421	0.0016	0.9372	0.9468
129	3	0.9568	0.0012	0.9537	0.9602
246	4	0.9643	0.0009	0.9619	0.9666
399	5	0.9482	0.0014	0.9435	0.9521
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9030	0.0029	0.8941	0.9106
47	2	0.9417	0.0016	0.9374	0.9465
128	3	0.9570	0.0011	0.9542	0.9607
245	4	0.9645	0.0009	0.9621	0.9666
398	5	0.9483	0.0013	0.9452	0.9526

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.25

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9375	0.0338	0.8354	0.9905
47	2	0.9469	0.0112	0.9215	0.9722
128	3	0.9288	0.0089	0.9053	0.9467
245	4	0.9106	0.0094	0.8838	0.9331
398	5	0.8947	0.0074	0.8736	0.9117
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9398	0.0295	0.8535	0.9855
46	2	0.9495	0.0122	0.9005	0.9747
127	3	0.9307	0.0087	0.8917	0.9494
244	4	0.9117	0.0079	0.8884	0.9282
397	5	0.8931	0.0082	0.8735	0.9139
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6146	0.0848	0.4297	0.7616
48	2	0.9040	0.0133	0.8703	0.9370
129	3	0.9042	0.0114	0.8657	0.9266
246	4	0.8951	0.0091	0.8704	0.9180
399	5	0.8906	0.0074	0.8676	0.9103
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6246	0.0950	0.3173	0.8136
47	2	0.9013	0.0155	0.8559	0.9332
128	3	0.9059	0.0091	0.8794	0.9263
245	4	0.8956	0.0080	0.8721	0.9141
398	5	0.8914	0.0073	0.8708	0.9152

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.26

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9672	0.0176	0.8996	0.9955
47	2	0.9737	0.0054	0.9551	0.9840
128	3	0.9651	0.0043	0.9523	0.9749
245	4	0.9564	0.0043	0.9433	0.9673
398	5	0.9400	0.0040	0.9273	0.9504
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9717	0.0134	0.9362	0.9971
46	2	0.9744	0.0054	0.9612	0.9851
127	3	0.9659	0.0045	0.9543	0.9777
244	4	0.9571	0.0037	0.9474	0.9645
397	5	0.9404	0.0041	0.9283	0.9498
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6463	0.0554	0.5315	0.7710
48	2	0.9265	0.0098	0.8982	0.9471
129	3	0.9400	0.0057	0.9230	0.9513
246	4	0.9390	0.0042	0.9247	0.9521
399	5	0.9364	0.0041	0.9246	0.9453
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6542	0.0577	0.5358	0.7644
47	2	0.9243	0.0102	0.8981	0.9475
128	3	0.9413	0.0056	0.9252	0.9547
245	4	0.9390	0.0047	0.9244	0.9492
398	5	0.9365	0.0040	0.9233	0.9439

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.27

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9845	0.0083	0.9605	0.9958
47	2	0.9895	0.0022	0.9779	0.9948
128	3	0.9857	0.0018	0.9807	0.9903
245	4	0.9825	0.0016	0.9782	0.9875
398	5	0.8671	0.0020	0.9622	0.9722
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9833	0.0702	0.0000	1.0000
46	2	0.9896	0.0022	0.9829	0.9947
127	3	0.9865	0.0017	0.9812	0.9906
244	4	0.9827	0.0016	0.9506	0.9699
397	5	0.9668	0.0019	0.9604	0.9714
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6334	0.0403	0.5532	0.7194
48	2	0.9401	0.0060	0.9240	0.9533
129	3	0.9602	0.0030	0.9514	0.9683
246	4	0.9649	0.0022	0.9601	0.9705
399	5	0.9634	0.0020	0.9576	0.9696
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6418	0.0351	0.5715	0.7359
47	2	0.9398	0.0061	0.9197	0.9531
128	3	0.9607	0.0032	0.9524	0.9687
245	4	0.9652	0.0024	0.9583	0.9713
398	5	0.9633	0.0021	0.9575	0.9689

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.28

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9922	0.0039	0.9920	0.9994
47	2	0.9946	0.0011	0.9911	0.9968
128	3	0.9931	0.0008	0.9904	0.9952
245	4	0.9913	0.0008	0.9891	0.9932
398	5	0.9756	0.0013	0.9729	0.9798
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9885	0.0703	0.0000	0.9997
46	2	0.9950	0.0010	0.9914	0.9970
127	3	0.9930	0.0009	0.9900	0.9949
244	4	0.9913	0.0008	0.9893	0.9932
397	5	0.9756	0.0014	0.9708	0.9786
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6530	0.0234	0.5706	0.7008
48	2	0.9445	0.0037	0.9329	0.9561
129	3	0.9671	0.0020	0.9619	0.9735
246	4	0.9736	0.0015	0.9703	0.9775
399	5	0.9719	0.0013	0.9674	0.9755
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6523	0.0238	0.5990	0.7147
47	2	0.9452	0.0036	0.9352	0.9560
128	3	0.9672	0.0022	0.9597	0.9717
245	4	0.9737	0.0013	0.9695	0.9771
398	5	0.9720	0.0012	0.9674	0.9754

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.29

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9961	0.0016	0.9910	0.9990
47	2	0.9973	0.0006	0.9958	0.9988
128	3	0.9965	0.0005	0.9948	0.9976
245	4	0.9956	0.0003	0.9945	0.9965
398	5	0.9800	0.0008	0.9778	0.9827
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9969	0.0015	0.9926	0.9994
46	2	0.9974	0.0005	0.9958	0.9986
127	3	0.9965	0.0004	0.9901	0.9975
244	4	0.9957	0.0004	0.9946	0.9967
397	5	0.9800	0.0009	0.9767	0.9820
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6544	0.0208	0.6186	0.7025
48	2	0.9477	0.0031	0.9398	0.9559
129	3	0.9704	0.0015	0.9661	0.9739
246	4	0.9778	0.0010	0.9752	0.9802
399	5	0.9764	0.0009	0.9730	0.9789
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6538	0.0170	0.6172	0.6998
47	2	0.9477	0.0031	0.9407	0.9549
128	3	0.9705	0.0015	0.9660	0.9742
245	4	0.9778	0.0010	0.9746	0.9809
398	5	0.9765	0.0009	0.9741	0.9789

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.30

Descriptive Statistics for the Normed Fit Index from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9985	0.0008	0.9954	0.9998
47	2	0.9989	0.0002	0.9983	0.9993
128	3	0.9986	0.0002	0.9981	0.9990
245	4	0.9983	0.0002	0.9979	1.0000
398	5	0.9826	0.0006	0.9800	0.9841
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9987	0.0007	0.9964	0.9999
46	2	0.9989	0.0002	0.9982	0.9994
127	3	0.9986	0.0002	0.9981	0.9991
244	4	0.9983	0.0002	0.9978	0.9986
397	5	0.9826	0.0005	0.9811	0.9838
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6558	0.0104	0.6257	0.6751
48	2	0.9493	0.0017	0.9443	0.9547
129	3	0.9725	0.0010	0.9696	0.9749
246	4	0.9804	0.0006	0.9786	0.9821
399	5	0.9791	0.0006	0.9771	0.9806
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6553	0.0113	0.6142	0.6900
47	2	0.9489	0.0017	0.9445	0.9539
128	3	0.9727	0.0008	0.9704	0.9755
245	4	0.9805	0.0006	0.9787	0.9820
398	5	0.9791	0.0005	0.9776	0.9809

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.31

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1.0023	0.0684	0.8085	1.1292
47	2	0.9943	0.0158	0.9597	1.0270
128	3	0.9920	0.0112	0.9618	1.0188
245	4	0.9878	0.0112	0.9572	1.0177
398	5	0.9705	0.0086	0.9410	0.9913
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9931	0.0720	0.8208	1.1715
46	2	0.9972	0.0186	0.9164	1.0352
127	3	0.9934	0.0114	0.9474	1.0218
244	4	0.9891	0.0100	0.9628	1.0214
397	5	0.9689	0.0095	0.9476	0.9901
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.4071	0.1603	0.0561	0.6858
48	2	0.9341	0.0206	0.8850	0.9861
129	3	0.9611	0.0156	0.9158	0.9921
246	4	0.9693	0.0111	0.9419	0.9979
399	5	0.9659	0.0088	0.9370	0.9909
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3398	0.2063	-0.3146	0.8536
47	2	0.9255	0.0233	0.8585	0.9779
128	3	0.9625	0.0121	0.9255	0.9884
245	4	0.9696	0.0101	0.9405	0.9948
398	5	0.9665	0.0087	0.9430	0.9910

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.32

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1.0027	0.0342	0.8575	1.0566
47	2	0.9987	0.0076	0.9739	1.0149
128	3	0.9984	0.0052	0.9818	1.0089
245	4	0.9976	0.0050	0.9811	1.0024
398	5	0.9798	0.0045	0.9666	0.9912
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	1.0034	0.0310	0.9133	1.0649
46	2	0.9990	0.0082	0.9781	1.0168
127	3	0.9991	0.0057	0.9838	1.0129
244	4	0.9982	0.0044	0.9874	1.0075
397	5	0.9801	0.0047	0.9670	0.9912
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.4383	0.0989	0.2307	0.6553
48	2	0.9320	0.0143	0.8912	0.9616
129	3	0.9677	0.0073	0.9483	0.9840
246	4	0.9775	0.0049	0.9610	0.9934
399	5	0.9759	0.0046	0.9625	0.9859
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3752	0.1154	0.1378	0.5891
47	2	0.9263	0.0156	0.8874	0.9676
128	3	0.9687	0.0071	0.9505	0.9873
245	4	0.9772	0.0057	0.9622	0.9895
398	5	0.9759	0.0046	0.9598	0.9843

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.33

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9974	0.0159	0.9507	1.0210
47	2	0.9998	0.0031	0.9828	1.0075
128	3	0.9993	0.0021	0.9942	1.0051
245	4	0.9996	0.0018	0.9941	1.0053
398	5	0.9828	0.0023	0.9773	0.9880
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9964	0.0728	0.0000	1.1000
46	2	0.9997	0.0031	0.9895	1.0073
127	3	1.0002	0.0021	0.9939	1.0047
244	4	0.9997	0.0018	0.9947	1.0042
397	5	0.9823	0.0021	0.9749	0.9879
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.3995	0.0690	0.2619	0.5470
48	2	0.9311	0.0085	0.9083	0.9498
129	3	0.9687	0.0037	0.9576	0.9790
246	4	0.9795	0.0025	0.9734	0.9863
399	5	0.9787	0.0023	0.9723	0.9863
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3372	0.0674	0.2019	0.5181
47	2	0.9290	0.0088	0.9007	0.9478
128	3	0.9689	0.0040	0.9592	0.9791
245	4	0.9796	0.0028	0.9716	0.9868
398	5	0.9785	0.0023	0.9724	0.9849

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.34

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9986	0.0074	0.9700	1.0117
47	2	0.9997	0.0016	0.9950	1.0031
128	3	1.0000	0.0010	0.9969	1.0025
245	4	0.9999	0.0009	0.9975	1.0020
398	5	0.9827	0.0014	0.9798	0.9872
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9943	0.0711	0.0000	1.0120
46	2	1.0002	0.0015	0.9948	1.0031
127	3	0.9999	0.0011	0.9962	1.0021
244	4	0.9998	0.0009	0.9976	1.0018
397	5	0.9828	0.0015	0.9774	0.9861
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.4272	0.0394	0.2883	0.5082
48	2	0.9304	0.0052	0.9144	0.9466
129	3	0.9690	0.0024	0.9629	0.9766
246	4	0.9798	0.0017	0.9762	0.9843
399	5	0.9788	0.0014	0.9736	0.9826
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3528	0.0451	0.2518	0.4712
47	2	0.9299	0.0051	0.9159	0.9451
128	3	0.9688	0.0027	0.9599	0.9742
245	4	0.9799	0.0015	0.9750	0.9839
398	5	0.9788	0.0013	0.9737	0.9826

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.35

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9994	0.0031	0.9905	1.0047
47	2	0.9999	0.0008	0.9977	1.0019
128	3	0.9999	0.0006	0.9979	1.0013
245	4	0.9999	0.0004	0.9987	1.0010
398	5	0.9829	0.0009	0.9804	0.9859
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9999	0.0032	0.9907	1.0057
46	2	0.9999	0.0008	0.9976	1.0018
127	3	0.9999	0.0005	0.9983	1.0012
244	4	0.9999	0.0005	0.9987	1.0012
397	5	0.9829	0.0010	0.9792	0.9851
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.4269	0.0349	0.3668	0.5073
48	2	0.9315	0.0042	0.9206	0.9429
129	3	0.9689	0.0018	0.9638	0.9730
246	4	0.9799	0.0011	0.9769	0.9826
399	5	0.9790	0.0010	0.9753	0.9818
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3533	0.0321	0.2841	0.4398
47	2	0.9300	0.0044	0.9200	0.9401
128	3	0.9687	0.0018	0.9633	0.9732
245	4	0.9798	0.0011	0.9761	0.9833
398	5	0.9790	0.0010	0.9764	0.9816

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.36

Descriptive Statistics for the Nonnormed Fit Index from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9999	0.0014	0.9940	1.0023
47	2	0.9999	0.0003	0.9991	1.0005
128	3	0.9999	0.0002	0.9994	1.0005
245	4	1.0001	0.0007	0.9996	1.0100
398	5	0.9829	0.0006	0.9801	0.9845
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9999	0.0015	0.9949	1.0024
46	2	0.9999	0.0003	0.9988	1.0006
127	3	0.9999	0.0002	0.9994	1.0005
244	4	0.9999	0.0002	0.9995	1.0004
397	5	0.9829	0.0005	0.9812	0.9841
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.4275	0.0174	0.3772	0.4597
48	2	0.9317	0.0023	0.9247	0.9390
129	3	0.9690	0.0011	0.9656	0.9719
246	4	0.9799	0.0007	0.9779	0.9818
399	5	0.9791	0.0006	0.9769	0.9807
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.3547	0.0213	0.2773	0.4199
47	2	0.9297	0.0024	0.9233	0.9366
128	3	0.9689	0.0010	0.9662	0.9724
245	4	0.9800	0.0007	0.9779	0.9816
398	5	0.9791	0.0006	0.9774	0.9810

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.37

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0276	0.0360	0.0000	0.1069
47	2	0.0259	0.0255	0.0000	0.0752
128	3	0.0273	0.0201	0.0000	0.0708
245	4	0.0318	0.0175	0.0000	0.0655
398	5	0.0549	0.0084	0.0291	0.0806
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0322	0.0364	0.0000	0.1089
46	2	0.0210	0.0259	0.0000	0.1106
127	3	0.0252	0.0197	0.0000	0.0771
244	4	0.0306	0.0161	0.0000	0.0628
397	5	0.0561	0.0092	0.0319	0.0739
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2089	0.0376	0.1304	0.3012
48	2	0.0926	0.0164	0.0420	0.1263
129	3	0.0670	0.0146	0.0303	0.1003
246	4	0.0551	0.0111	0.0143	0.0782
399	5	0.0591	0.0082	0.0301	0.0818
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2133	0.0390	0.0688	0.3283
47	2	0.0996	0.0164	0.0531	0.1388
128	3	0.0662	0.0113	0.0374	0.0962
245	4	0.0550	0.0102	0.0229	0.0780
398	5	0.0587	0.0081	0.0312	0.0778

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.38

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0173	0.0244	0.0000	0.1126
47	2	0.0148	0.0163	0.0000	0.0584
128	3	0.0138	0.0131	0.0000	0.0478
245	4	0.0144	0.0118	0.0000	0.0452
398	5	0.0454	0.0053	0.0303	0.0589
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0168	0.0232	0.0000	0.0867
46	2	0.0159	0.0170	0.0000	0.0566
127	3	0.0123	0.0133	0.0000	0.0445
244	4	0.0124	0.0113	0.0000	0.0366
397	5	0.0451	0.0055	0.0295	0.0578
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2056	0.0253	0.1554	0.2721
48	2	0.0960	0.0110	0.0713	0.1230
129	3	0.0619	0.0074	0.0420	0.0823
246	4	0.0477	0.0054	0.0259	0.0628
399	5	0.0498	0.0048	0.0384	0.0622
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2157	0.0238	0.1716	0.2712
47	2	0.1004	0.0113	0.0605	0.1261
128	3	0.0609	0.0075	0.0377	0.0754
245	4	0.0479	0.0063	0.0327	0.0608
398	5	0.0497	0.0048	0.0401	0.0651

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.39

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0152	0.0179	0.0000	0.0614
47	2	0.0088	0.0103	0.0000	0.0493
128	3	0.0090	0.0082	0.0000	0.0267
245	4	0.0071	0.0068	0.0000	0.0250
398	5	0.0420	0.0028	0.0348	0.0484
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0110	0.0163	0.0000	0.0619
46	2	0.0089	0.0103	0.0000	0.0384
127	3	0.0054	0.0075	0.0000	0.0272
244	4	0.0067	0.0070	0.0000	0.0233
397	5	0.0426	0.0026	0.0349	0.0513
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2104	0.0153	0.1810	0.2404
48	2	0.0965	0.0065	0.0820	0.1131
129	3	0.0612	0.0039	0.0492	0.0727
246	4	0.0456	0.0029	0.0369	0.0529
399	5	0.0469	0.0026	0.0370	0.0541
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2228	0.0142	0.1902	0.2588
47	2	0.0980	0.0067	0.0848	0.1148
128	3	0.0610	0.0042	0.0492	0.0710
245	4	0.0456	0.0033	0.0366	0.0540
398	5	0.0471	0.0026	0.0394	0.0530

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.40

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0106	0.0124	0.0000	0.0450
47	2	0.0067	0.0077	0.0000	0.0260
128	3	0.0045	0.0052	0.0000	0.0190
245	4	0.0042	0.0047	0.0000	0.0160
398	5	0.0421	0.0018	0.0368	0.0458
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0089	0.0124	0.0000	0.0481
46	2	0.0047	0.0067	0.0000	0.0268
127	3	0.0050	0.0060	0.0000	0.0214
244	4	0.0045	0.0050	0.0000	0.0158
397	5	0.0421	0.0019	0.0377	0.0485
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2075	0.0084	0.1893	0.2310
48	2	0.0974	0.0041	0.0851	0.1084
129	3	0.0610	0.0025	0.0530	0.0665
246	4	0.0453	0.0019	0.0396	0.0498
399	5	0.0467	0.0016	0.0427	0.0529
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2181	0.0089	0.1981	0.2451
47	2	0.0975	0.0040	0.0867	0.1059
128	3	0.0612	0.0028	0.0553	0.0692
245	4	0.0453	0.0018	0.0403	0.0508
398	5	0.0467	0.0015	0.0424	0.0520

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.41

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0070	0.0081	0.0000	0.0251
47	2	0.0048	0.0055	0.0000	0.0177
128	3	0.0038	0.0043	0.0000	0.0158
245	4	0.0029	0.0032	0.0000	0.0117
398	5	0.0420	0.0011	0.0383	0.0450
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0059	0.0080	0.0000	0.0263
46	2	0.0046	0.0053	0.0000	0.0183
127	3	0.0036	0.0041	0.0000	0.0144
244	4	0.0030	0.0033	0.0000	0.0115
397	5	0.0420	0.0012	0.0394	0.0464
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2068	0.0070	0.1923	0.2243
48	2	0.0964	0.0032	0.0880	0.1042
129	3	0.0611	0.0019	0.0566	0.0661
246	4	0.0453	0.0013	0.0419	0.0488
399	5	0.0465	0.0012	0.0434	0.0505
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2194	0.0074	0.1928	0.2388
47	2	0.0975	0.0034	0.0897	0.1056
128	3	0.0613	0.0018	0.0563	0.0669
245	4	0.0454	0.0013	0.0413	0.0497
398	5	0.0465	0.0011	0.0435	0.0494

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.42

Descriptive Statistics for the Root Mean Square Error of Approximation from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.0039	0.0053	0.0000	0.0214
47	2	0.0033	0.0036	0.0000	0.0108
128	3	0.0023	0.0026	0.0000	0.0087
245	4	0.0016	0.0020	0.0000	0.0065
398	5	0.0420	0.0008	0.0400	0.0457
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.0042	0.0055	0.0000	0.0197
46	2	0.0033	0.0035	0.0000	0.0130
127	3	0.0024	0.0024	0.0000	0.0082
244	4	0.0018	0.0021	0.0000	0.0075
397	5	0.0421	0.0006	0.0406	0.0441
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.2072	0.0040	0.1951	0.2162
48	2	0.0964	0.0018	0.0911	0.1018
129	3	0.0610	0.0012	0.0577	0.0642
246	4	0.0452	0.0008	0.0432	0.0475
399	5	0.0464	0.0007	0.0443	0.0488
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.2199	0.0045	0.2083	0.2335
47	2	0.0978	0.0018	0.0923	0.1027
128	3	0.0611	0.0011	0.0574	0.0640
245	4	0.0452	0.0008	0.0434	0.0475
398	5	0.0464	0.0007	0.0443	0.0481

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.43

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1.0012	0.0365	0.8979	1.0689
47	2	0.9960	0.0112	0.9712	1.0192
128	3	0.9934	0.0093	0.9685	1.0155
245	4	0.9893	0.0099	0.9624	1.0156
398	5	0.9733	0.0078	0.9464	0.9921
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9968	0.0336	0.9163	1.0800
46	2	0.9980	0.0130	0.9417	1.0246
127	3	0.9946	0.0093	0.9570	1.0178
244	4	0.9905	0.0088	0.9675	1.0187
397	5	0.9718	0.0086	0.9525	0.9911
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6443	0.0962	0.4337	0.8115
48	2	0.9521	0.0150	0.9163	0.9899
129	3	0.9676	0.0130	0.9300	0.9934
246	4	0.9730	0.0098	0.9488	0.9981
399	5	0.9690	0.0080	0.9427	0.9918
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6479	0.1100	0.2989	0.9220
47	2	0.9470	0.0166	0.8992	0.9843
128	3	0.9691	0.0100	0.9385	0.9904
245	4	0.9733	0.0089	0.9477	0.9954
398	5	0.9696	0.0079	0.9483	0.9919

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.44

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	1.0015	0.0182	0.9240	1.0302
47	2	0.9991	0.0054	0.9814	1.0106
128	3	0.9986	0.0043	0.9849	1.0074
245	4	0.9978	0.0044	0.9833	1.0109
398	5	0.9816	0.0041	0.9696	0.9920
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	1.0016	0.0145	0.9595	1.0303
46	2	0.9993	0.0057	0.9847	1.0117
127	3	0.9993	0.0046	0.9866	1.0106
244	4	0.9984	0.0038	0.9889	1.0066
397	5	0.9819	0.0042	0.9700	0.9920
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6630	0.0594	0.5384	0.7932
48	2	0.9506	0.0104	0.9208	0.9721
129	3	0.9730	0.0061	0.9567	0.9866
246	4	0.9800	0.0043	0.9654	0.9941
399	5	0.9780	0.0042	0.9658	0.9871
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6668	0.0616	0.5401	0.7809
47	2	0.9475	0.0108	0.9198	0.9769
128	3	0.9740	0.0059	0.9589	0.9895
245	4	0.9798	0.0050	0.9667	0.9907
398	5	0.9780	0.0042	0.9634	0.9857

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.45

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9986	0.0085	0.9737	1.0112
47	2	0.9998	0.0022	0.9877	1.0054
128	3	0.9994	0.0018	0.9951	1.0042
245	4	0.9996	0.0016	0.9947	1.0047
398	5	0.9843	0.0021	0.9793	0.9890
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9983	0.0317	0.5636	1.0122
46	2	0.9998	0.0022	0.9927	1.0051
127	3	1.0002	0.0017	0.9949	1.0039
244	4	0.9997	0.0016	0.9953	1.0037
397	5	0.9839	0.0019	0.9771	0.9890
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6397	0.0414	0.5571	0.7282
48	2	0.9499	0.0062	0.9333	0.9635
129	3	0.9737	0.0031	0.9643	0.9823
246	4	0.9818	0.0022	0.9764	0.9878
399	5	0.9805	0.0021	0.9746	0.9874
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6465	0.0360	0.5744	0.7430
47	2	0.9494	0.0063	0.9293	0.9628
128	3	0.9740	0.0033	0.9659	0.9826
245	4	0.9819	0.0025	0.9748	0.9883
398	5	0.9803	0.0021	0.9748	0.9862

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.46

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9992	0.0039	0.9840	1.0062
47	2	0.9998	0.0011	0.9964	1.0022
128	3	0.9999	0.0008	0.9974	1.0021
245	4	0.9999	0.0008	0.9978	1.0018
398	5	0.9842	0.0013	0.9815	0.9883
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9975	0.0314	0.5585	1.0056
46	2	1.0001	0.0010	0.9964	1.0021
127	3	0.9999	0.0009	0.9968	1.0017
244	4	0.9998	0.0008	0.9979	1.0016
397	5	0.9843	0.0014	0.9794	0.9874
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6563	0.0237	0.5730	0.7049
48	2	0.9494	0.0038	0.9377	0.9611
129	3	0.9740	0.0020	0.9687	0.9803
246	4	0.9821	0.0015	0.9788	0.9860
399	5	0.9806	0.0013	0.9758	0.9841
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6549	0.0241	0.6010	0.7179
47	2	0.9501	0.0037	0.9401	0.9609
128	3	0.9740	0.0022	0.9665	0.9784
245	4	0.9822	0.0013	0.9779	0.9857
398	5	0.9806	0.0012	0.9760	0.9841

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.47

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9997	0.0016	0.9949	1.0025
47	2	0.9999	0.0006	0.9984	1.0014
128	3	0.9999	0.0005	0.9982	1.0011
245	4	0.9999	0.0003	0.9988	1.0009
398	5	0.9843	0.0008	0.9821	0.9871
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9999	0.0015	0.9957	1.0026
46	2	0.9999	0.0005	0.9983	1.0012
127	3	0.9999	0.0004	0.9986	1.0010
244	4	0.9999	0.0004	0.9989	1.0010
397	5	0.9844	0.0009	0.9810	0.9864
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6561	0.0209	0.6201	0.7044
48	2	0.9502	0.0031	0.9422	0.9585
129	3	0.9738	0.0015	0.9695	0.9773
246	4	0.9821	0.0010	0.9794	0.9845
399	5	0.9807	0.0009	0.9774	0.9833
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6551	0.0171	0.6182	0.7012
47	2	0.9502	0.0032	0.9430	0.9573
128	3	0.9739	0.0015	0.9693	0.9776
245	4	0.9821	0.0010	0.9787	0.9851
398	5	0.9808	0.0009	0.9784	0.9832

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table L.48

Descriptive Statistics for the Relative Noncentrality Index from the Moderate Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.9999	0.0008	0.9968	1.0012
47	2	0.9999	0.0002	0.9994	1.0004
128	3	0.9999	0.0002	0.9995	1.0004
245	4	1.0000	0.0002	0.9996	1.0006
398	5	0.9843	0.0006	0.9818	0.9859
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
7	1	0.9968	0.0336	0.9163	1.0800
46	2	0.9980	0.0130	0.9417	1.0246
127	3	0.9946	0.0093	0.9570	1.0178
244	4	0.9905	0.0088	0.9675	1.0187
397	5	0.9718	0.0086	0.9525	0.9911
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
9	1	0.6565	0.0104	0.6263	0.6758
48	2	0.9503	0.0017	0.9452	0.9557
129	3	0.9739	0.0010	0.9710	0.9763
246	4	0.9821	0.0006	0.9803	0.9838
399	5	0.9808	0.0006	0.9788	0.9823
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
8	1	0.6479	0.1100	0.2989	0.9220
47	2	0.9470	0.0166	0.8992	0.9843
128	3	0.9691	0.0100	0.9385	0.9904
245	4	0.9733	0.0089	0.9477	0.9954
398	5	0.9696	0.0079	0.9483	0.9919

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

APPENDIX M

Descriptive Statistics for the Complex Model

Table M.01

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	25.7748	8.6438	5.2800	51.3050
116	2	168.8253	20.2835	123.4400	216.9800
305	3	356.5109	27.1023	288.9600	437.2600
575	4	786.0013	46.6107	679.6500	957.3500
926	5	1465.7900	67.1709	1304.6000	1648.7000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	22.9600	6.8215	6.3786	37.7770
115	2	166.4210	20.0393	117.7900	228.3500
304	3	362.5018	28.8223	289.9600	441.6700
574	4	780.5847	45.0290	664.0200	897.3100
925	5	1464.0600	65.2456	1282.5000	1637.1000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	65.4145	17.7180	33.0370	116.0500
117	2	235.7410	24.8428	179.1900	305.1100
306	3	431.1903	29.9161	364.4500	514.7100
576	4	857.9138	45.8609	744.7400	986.0000
927	5	1549.2700	61.5478	1402.8000	1711.6000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	54.9739	17.6980	19.9730	98.3190
116	2	236.5247	28.4341	174.6600	340.0700
305	3	431.7339	31.3517	352.4100	507.9100
575	4	859.9384	46.6974	756.5000	998.3000
926	5	1546.6000	67.8729	1380.7000	1759.3000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.02

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	31.9762	9.6103	10.1120	66.0270
116	2	209.7643	28.3601	148.7900	293.3400
305	3	355.0114	30.8188	266.1500	425.9700
575	4	840.4146	48.3803	717.2400	965.8300
926	5	1658.9000	66.5922	1516.5000	1869.3000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	29.6767	8.5676	9.3320	61.2590
115	2	208.7410	24.8404	149.7400	278.7400
304	3	354.9298	27.8825	274.6300	449.6000
574	4	841.4952	41.2246	740.1500	946.5100
925	5	1686.4300	70.9453	1453.9000	1893.3000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	115.3160	23.7843	70.8070	171.3700
117	2	340.7604	33.3388	245.5800	416.2900
306	3	498.4429	35.3643	421.4800	592.7700
576	4	1001.0900	56.9860	842.6000	1096.1000
927	5	1855.2500	74.1735	1672.3000	2085.4000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	108.0783	21.4518	66.6580	158.3200
116	2	341.9724	29.3589	280.9400	431.2700
305	3	500.3566	37.7758	406.7300	586.8300
575	4	993.6674	45.7571	905.4400	1120.5000
926	5	1858.2000	75.1014	1660.2000	2037.4000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.03

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	53.1032	13.0541	28.4680	86.9820
116	2	343.5221	30.1186	275.4300	454.3700
305	3	388.3984	30.4994	299.4700	468.5900
575	4	1149.3500	59.2467	1015.2000	1320.6000
926	5	2656.9600	85.0182	2470.5000	2875.3000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	47.3470	11.9504	15.1660	83.8810
115	2	343.8949	32.4659	261.7000	434.4300
304	3	391.2784	32.1290	296.3300	485.0900
574	4	1150.7300	57.4261	977.9500	1302.6000
925	5	2656.5000	85.7521	2421.4000	2940.4000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	261.7004	35.1254	174.7200	350.9000
117	2	671.2482	45.5649	561.6400	790.6800
306	3	749.8829	44.5248	646.9600	872.8600
576	4	1524.7900	64.0054	1363.1000	1714.7000
927	5	3052.9700	97.6119	2843.8000	3305.4000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	259.0007	31.3224	184.7700	328.5900
116	2	663.5008	41.2764	555.9900	771.3200
305	3	743.4279	43.6678	623.6600	865.5200
575	4	1529.1100	65.7937	1379.4000	1705.0000
926	5	3053.4900	85.4160	2847.8000	3317.0000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.04

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	88.5364	19.1692	47.8790	134.4000
116	2	571.5627	39.2255	465.3700	657.2200
305	3	465.9295	35.0999	388.1600	572.9100
575	4	1691.7700	66.1473	1502.8000	1879.4000
926	5	4346.6400	120.1482	3993.3000	4712.5000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	81.4032	17.3156	40.4650	131.4900
115	2	569.6528	40.7387	466.0700	662.8000
304	3	469.5406	33.8889	386.5500	571.0000
574	4	1690.6100	72.8259	1508.6000	1868.9000
925	5	4348.6700	121.4347	4001.3000	4667.7000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	519.4644	43.9182	406.1000	602.2100
117	2	1217.3800	57.0294	1101.0000	1340.6000
306	3	1177.0300	53.8208	1036.0000	1364.5000
576	4	2461.7800	80.9790	2241.9000	2702.7000
927	5	5152.7900	111.8787	4865.4000	5536.9000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	498.4541	42.5185	363.8800	587.5900
116	2	1225.4800	62.1477	1068.7000	1395.5000
305	3	1182.6800	48.4193	1057.0000	1297.2000
575	4	2459.5100	89.4318	2202.9000	2762.6000
926	5	5133.3100	130.3842	4782.4000	5507.5000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.05

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	159.5200	25.1338	104.7400	230.4000
116	2	1022.9800	56.5781	871.2300	1178.3000
305	3	626.4288	40.4304	508.9700	722.1500
575	4	2799.7200	89.6429	2544.8000	3030.3100
926	5	7737.6300	150.0011	7289.4000	8151.5000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	145.6053	20.0889	102.8300	199.1100
115	2	1012.2600	57.9321	848.6100	1151.3000
304	3	626.2828	42.5513	487.3500	764.1300
574	4	2803.4600	93.4635	2561.2000	3027.5000
925	5	7747.0900	163.1968	7311.2000	8161.8000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	1020.2000	61.6251	895.8900	1199.5000
117	2	2342.7100	73.3945	2168.0000	2548.9000
306	3	2052.8000	70.2838	1873.4000	2267.2000
576	4	4333.6600	113.1528	4015.6000	4677.0000
927	5	9339.2400	162.6459	8923.4000	9849.6000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	990.0423	59.7299	783.3400	1137.6000
116	2	2337.5000	72.7051	2159.0000	2518.7000
305	3	2053.5800	81.8456	1859.2000	2286.8000
575	4	4336.8300	117.7626	4032.6000	4604.9000
926	5	9341.4200	167.0745	8932.7000	9743.9000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.06

Descriptive Statistics for the Chi-Square Test Statistic from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	370.2448	35.1936	275.1100	467.1400
116	2	2387.1300	93.9676	2153.9000	2626.3000
305	3	1111.1800	65.0520	925.7600	1316.4000
575	4	6160.8300	134.2881	5820.9000	6552.3000
926	5	17935.1000	255.6439	17348.0000	18535.0000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	337.9333	34.8158	254.0800	433.3000
115	2	2381.1200	106.3948	2108.4000	2672.2000
304	3	1095.3800	60.6598	906.6300	1253.0000
574	4	6150.4800	151.8884	5771.9000	6561.6000
925	5	18007.2900	257.2950	17322.0000	18618.0000
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	2563.4000	93.5510	2352.2000	2813.1000
117	2	5564.1500	125.1388	5344.1000	5961.1000
306	3	4682.5800	111.8910	4371.0000	4952.2000
576	4	9981.2900	183.5006	9554.9000	10457.0000
927	5	21961.4100	248.7745	21341.0000	22598.0000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	2473.9600	95.1030	2219.1000	2703.7000
116	2	5562.2800	119.5387	5310.4000	5936.1000
305	3	4663.1000	98.8251	4371.9000	4912.9000
575	4	9954.3300	178.7633	9459.4000	10504.0000
926	5	21937.9800	279.6972	21242.0000	22613.0000

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.07

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9630	0.0336	0.8671	1.0000
116	2	0.9623	0.0145	0.9234	0.9942
305	3	0.9805	0.0100	0.9487	1.0000
575	4	0.9530	0.0103	0.9142	0.9766
926	5	0.9121	0.0106	0.8796	0.9375
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9695	0.0259	0.9100	1.0000
115	2	0.9637	0.0136	0.9240	0.9981
304	3	0.9781	0.0104	0.9515	1.0000
574	4	0.9541	0.0097	0.9258	0.9793
925	5	0.9125	0.0107	0.8791	0.9414
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8059	0.0718	0.5227	0.9413
117	2	0.9155	0.0160	0.8735	0.9540
306	3	0.9530	0.0106	0.9223	0.9767
576	4	0.9373	0.0094	0.9153	0.9636
927	5	0.8998	0.0095	0.8732	0.9205
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8433	0.0727	0.6723	0.9868
116	2	0.9147	0.0181	0.8553	0.9553
305	3	0.9526	0.0110	0.9288	0.9823
575	4	0.9367	0.0096	0.9104	0.9579
926	5	0.8993	0.0101	0.8741	0.9235

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.08

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9690	0.0194	0.8964	1.0000
116	2	0.9659	0.0105	0.9331	0.9890
305	3	0.9904	0.0055	0.9773	1.0000
575	4	0.9700	0.0055	0.9556	0.9851
926	5	0.9371	0.0056	0.9209	0.9510
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9715	0.0177	0.9019	1.0000
115	2	0.9664	0.0084	0.9436	0.9871
304	3	0.9903	0.0050	0.9725	1.0000
574	4	0.9700	0.0045	0.9578	0.9814
925	5	0.9370	0.0058	0.9226	0.9575
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8019	0.0471	0.6864	0.9068
117	2	0.9194	0.0110	0.8965	0.9486
306	3	0.9637	0.0064	0.9465	0.9774
576	4	0.9522	0.0062	0.9404	0.9701
927	5	0.9236	0.0060	0.9074	0.9394
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8113	0.0437	0.6993	0.9089
116	2	0.9195	0.0103	0.8824	0.9463
305	3	0.9632	0.0067	0.9505	0.9810
575	4	0.9531	0.0050	0.9406	0.9623
926	5	0.9228	0.0059	0.9072	0.9375

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.09

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9704	0.0106	0.9407	0.9891
116	2	0.9674	0.0043	0.9514	0.9771
305	3	0.9937	0.0023	0.9879	1.0000
575	4	0.9741	0.0026	0.9669	0.9805
926	5	0.9426	0.0029	0.9339	0.9488
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9739	0.0101	0.9462	1.0000
115	2	0.9671	0.0046	0.9541	1.0000
304	3	0.9934	0.0024	0.9862	1.0000
574	4	0.9742	0.0025	0.9674	0.9819
925	5	0.9425	0.0029	0.9345	0.9514
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8002	0.0290	0.7237	0.8683
117	2	0.9208	0.0060	0.9035	0.9356
306	3	0.9664	0.0032	0.9566	0.9730
576	4	0.9572	0.0028	0.9491	0.9640
927	5	0.9295	0.0033	0.9193	0.9384
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8030	0.0261	0.7390	0.8690
116	2	0.9213	0.0053	0.9078	0.9343
305	3	0.9668	0.0031	0.9579	0.9745
575	4	0.9572	0.0027	0.9504	0.9644
926	5	0.9295	0.0028	0.9224	0.9377

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.10

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9705	0.0077	0.9546	0.9878
116	2	0.9874	0.0028	0.9610	0.9947
305	3	0.9939	0.0013	0.9902	0.9969
575	4	0.9749	0.0015	0.9707	0.9787
926	5	0.9433	0.0020	0.9376	0.9499
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9732	0.0071	0.9505	0.9803
115	2	0.9847	0.0030	0.9611	0.9891
304	3	0.9937	0.0013	0.9900	0.9969
574	4	0.9749	0.0016	0.9710	0.9788
925	5	0.9431	0.0021	0.9389	0.9490
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7948	0.0191	0.7535	0.8526
117	2	0.9216	0.0042	0.9135	0.9302
306	3	0.9669	0.0019	0.9612	0.9725
576	4	0.9576	0.0018	0.9527	0.9627
927	5	0.9298	0.0019	0.9235	0.9351
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8016	0.0171	0.7658	0.8570
116	2	0.9206	0.0040	0.9091	0.9297
305	3	0.9669	0.0017	0.9629	0.9720
575	4	0.9576	0.0018	0.9523	0.9635
926	5	0.9302	0.0019	0.9240	0.9364

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.11

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9630	0.0336	0.8671	1.0000
116	2	0.9623	0.0145	0.9234	0.9942
305	3	0.9805	0.0100	0.9487	1.0000
575	4	0.9530	0.0103	0.9142	0.9766
926	5	0.9121	0.0106	0.8796	0.9375
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9695	0.0259	0.9100	1.0000
115	2	0.9637	0.0136	0.9240	0.9981
304	3	0.9781	0.0104	0.9515	1.0000
574	4	0.9541	0.0097	0.9258	0.9793
925	5	0.9125	0.0107	0.8791	0.9414
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8059	0.0718	0.5227	0.9413
117	2	0.9155	0.0160	0.8735	0.9540
306	3	0.9530	0.0106	0.9223	0.9767
576	4	0.9373	0.0094	0.9153	0.9636
927	5	0.8998	0.0095	0.8732	0.9205
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8433	0.0727	0.6723	0.9868
116	2	0.9147	0.0181	0.8553	0.9553
305	3	0.9526	0.0110	0.9288	0.9823
575	4	0.9367	0.0096	0.9104	0.9579
926	5	0.8993	0.0101	0.8741	0.9235

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.12

Descriptive Statistics for the Comparative Fit Index from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9711	0.0029	0.9638	0.9790
116	2	0.9675	0.0013	0.9640	0.9706
305	3	0.9939	0.0005	0.9925	0.9953
575	4	0.9749	0.0006	0.9731	0.9765
926	5	0.9436	0.0009	0.9412	0.9455
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9737	0.0029	0.9657	0.9808
115	2	0.9676	0.0015	0.9635	0.9715
304	3	0.9940	0.0005	0.9929	0.9955
574	4	0.9750	0.0007	0.9732	0.9768
925	5	0.9433	0.0009	0.9409	0.9456
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7925	0.0078	0.7669	0.8079
117	2	0.9207	0.0017	0.9174	0.9249
306	3	0.9669	0.0008	0.9650	0.9690
576	4	0.9577	0.0007	0.9555	0.9597
927	5	0.9302	0.0008	0.9281	0.9321
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7990	0.0073	0.7790	0.8167
116	2	0.9208	0.0016	0.9161	0.9250
305	3	0.9670	0.0007	0.9653	0.9693
575	4	0.9579	0.0008	0.9554	0.9600
926	5	0.9303	0.0009	0.9282	0.9326

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.13

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	147.5654	67.7334	83.7260	627.4600
116	2	103.0474	11.6615	71.4220	126.1800
305	3	92.8829	7.7704	68.9220	124.7800
575	4	84.0175	4.8937	65.4710	96.6750
926	5	70.6485	3.1848	62.7920	79.0910
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	156.1235	66.9831	84.8610	497.6600
115	2	101.1223	11.0345	82.6550	129.7600
304	3	93.4308	8.0616	73.3490	125.3800
574	4	84.4449	4.8352	67.4140	98.7680
925	5	70.6506	3.0893	63.1670	80.3550
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	85.5451	14.1547	71.4880	105.3000
117	2	77.1355	7.1009	67.0560	100.5500
306	3	67.0364	5.8699	60.5810	88.4500
576	4	66.9290	4.0930	51.4540	86.9070
927	5	57.3262	2.6197	30.6920	73.6960
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	85.2377	25.0644	72.2190	166.6100
116	2	76.8348	7.5937	66.1360	103.6400
305	3	68.5497	6.2944	58.9070	88.4850
575	4	66.4943	4.0496	45.9320	86.9560
926	5	66.9987	2.9055	34.6430	74.7880

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.14

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	229.4162	80.5204	171.6900	658.5200
116	2	207.4029	19.7866	136.3300	274.2000
305	3	157.0419	18.5557	110.5500	207.4300
575	4	150.0397	8.9940	105.7000	183.2400
926	5	122.6583	4.8307	101.7000	136.0400
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	234.6290	75.7297	162.2400	683.3800
115	2	206.5169	17.4180	138.8700	264.9600
304	3	156.4542	16.3789	110.3700	204.5800
574	4	149.0746	7.7890	109.0500	177.3100
925	5	122.5216	5.1831	104.9500	141.7100
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	148.0319	13.5954	124.0300	174.0300
117	2	132.2139	10.2341	120.4400	156.3800
306	3	111.6680	9.3493	99.2980	127.0000
576	4	92.7077	7.7123	75.3320	123.5800
927	5	63.7746	4.3855	41.4170	98.8190
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	147.1591	12.8859	124.9000	179.7700
116	2	132.8157	11.2438	117.6500	145.3600
305	3	111.3848	7.6760	101.5100	124.3500
575	4	91.4672	5.9987	72.2190	110.3300
926	5	64.9919	4.4731	42.9960	100.7400

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.15

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	473.3788	82.7780	390.0900	609.8200
116	2	334.3583	38.0136	249.1800	586.6500
305	3	286.9205	20.1186	192.6700	323.8600
575	4	226.9607	14.7179	179.5900	280.6300
926	5	194.4628	6.1610	170.5100	208.8600
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	468.7287	109.6931	375.7300	1053.9000
115	2	363.3912	38.8988	252.2100	614.4400
304	3	286.0708	21.3050	191.3700	335.6000
574	4	226.9607	14.3124	176.9600	293.1000
925	5	194.3015	6.2237	175.4600	212.8500
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	245.7248	14.5769	210.5100	283.6600
117	2	216.6804	9.5670	192.4600	241.8400
306	3	169.5415	9.0947	156.5100	181.7500
576	4	117.1289	7.9407	99.1340	139.1600
927	5	68.6228	5.4035	50.4950	100.4000
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	247.1040	14.6645	211.6500	293.3500
116	2	215.7388	9.2625	193.2300	238.6000
305	3	169.2998	8.0626	155.8100	181.3200
575	4	117.5287	7.3030	100.8500	139.5200
926	5	66.3306	4.7115	51.7390	91.2310

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.16

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	788.8153	89.3190	638.1300	941.3700
116	2	396.6080	59.0604	350.1300	698.1300
305	3	389.4508	18.8732	249.3400	437.6400
575	4	272.0514	15.2252	235.6100	332.3300
926	5	237.6920	6.5440	219.1500	258.4400
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	780.1160	87.3834	638.3400	942.4600
115	2	411.4696	56.7564	351.5300	791.0200
304	3	389.2029	19.8943	244.1220	425.2400
574	4	271.0596	16.5586	231.9000	329.3600
925	5	237.3443	6.6421	221.0200	257.6600
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	312.6897	14.2014	269.3000	354.3900
117	2	268.2650	8.8513	244.1800	294.1600
306	3	200.8079	6.0891	186.8600	212.5100
576	4	128.8830	6.0233	116.8700	142.0900
927	5	68.4444	4.3169	58.87300	86.6210
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	310.1560	12.8220	282.3800	346.3300
116	2	268.1368	9.6497	238.5200	298.8700
305	3	201.3959	6.3816	187.6600	215.9600
575	4	127.1413	6.2411	111.4900	145.2700
926	5	68.4870	5.1038	57.8050	92.7280

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.17

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	1171.9300	77.5621	1012.4000	1436.0000
116	2	470.4510	70.0174	434.3200	638.6800
305	3	430.4237	16.6439	290.8900	516.9500
575	4	303.5164	15.0450	262.8400	355.1400
926	5	266.9563	5.1791	253.3600	283.2000
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	1169.1500	80.3580	953.9900	1495.2000
115	2	469.1065	65.5996	433.9900	623.0800
304	3	449.1962	17.5548	322.2600	512.8200
574	4	304.5156	15.6814	266.0600	361.8600
925	5	266.3765	5.5939	252.7800	282.0800
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	358.2849	12.2071	324.1300	392.0500
117	2	304.6741	7.9199	282.1900	328.5000
306	3	221.5553	4.1733	210.0700	231.7600
576	4	133.8124	4.0727	122.9500	144.3700
927	5	69.4429	3.8319	59.0020	78.6610
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	357.2275	14.0903	320.4000	393.8500
116	2	303.9784	8.8250	286.1300	326.6000
305	3	221.2823	4.2255	212.1200	231.2900
575	4	133.1208	4.1495	123.5000	143.9000
926	5	68.7130	3.9356	59.7090	86.2620

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.18

Descriptive Statistics for the Critical N from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	1650.3500	96.0565	1338.5000	1974.0000
116	2	534.2103	13.9445	504.4200	608.1000
305	3	456.2273	12.7148	358.5400	565.0900
575	4	324.7163	11.5988	294.7900	359.2200
926	5	287.8858	4.0757	278.5400	297.5400
INCLUSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
16	1	1668.7200	94.9062	1454.4000	2009.6000
115	2	534.3097	14.3536	500.5900	630.6100
304	3	479.4617	13.1352	370.1900	568.9400
574	4	323.2507	12.7488	287.5800	364.2100
925	5	286.4441	4.0872	277.0300	297.6800
OMISSION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
18	1	392.4633	9.4342	370.9400	420.1300
117	2	330.6078	6.0521	315.5200	345.2300
306	3	235.5120	3.0451	228.8800	242.3000
576	4	138.3032	2.6625	131.4000	146.4600
927	5	68.9656	2.4842	62.8500	74.9690
COMBINATION		**M**	**SD**	**Minimum**	**Maximum**
df	Indicators per LV				
17	1	392.8777	8.3808	372.7900	418.7900
116	2	330.9586	5.9219	313.6100	348.1100
305	3	235.5301	2.9975	228.4900	243.1800
575	4	137.5663	2.9029	130.9800	146.2900
926	5	68.6106	2.5832	62.7760	76.2670

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.19

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9479	0.0161	0.9058	0.9883
116	2	0.8542	0.0150	0.8176	0.8913
305	3	0.8093	0.0122	0.7709	0.8424
575	4	0.7253	0.0115	0.6942	0.7529
926	5	0.6502	0.0104	0.6272	0.6778
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9535	0.0129	0.9216	0.9863
115	2	0.8559	0.0145	0.8119	0.8937
304	3	0.8070	0.0112	0.7794	0.8350
574	4	0.7269	0.0116	0.7032	0.7650
925	5	0.6501	0.0114	0.6144	0.6854
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8824	0.0243	0.8220	0.9270
117	2	0.8233	0.0133	0.7833	0.8576
306	3	0.7891	0.0108	0.7557	0.8147
576	4	0.7152	0.0111	0.6842	0.7404
927	5	0.6410	0.0098	0.6169	0.6657
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8949	0.0253	0.8296	0.9586
116	2	0.8220	0.0158	0.7779	0.8582
305	3	0.7887	0.0114	0.7621	0.8160
575	4	0.7153	0.0115	0.6889	0.7441
926	5	0.6428	0.0095	0.6181	0.6706

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.20

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9663	0.0097	0.9375	0.9883
116	2	0.9659	0.0105	0.9331	0.9890
305	3	0.8895	0.0084	0.8697	0.9148
575	4	0.8213	0.0088	0.8000	0.8432
926	5	0.7492	0.0078	0.7233	0.7685
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9692	0.0082	0.9387	0.9897
115	2	0.9027	0.0101	0.8748	0.9269
304	3	0.8896	0.0075	0.8691	0.9115
574	4	0.8211	0.0075	0.8021	0.8414
925	5	0.7491	0.0087	0.7255	0.7745
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8953	0.0170	0.8505	0.9295
117	2	0.8669	0.0108	0.8384	0.8994
306	3	0.8651	0.0073	0.8463	0.8798
576	4	0.8058	0.0085	0.7892	0.8319
927	5	0.7382	0.0083	0.7148	0.7576
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8987	0.0150	0.8463	0.9271
116	2	0.8665	0.0091	0.8401	0.8831
305	3	0.8652	0.0079	0.8476	0.8835
575	4	0.8057	0.0076	0.7872	0.8215
926	5	0.7378	0.0086	0.7170	0.7620

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.21

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9772	0.0053	0.9621	0.9875
116	2	0.9334	0.0053	0.9142	0.9453
305	3	0.9473	0.0039	0.9364	0.9585
575	4	0.8913	0.0051	0.8758	0.9033
926	5	0.8241	0.0050	0.8113	0.8361
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9799	0.0048	0.9660	0.9932
115	2	0.9333	0.0058	0.9189	0.9491
304	3	0.9470	0.0039	0.9357	0.9585
574	4	0.8911	0.0049	0.8775	0.9044
925	5	0.8241	0.0053	0.8099	0.8390
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.9044	0.0096	0.8754	0.9282
117	2	0.8942	0.0058	0.8799	0.9065
306	3	0.9189	0.0040	0.9084	0.9282
576	4	0.8731	0.0048	0.8609	0.8843
927	5	0.8106	0.0053	0.7991	0.8243
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9065	0.0091	0.8774	0.9265
116	2	0.8952	0.0058	0.8785	0.9071
305	3	0.9193	0.0037	0.9099	0.9298
575	4	0.8726	0.0048	0.8602	0.8848
926	5	0.8110	0.0048	0.7978	0.8231

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.22

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9809	0.0040	0.9705	0.9898
116	2	0.9443	0.0036	0.9357	0.9547
305	3	0.9678	0.0023	0.9609	0.9727
575	4	0.9174	0.0031	0.9090	0.9260
926	5	0.8525	0.0038	0.8418	0.8627
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9827	0.0035	0.9727	0.9910
115	2	0.9443	0.0037	0.9357	0.9532
304	3	0.9676	0.0022	0.9616	0.9727
574	4	0.9172	0.0034	0.9077	0.9262
925	5	0.8523	0.0041	0.8408	0.8627
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.9080	0.0074	0.8705	0.9231
117	2	0.9047	0.0038	0.8975	0.9120
306	3	0.9383	0.0021	0.9300	0.9446
576	4	0.8971	0.0034	0.8874	0.9076
927	5	0.8375	0.0033	0.8253	0.8473
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9110	0.0059	0.8888	0.9257
116	2	0.9042	0.0042	0.8935	0.9138
305	3	0.9382	0.0021	0.9335	0.9430
575	4	0.8971	0.0032	0.8868	0.9065
926	5	0.8381	0.0039	0.8276	0.8471

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.23

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9827	0.0026	0.9751	0.9887
116	2	0.9499	0.0025	0.9429	0.9561
305	3	0.9783	0.0013	0.9755	0.9822
575	4	0.9307	0.0021	0.9250	0.9365
926	5	0.8675	0.0026	0.8614	0.8753
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9845	0.0021	0.9793	0.9889
115	2	0.9503	0.0027	0.9435	0.9579
304	3	0.9783	0.0014	0.9742	0.9827
574	4	0.9305	0.0022	0.9255	0.9362
925	5	0.8676	0.0028	0.8609	0.8748
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.9118	0.0041	0.8993	0.9208
117	2	0.9091	0.0024	0.9007	0.9166
306	3	0.9481	0.0014	0.9442	0.9512
576	4	0.9100	0.0023	0.9012	0.9159
927	5	0.8523	0.0025	0.8441	0.8596
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9128	0.0047	0.8936	0.9226
116	2	0.9089	0.0023	0.9036	0.9145
305	3	0.9480	0.0016	0.9433	0.9520
575	4	0.9098	0.0022	0.9036	0.9159
926	5	0.8525	0.0026	0.8458	0.8585

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.24

Descriptive Statistics for the Goodness of Fit Index from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9839	0.0015	0.9780	0.9879
116	2	0.9533	0.0018	0.9485	0.9576
305	3	0.9847	0.0008	0.9822	0.9871
575	4	0.9388	0.0013	0.9355	0.9426
926	5	0.8768	0.0017	0.8719	0.8811
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9856	0.0014	0.9816	0.9890
115	2	0.9532	0.0020	0.9475	0.9584
304	3	0.9849	0.0008	0.9829	0.9874
574	4	0.9387	0.0014	0.9354	0.9420
925	5	0.8764	0.0018	0.8715	0.8813
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.9116	0.0026	0.9054	0.9181
117	2	0.9121	0.0017	0.9071	0.9171
306	3	0.9539	0.0008	0.9521	0.9561
576	4	0.9177	0.0014	0.9140	0.9211
927	5	0.8611	0.0016	0.8574	0.8649
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9141	0.0024	0.9075	0.9214
116	2	0.9121	0.0017	0.9078	0.9182
305	3	0.9541	0.0007	0.9524	0.9563
575	4	0.9177	0.0014	0.9134	0.9218
926	5	0.8612	0.0017	0.8571	0.8658

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.25

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9082	0.0313	0.8133	0.9833
116	2	0.8912	0.0132	0.8468	0.9179
305	3	0.8805	0.0096	0.8508	0.9062
575	4	0.8466	0.0100	0.8117	0.8729
926	5	0.7944	0.0104	0.7630	0.8177
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9155	0.0249	0.8477	0.9761
115	2	0.8935	0.0125	0.8611	0.9268
304	3	0.8796	0.0092	0.8551	0.9014
574	4	0.8477	0.0092	0.8200	0.8702
925	5	0.7951	0.0107	0.7605	0.8192
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7663	0.0627	0.5193	0.8870
117	2	0.8484	0.0143	0.8140	0.8825
306	3	0.8565	0.0097	0.8270	0.8769
576	4	0.8324	0.0089	0.8074	0.8585
927	5	0.7847	0.0096	0.7560	0.8077
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8028	0.0650	0.6515	0.9233
116	2	0.8486	0.0165	0.7991	0.8855
305	3	0.8569	0.0100	0.8304	0.8834
575	4	0.8323	0.0089	0.8105	0.8575
926	5	0.7836	0.0098	0.7599	0.8050

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.26

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9387	0.0190	0.8672	0.9803
116	2	0.9279	0.0106	0.8954	0.9527
305	3	0.9369	0.0053	0.9229	0.9500
575	4	0.9112	0.0057	0.8965	0.9297
926	5	0.8711	0.0059	0.8548	0.8850
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9428	0.0174	0.8769	0.9816
115	2	0.9290	0.0080	0.9071	0.9473
304	3	0.9372	0.0050	0.9204	0.9521
574	4	0.9117	0.0046	0.8998	0.9234
925	5	0.8711	0.0059	0.8555	0.8917
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7812	0.0442	0.6736	0.8836
117	2	0.8836	0.0104	0.8613	0.9078
306	3	0.9117	0.0062	0.8945	0.9236
576	4	0.8948	0.0062	0.8828	0.9118
927	5	0.8588	0.0060	0.8435	0.8741
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7916	0.0413	0.6871	0.8864
116	2	0.8845	0.0102	0.8478	0.9129
305	3	0.9114	0.0063	0.8971	0.9286
575	4	0.8960	0.0052	0.8849	0.9077
926	5	0.8577	0.0059	0.8414	0.8703

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.27

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9577	0.0103	0.9285	0.9753
116	2	0.9518	0.0043	0.9361	0.9618
305	3	0.9713	0.0022	0.9657	0.9778
575	4	0.9496	0.0026	0.9426	0.9563
926	5	0.9147	0.0030	0.9057	0.9218
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9618	0.0101	0.9354	0.9880
115	2	0.9516	0.0045	0.9380	0.9634
304	3	0.9711	0.0024	0.9640	0.9782
574	4	0.9498	0.0025	0.9433	0.9573
925	5	0.9146	0.0030	0.9071	0.9237
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7916	0.0284	0.7168	0.8574
117	2	0.9061	0.0059	0.8888	0.9207
306	3	0.9447	0.0031	0.9349	0.9511
576	4	0.9332	0.0027	0.9255	0.9399
927	5	0.9020	0.0033	0.8915	0.9115
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7952	0.0255	0.7323	0.8596
116	2	0.9066	0.0052	0.8934	0.9195
305	3	0.9452	0.0030	0.9367	0.9515
575	4	0.9332	0.0026	0.9264	0.9406
926	5	0.9020	0.0028	0.8946	0.9107

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.28

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9640	0.0076	0.9484	0.9815
116	2	0.9596	0.0028	0.9532	0.9666
305	3	0.9826	0.0013	0.9793	0.9856
575	4	0.9626	0.0016	0.9584	0.9662
926	5	0.9291	0.0021	0.9235	0.9358
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9671	0.0070	0.9441	0.9842
115	2	0.9596	0.0030	0.9535	0.9673
304	3	0.9825	0.0012	0.9789	0.9858
574	4	0.9626	0.0016	0.9586	0.9663
925	5	0.9290	0.0021	0.9245	0.9348
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7905	0.0189	0.7494	0.8480
117	2	0.9142	0.0042	0.9062	0.9229
306	3	0.9559	0.0018	0.9506	0.9615
576	4	0.9455	0.0018	0.9407	0.9508
927	5	0.9158	0.0019	0.9096	0.9212
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7976	0.0169	0.7623	0.8524
116	2	0.9133	0.0040	0.9018	0.9224
305	3	0.9560	0.0017	0.9521	0.9611
575	4	0.9455	0.0018	0.9406	0.9513
926	5	0.9162	0.0022	0.9097	0.9223

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.29

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9674	0.0051	0.9520	0.9780
116	2	0.9636	0.0021	0.9575	0.9697
305	3	0.9882	0.0008	0.9865	0.9906
575	4	0.9688	0.0010	0.9660	0.9719
926	5	0.9363	0.0013	0.9331	0.9402
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9704	0.0043	0.9567	0.9793
115	2	0.9639	0.0021	0.9583	0.9698
304	3	0.9883	0.0008	0.9857	0.9907
574	4	0.9687	0.0011	0.9660	0.9715
925	5	0.9363	0.0014	0.9324	0.9402
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7922	0.0124	0.7669	0.8170
117	2	0.9168	0.0024	0.9091	0.9227
306	3	0.9615	0.0012	0.9580	0.9647
576	4	0.9516	0.0012	0.9479	0.9553
927	5	0.9231	0.0014	0.9188	0.9265
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7991	0.0112	0.7680	0.8350
116	2	0.9169	0.0026	0.9109	0.9247
305	3	0.9614	0.0014	0.9574	0.9648
575	4	0.9516	0.0013	0.9485	0.9546
926	5	0.9231	0.0015	0.9195	0.9274

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.30

Descriptive Statistics for the Normed Fit Index from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9698	0.0029	0.9626	0.9777
116	2	0.9660	0.0013	0.9624	0.9690
305	3	0.9916	0.0005	0.9902	0.9928
575	4	0.9724	0.0006	0.9706	0.9740
926	5	0.9407	0.0009	0.9384	0.9426
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9725	0.0028	0.9645	0.9795
115	2	0.9660	0.0015	0.9620	0.9699
304	3	0.9917	0.0004	0.9906	0.9932
574	4	0.9725	0.0007	0.9707	0.9743
925	5	0.9404	0.0009	0.9380	0.9427
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7916	0.0077	0.7661	0.8070
117	2	0.9192	0.0017	0.9159	0.9234
306	3	0.9647	0.0008	0.9628	0.9668
576	4	0.9553	0.0007	0.9531	0.9572
927	5	0.9273	0.0008	0.9252	0.9293
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7982	0.0073	0.7782	0.8159
116	2	0.9193	0.0016	0.9146	0.9235
305	3	0.9648	0.0007	0.9630	0.9671
575	4	0.9554	0.0008	0.9529	0.9575
926	5	0.9274	0.0009	0.9254	0.9298

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.31

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9266	0.0777	0.7186	1.0899
116	2	0.9503	0.0191	0.8989	0.9923
305	3	0.9776	0.0116	0.9410	1.0078
575	4	0.9486	0.0113	0.9059	0.9744
926	5	0.9060	0.0113	0.8712	0.9331
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9361	0.0665	0.7976	1.1202
115	2	0.9517	0.0181	0.8988	0.9975
304	3	0.9748	0.0121	0.9440	1.0070
574	4	0.9496	0.0107	0.9185	0.9773
925	5	0.9063	0.0114	0.8706	0.9373
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.6118	0.1436	0.0454	0.8826
117	2	0.8895	0.0209	0.8346	0.9398
306	3	0.9460	0.0122	0.9109	0.9733
576	4	0.9314	0.0103	0.9073	0.9602
927	5	0.8930	0.0101	0.8646	0.9150
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.6683	0.1538	0.3059	0.9719
116	2	0.8876	0.0238	0.8091	0.9410
305	3	0.9455	0.0127	0.9181	0.9796
575	4	0.9307	0.0105	0.9019	0.9539
926	5	0.8923	0.0108	0.8654	0.9182

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.32

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9348	0.0421	0.7805	1.0305
116	2	0.9551	0.0138	0.9118	0.9855
305	3	0.9892	0.0066	0.9739	1.0091
575	4	0.9670	0.0060	0.9514	0.9837
926	5	0.9328	0.0060	0.9154	0.9477
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9362	0.0405	0.7793	1.0319
115	2	0.9554	0.0112	0.9250	0.9828
304	3	0.9889	0.0060	0.9683	1.0063
574	4	0.9670	0.0050	0.9536	0.9796
925	5	0.9326	0.0062	0.9171	0.9545
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.6039	0.0943	0.3728	0.8134
117	2	0.8946	0.0144	0.8647	0.9328
306	3	0.9583	0.0073	0.9386	0.9741
576	4	0.9477	0.0068	0.9349	0.9673
927	5	0.9184	0.0064	0.9011	0.9352
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.6004	0.0926	0.3632	0.8072
116	2	0.8938	0.0136	0.8449	0.9292
305	3	0.9576	0.0077	0.9430	0.9781
575	4	0.9486	0.0055	0.9349	0.9587
926	5	0.9174	0.0064	0.9008	0.9332

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.33

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9373	0.0224	0.8744	0.9770
116	2	0.9570	0.0057	0.9359	0.9698
305	3	0.9927	0.0026	0.9860	1.0005
575	4	0.9716	0.0029	0.9637	0.9786
926	5	0.9386	0.0031	0.9294	0.9452
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9413	0.0228	0.8791	1.0015
115	2	0.9562	0.0061	0.9389	0.9716
304	3	0.9924	0.0028	0.9841	1.0007
574	4	0.9716	0.0028	0.9642	0.9801
925	5	0.9384	0.0031	0.9299	0.9479
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.6005	0.0580	0.4473	0.7365
117	2	0.8964	0.0079	0.8737	0.9158
306	3	0.9615	0.0036	0.9502	0.9690
576	4	0.9532	0.0030	0.9444	0.9607
927	5	0.9247	0.0035	0.9138	0.9342
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.5828	0.0553	0.4473	0.7225
116	2	0.8961	0.0070	0.8783	0.9133
305	3	0.9618	0.0036	0.9516	0.9707
575	4	0.9531	0.0030	0.9457	0.9610
926	5	0.9246	0.0029	0.9171	0.9334

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.34

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9375	0.0164	0.9039	0.9743
116	2	0.9570	0.0037	0.9486	0.9666
305	3	0.9930	0.0015	0.9887	0.9964
575	4	0.9725	0.0017	0.9679	0.9767
926	5	0.9393	0.0022	0.9333	0.9464
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9397	0.0159	0.8885	0.9782
115	2	0.9567	0.0039	0.9483	0.9669
304	3	0.9928	0.0015	0.9885	0.9965
574	4	0.9725	0.0018	0.9682	0.9768
925	5	0.9392	0.0022	0.9346	0.9455
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.5895	0.0381	0.5070	0.7051
117	2	0.8975	0.0054	0.8868	0.9087
306	3	0.9621	0.0021	0.9555	0.9684
576	4	0.9537	0.0020	0.9483	0.9592
927	5	0.9251	0.0020	0.9183	0.9307
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.5798	0.0363	0.5040	0.6972
116	2	0.8953	0.0053	0.8801	0.9073
305	3	0.9619	0.0020	0.9573	0.9677
575	4	0.9536	0.0020	0.9478	0.9600
926	5	0.9254	0.0023	0.9187	0.9320

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.35

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9379	0.0109	0.9052	0.9606
116	2	0.9572	0.0027	0.9492	0.9651
305	3	0.9930	0.0009	0.9910	0.9956
575	4	0.9726	0.0011	0.9697	0.9760
926	5	0.9396	0.0014	0.9361	0.9437
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9402	0.0096	0.9098	0.9603
115	2	0.9573	0.0027	0.9497	0.9651
304	3	0.9930	0.0009	0.9900	0.9959
574	4	0.9725	0.0011	0.9695	0.9755
925	5	0.9394	0.0015	0.9353	0.9436
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.5888	0.0249	0.5378	0.6383
117	2	0.8961	0.0031	0.8859	0.9037
306	3	0.9621	0.0014	0.9580	0.9658
576	4	0.9538	0.0013	0.9497	0.9578
927	5	0.9254	0.0015	0.9208	0.9291
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.5788	0.0238	0.5127	0.6556
116	2	0.8953	0.0034	0.8873	0.9055
305	3	0.9620	0.0016	0.9572	0.9659
575	4	0.9537	0.0014	0.9503	0.9570
926	5	0.9253	0.0016	0.9215	0.9298

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.36

Descriptive Statistics for the Nonnormed Fit Index from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9388	0.0060	0.9234	0.9556
116	2	0.9572	0.0017	0.9525	0.9612
305	3	0.9930	0.0006	0.9913	0.9946
575	4	0.9725	0.0007	0.9705	0.9743
926	5	0.9397	0.0009	0.9372	0.9417
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9408	0.0064	0.9228	0.9567
115	2	0.9569	0.0020	0.9515	0.9620
304	3	0.9931	0.0005	0.9918	0.9948
574	4	0.9725	0.0007	0.9706	0.9745
925	5	0.9393	0.0010	0.9367	0.9418
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.5849	0.0154	0.5338	0.6158
117	2	0.8964	0.0022	0.8920	0.9018
306	3	0.9621	0.0009	0.9599	0.9645
576	4	0.9538	0.0008	0.9514	0.9559
927	5	0.9254	0.0008	0.9232	0.9275
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.5744	0.0154	0.5320	0.6118
116	2	0.8955	0.0021	0.8893	0.9010
305	3	0.9621	0.0008	0.9600	0.9647
575	4	0.9538	0.0008	0.9511	0.9561
926	5	0.9254	0.0009	0.9232	0.9280

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.37

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0632	0.0389	0.0000	0.1428
116	2	0.0663	0.0144	0.0255	0.0938
305	3	0.0395	0.0125	0.0000	0.0662
575	4	0.0605	0.0677	0.0429	0.0820
926	5	0.0766	0.0048	0.0643	0.0888
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0584	0.0355	0.0000	0.1173
115	2	0.0658	0.0137	0.0156	0.0999
304	3	0.0424	0.0122	0.0000	0.0676
574	4	0.0599	0.0067	0.0398	0.0754
925	5	0.0766	0.0046	0.0625	0.0882
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1604	0.0296	0.0919	0.2346
117	2	0.1007	0.0107	0.0733	0.1274
306	3	0.0638	0.0078	0.0439	0.0830
576	4	0.0701	0.0058	0.0544	0.0848
927	5	0.0822	0.0041	0.0720	0.0925
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1456	0.0371	0.0420	0.2198
116	2	0.1018	0.0119	0.0715	0.1397
305	3	0.0642	0.0083	0.0396	0.0820
575	4	0.0705	0.0058	0.0565	0.0862
926	5	0.0822	0.0045	0.0704	0.0953

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.38

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0630	0.0224	0.0000	0.1204
116	2	0.0630	0.0096	0.0377	0.0877
305	3	0.0271	0.0102	0.0000	0.0446
575	4	0.0480	0.0044	0.0353	0.0584
926	5	0.0642	0.0028	0.0566	0.0715
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0622	0.0214	0.0000	0.1192
115	2	0.0634	0.0085	0.0390	0.0846
304	3	0.0278	0.0089	0.0000	0.0491
574	4	0.0482	0.0038	0.0381	0.0571
925	5	0.0642	0.0030	0.0536	0.0725
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1636	0.0203	0.1214	0.2069
117	2	0.0978	0.0074	0.0743	0.1134
306	3	0.0560	0.0051	0.0435	0.0686
576	4	0.0608	0.0042	0.0482	0.0674
927	5	0.0709	0.0028	0.0636	0.0792
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1629	0.0193	0.1212	0.2044
116	2	0.0987	0.0064	0.0845	0.1169
305	3	0.0565	0.0056	0.0409	0.0681
575	4	0.0604	0.0033	0.0537	0.0690
926	5	0.0711	0.0029	0.0631	0.0777

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.39

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0642	0.0118	0.0368	0.0908
116	2	0.0626	0.0042	0.0525	0.0765
305	3	0.0229	0.0048	0.0000	0.0328
575	4	0.0447	0.0023	0.0392	0.0510
926	5	0.0612	0.0015	0.0578	0.0650
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0613	0.0129	0.0000	0.0922
115	2	0.0630	0.0045	0.0506	0.0746
304	3	0.0235	0.0049	0.0000	0.0346
574	4	0.0448	0.0022	0.0376	0.0504
925	5	0.0612	0.0015	0.0569	0.0661
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1643	0.0120	0.1321	0.1925
117	2	0.0974	0.0040	0.0873	0.1074
306	3	0.0538	0.0027	0.0473	0.0609
576	4	0.0574	0.0019	0.0523	0.0629
927	5	0.0678	0.0016	0.0644	0.0717
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1685	0.0110	0.1406	0.1919
116	2	0.0972	0.0037	0.0872	0.1064
305	3	0.0536	0.0027	0.0458	0.0607
575	4	0.0576	0.0020	0.0529	0.0628
926	5	0.0678	0.0014	0.0645	0.0719

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.40

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0643	0.0088	0.0426	0.0831
116	2	0.0626	0.0027	0.0549	0.0684
305	3	0.0228	0.0025	0.0165	0.0297
575	4	0.0441	0.0013	0.0402	0.0477
926	5	0.0608	0.0011	0.0576	0.0640
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0634	0.0084	0.0391	0.0850
115	2	0.0628	0.0028	0.0553	0.0691
304	3	0.0232	0.0024	0.0165	0.0297
574	4	0.0441	0.0014	0.0404	0.0475
925	5	0.0609	0.0011	0.0577	0.0636
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1668	0.0074	0.1469	0.1803
117	2	0.0970	0.0025	0.0918	0.1023
306	3	0.0534	0.0016	0.0489	0.0588
576	4	0.0572	0.0012	0.0538	0.0608
927	5	0.0675	0.0009	0.0652	0.0706
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1682	0.0076	0.1429	0.1833
116	2	0.0978	0.0027	0.0907	0.1051
305	3	0.0536	0.0015	0.0497	0.0571
575	4	0.0573	0.0014	0.0532	0.0617
926	5	0.0674	0.0010	0.0646	0.0704

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.41

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0645	0.0057	0.0508	0.0792
116	2	0.0625	0.0019	0.0571	0.0677
305	3	0.0229	0.0015	0.0183	0.0262
575	4	0.0440	0.0009	0.0414	0.0462
926	5	0.0607	0.0007	0.0586	0.0625
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0635	0.0050	0.0521	0.0757
115	2	0.0624	0.0020	0.0565	0.0673
304	3	0.0230	0.0015	0.0174	0.0275
574	4	0.0441	0.0009	0.0416	0.0462
925	5	0.0607	0.0008	0.0588	0.0626
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1668	0.0051	0.1562	0.1812
117	2	0.0975	0.0016	0.0936	0.1020
306	3	0.0534	0.0011	0.0506	0.0566
576	4	0.0571	0.0009	0.0547	0.0597
927	5	0.0674	0.0007	0.0657	0.0694
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1691	0.0523	0.1502	0.1816
116	2	0.0979	0.0016	0.0939	0.1018
305	3	0.0535	0.0013	0.0505	0.0570
575	4	0.0572	0.0009	0.0548	0.0592
926	5	0.0674	0.0007	0.0658	0.0690

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.42

Descriptive Statistics for the Root Mean Square Error of Approximation from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.0644	0.0032	0.0551	0.0728
116	2	0.0626	0.0013	0.0593	0.0658
305	3	0.0230	0.0009	0.0202	0.0258
575	4	0.0441	0.0005	0.0427	0.0455
926	5	0.0606	0.0005	0.0596	0.0617
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.0634	0.0034	0.0546	0.0722
115	2	0.0628	0.0015	0.0589	0.0670
304	3	0.0228	0.0009	0.0199	0.0250
574	4	0.0441	0.0006	0.0426	0.0457
925	5	0.0608	0.0005	0.0595	0.0619
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.1682	0.0031	0.1611	0.1763
117	2	0.0974	0.0011	0.0945	0.1000
306	3	0.0535	0.0007	0.0516	0.0551
576	4	0.0571	0.0006	0.0558	0.0586
927	5	0.0674	0.0004	0.0664	0.0684
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.1700	0.0328	0.1610	0.1778
116	2	0.0977	0.0011	0.0946	0.1002
305	3	0.0535	0.0006	0.0516	0.0550
575	4	0.0571	0.0006	0.0556	0.0588
926	5	0.0674	0.0004	0.0662	0.0684

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.43

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 100

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9654	0.0367	0.8671	1.0419
116	2	0.9623	0.0145	0.9234	0.9942
305	3	0.9805	0.0101	0.9487	1.0068
575	4	0.9531	0.0103	0.9141	0.9766
926	5	0.9121	0.0106	0.8796	0.9374
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9716	0.0295	0.9100	1.0534
115	2	0.9637	0.0136	0.9240	0.9981
304	3	0.9782	0.0105	0.9515	1.0060
574	4	0.9541	0.0097	0.9258	0.9793
925	5	0.9125	0.0107	0.8791	0.9414
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8059	0.0718	0.5227	0.9413
117	2	0.9155	0.0160	0.8735	0.9540
306	3	0.9530	0.0106	0.9223	0.9767
576	4	0.9373	0.0094	0.9153	0.9636
927	5	0.8998	0.0095	0.8732	0.9204
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8433	0.0727	0.6723	0.9867
116	2	0.9147	0.0181	0.8553	0.9553
305	3	0.9526	0.0110	0.9288	0.9822
575	4	0.9367	0.0096	0.9104	0.9579
926	5	0.8993	0.0101	0.8741	0.9235

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.44

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 200

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9692	0.0199	0.8964	1.0144
116	2	0.9659	0.0105	0.9331	0.9890
305	3	0.9906	0.0058	0.9773	1.0079
575	4	0.9700	0.0055	0.9556	0.9851
926	5	0.9371	0.0056	0.9209	0.9510
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9716	0.0180	0.9019	1.0141
115	2	0.9664	0.0084	0.9436	0.9871
304	3	0.9904	0.0052	0.9725	1.0054
574	4	0.9700	0.0045	0.9578	0.9814
925	5	0.9370	0.0058	0.9226	0.9574
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8019	0.0471	0.6864	0.9068
117	2	0.9194	0.0110	0.8965	0.9486
306	3	0.9637	0.0064	0.9465	0.9774
576	4	0.9522	0.0062	0.9404	0.9701
927	5	0.9236	0.0060	0.9074	0.9394
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8113	0.0437	0.6993	0.9089
116	2	0.9195	0.0103	0.8824	0.9463
305	3	0.9631	0.0067	0.9505	0.9810
575	4	0.9531	0.0050	0.9406	0.9623
926	5	0.9228	0.0060	0.9072	0.9375

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.45

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 500

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9704	0.0106	0.9407	0.9891
116	2	0.9674	0.0044	0.9514	0.9771
305	3	0.9937	0.0023	0.9879	1.0004
575	4	0.9741	0.0026	0.9669	0.9805
926	5	0.9426	0.0029	0.9339	0.9488
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9739	0.0101	0.9462	1.0007
115	2	0.9671	0.0046	0.9541	0.9787
304	3	0.9934	0.0024	0.9862	1.0006
574	4	0.9742	0.0025	0.9674	0.9819
925	5	0.9425	0.0029	0.9345	0.9514
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.8002	0.0290	0.7237	0.8683
117	2	0.9208	0.0060	0.9034	0.9356
306	3	0.9664	0.0032	0.9566	0.9730
576	4	0.9572	0.0028	0.9491	0.9640
927	5	0.9295	0.0033	0.9193	0.9384
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8030	0.0261	0.7390	0.8690
116	2	0.9213	0.0053	0.9078	0.9343
305	3	0.9668	0.0031	0.9579	0.9745
575	4	0.9572	0.0027	0.9504	0.9644
926	5	0.9295	0.0028	0.9224	0.9377

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.46

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 1000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9705	0.0077	0.9546	0.9879
116	2	0.9674	0.0028	0.9610	0.9747
305	3	0.9939	0.0013	0.9902	0.9969
575	4	0.9750	0.0015	0.9707	0.9787
926	5	0.9433	0.0020	0.9376	0.9499
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9732	0.0071	0.9504	0.9903
115	2	0.9674	0.0030	0.9611	0.9751
304	3	0.9937	0.0013	0.9900	0.9969
574	4	0.9749	0.0016	0.9710	0.9788
925	5	0.9432	0.0021	0.9389	0.9490
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7948	0.0191	0.7535	0.8526
117	2	0.9216	0.0042	0.9134	0.9302
306	3	0.9669	0.0019	0.9612	0.9725
576	4	0.9576	0.0018	0.9527	0.9627
927	5	0.9298	0.0019	0.9235	0.9351
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8016	0.0171	0.7658	0.8570
116	2	0.9206	0.0040	0.9091	0.9297
305	3	0.9669	0.0017	0.9629	0.9720
575	4	0.9576	0.0018	0.9523	0.9635
926	5	0.9302	0.0022	0.9240	0.9364

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.47

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 2000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9707	0.0052	0.9552	0.9814
116	2	0.9675	0.0021	0.9615	0.9736
305	3	0.9939	0.0008	0.9922	0.9962
575	4	0.9750	0.0010	0.9723	0.9781
926	5	0.9435	0.0013	0.9402	0.9473
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9734	0.0043	0.9599	0.9824
115	2	0.9679	0.0021	0.9622	0.9738
304	3	0.9939	0.0008	0.9913	0.9965
574	4	0.9750	0.0011	0.9722	0.9777
925	5	0.9434	0.0014	0.9396	0.9473
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7944	0.0125	0.7689	0.8191
117	2	0.9205	0.0024	0.9128	0.9263
306	3	0.9670	0.0013	0.9634	0.9702
576	4	0.9578	0.0012	0.9540	0.9614
927	5	0.9302	0.0014	0.9258	0.9336
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.8011	0.0113	0.7699	0.8374
116	2	0.9206	0.0026	0.9146	0.9284
305	3	0.9669	0.0014	0.9628	0.9704
575	4	0.9578	0.0013	0.9546	0.9608
926	5	0.9301	0.0015	0.9266	0.9344

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

Table M.48

Descriptive Statistics for the Relative Noncentrality Index from the Complex Model, Sample Size of 5000

TRUE		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.9711	0.0029	0.9638	0.9790
116	2	0.9675	0.0013	0.9640	0.9706
305	3	0.9939	0.0005	0.9925	0.9953
575	4	0.9749	0.0006	0.9731	0.9765
926	5	0.9436	0.0009	0.9412	0.9455
INCLUSION		M	SD	Minimum	Maximum
df	Indicators per LV				
16	1	0.9737	0.0028	0.9657	0.9808
115	2	0.9676	0.0015	0.9635	0.9715
304	3	0.9940	0.0005	0.9929	0.9955
574	4	0.9750	0.0007	0.9732	0.9768
925	5	0.9433	0.0009	0.9409	0.9456
OMISSION		M	SD	Minimum	Maximum
df	Indicators per LV				
18	1	0.7925	0.0078	0.7669	0.8079
117	2	0.9207	0.0017	0.9174	0.9249
306	3	0.9669	0.0008	0.9650	0.9690
576	4	0.9577	0.0007	0.9555	0.9597
927	5	0.9302	0.0008	0.9281	0.9321
COMBINATION		M	SD	Minimum	Maximum
df	Indicators per LV				
17	1	0.7990	0.0073	0.7790	0.8167
116	2	0.9208	0.0016	0.9161	0.9250
305	3	0.9670	0.0007	0.9653	0.9693
575	4	0.9579	0.0008	0.9554	0.9600
926	5	0.9303	0.0009	0.9282	0.9326

Note. The following abbreviations have been used: df = Degrees of freedom for the hypothesized model; LV = Latent variable.

APPENDIX N

Mean Scores for the Goodness-of-Fit Indices as a Function of Sample Size in the Simple, Moderate, and Complex Models

Model	Index							
Simple								
SS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
100	118.19	.961	165.55	.884	.923	.934	.089	.962
200	160.55	.964	284.47	.915	.944	.936	.091	.964
500	294.44	.964	429.44	.935	.956	.934	.093	.964
1000	504.28	.964	547.41	.942	.960	.935	.093	.964
2000	841.96	.964	574.00	.946	.962	.934	.094	.964
5000	1854.02	.964	639.75	.948	.963	.934	.094	.964
Moderate								
SS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
100	217.57	.944	121.32	.856	.883	.914	.077	.946
200	240.56	.951	211.13	.908	.924	.924	.071	.952
500	336.85	.950	414.79	.943	.938	.920	.070	.952
1000	520.70	.952	525.10	.955	.946	.923	.070	.952
2000	975.76	.953	585.84	.962	.949	.923	.070	.952
5000	2342.83	.952	648.08	.966	.951	.923	.070	.953
Complex								
SS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
100	598.06	.930	86.24	.784	.843	.901	.065	.931
200	694.00	.940	141.66	.850	.892	.910	.057	.940
500	1084.51	.943	234.38	.898	.923	.913	.055	.943
1000	1767.61	.943	306.41	.915	.932	.912	.053	.943
2000	3141.45	.943	373.69	.924	.938	.912	.052	.943
5000	7273.56	.942	443.85	.930	.940	.912	.052	.942

Note. The following abbreviations have been used: χ^2 = Chi-square statistic; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; SS = Sample size.

APPENDIX O

Mean Scores for the Goodness-of-Fit Indices as a Function of Number of Indicators per Latent Variable in the Simple, Moderate, and Complex Models

Model	Index							
Simple								
IND	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
1	58.53	.946	594.08	.979	.939	.838	.131	.947
2	191.31	.980	495.65	.961	.972	.964	.084	.980
3	502.31	.974	444.93	.932	.962	.966	.079	.974
4	1142.25	.962	379.44	.897	.946	.954	.083	.962
5	1783.64	.956	288.76	.872	.938	.950	.085	.956
Moderate								
IND	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
1	291.68	.824	618.35	.945	.812	.693	.113	.827
2	378.47	.974	526.10	.951	.960	.965	.081	.975
3	482.73	.985	424.81	.941	.966	.983	.041	.988
4	621.84	.989	333.80	.885	.964	.988	.054	.989
5	1565.05	.980	202.16	.874	.935	.968	.067	.980
Complex								
IND	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
1	430.40	.888	500.89	.939	.872	.767	.113	.888
2	1275.13	.943	282.98	.905	.922	.925	.054	.943
3	1373.76	.977	236.68	.903	.946	.974	.036	.977
4	2797.47	.962	169.65	.862	.927	.958	.029	.962
5	6563.33	.931	131.61	.797	.891	.926	.047	.930

Note. The following abbreviations have been used: χ^2 = Chi-square statistic; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; IND = Number of indicators per latent variable; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index.

APPENDIX P

Mean Scores for the Goodness-of-Fit Indices as a Function of Model Misspecifications in the Simple, Moderate, and Complex Models

Model	Index							
Simple								
MS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
T	715.03	.966	689.21	.931	.954	.941	.088	.966
I	700.14	.970	720.29	.934	.959	.936	.090	.971
O	779.18	.956	170.79	.924	.944	.933	.095	.956
C	755.35	.961	180.13	.926	.949	.928	.096	.961
Moderate								
MS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
T	376.13	.994	593.01	.953	.974	.995	.053	.996
I	374.34	.994	666.40	.953	.975	.995	.053	.996
O	959.15	.907	211.72	.910	.888	.855	.093	.907
C	957.07	.907	210.15	.810	.889	.840	.095	.907
Complex								
MS	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
T	1936.60	.967	362.09	.900	.937	.956	.018	.967
I	1934.52	.968	365.37	.900	.938	.957	.017	.968
O	2930.75	.912	165.38	.867	.884	.864	.090	.912
C	2923.46	.914	165.43	.868	.887	.864	.090	.914

Note. The following abbreviations have been used: χ^2 = Chi-square statistic; C = Combination; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; I = Inclusion; MS = Model Misspecifications; NFI = Normed fit index; NNFI = Nonnormed fit index; O = Omission; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; T = True.

APPENDIX Q

Data Transformations for the Percentages of Model Acceptance for the Goodness-of-Fit Indices

Chi-square test statistic (χ^2):
Transformed χ^2 = $[((\chi^2+0)\log -.257)-1]/-.257$

Comparative fit index (CFI):
Transformed CFI = [((CFI+1)log 3.998)-1]/3.998

Critical N (CN):
Transformed CN = [((CN+0)log .688)-1]/.688

Goodness-of-fit index (GFI):
Transformed GFI = [((GFI+0)log .538)-1]/.538

Normed fit index (NFI):
Transformed NFI = [((NFI+0)log 2.999)-1]/2.999

Nonnormed fit index (NNFI):
Transformed NNFI = [((NNFI+0)log 2.999)-1]/2.999

Root mean square error of approximation (RMSEA):
Transformed RMSEA = [((RMSEA+0)log 1.287)-1]/1.287

Relative noncentrality index (RNI):
Transformed RNI = [((RNI+1)log 3.998)-1]/3.998

APPENDIX R

Percentages of Model Acceptance For the Recommended Cutoff Values on the Fit Indices as a Function of Sample Size, Number of Indicators per Latent Variable, and Model Misspecifications in the Simple, Moderate, and Complex Models

Model	Index							
Simple								
	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
SS								
100	47	95	43	41	75	87	46	94
200	41	98	48	59	96	89	51	98
500	37	98	54	77	97	90	58	98
1000	37	99	68	85	96	90	59	99
2000	37	100	83	88	96	90	61	100
5000	37	100	88	89	96	90	63	100
IND								
1	37	92	100	100	88	59	12	92
2	36	100	98	98	98	98	49	98
3	36	100	49	86	100	100	57	100
4	34	100	44	64	97	100	83	100
5	0	100	42	39	88	100	80	100
MS								
T	44	99	99	86	96	86	46	99
I	44	100	99	87	97	85	47	100
O	16	97	48	76	91	83	34	97
C	19	98	49	77	95	82	39	98

Note. N = 120. The following abbreviations have been used: χ^2 = Chi-square statistic; C = Combination; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; I = Inclusion; IND = Number of indicators per latent variable; MS = Model misspecifications; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; SS = Sample size; T = True.

Model				Index				
Moderate								
	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
SS								
100	27	85	35	23	57	80	64	85
200	14	90	39	42	89	81	69	89
500	3	90	47	53	90	83	70	90
1000	1	90	47	66	90	84	70	90
2000	0	90	47	78	90	87	70	90
5000	0	90	47	79	90	87	70	90
IND								
1	25	50	48	91	49	49	46	50
2	10	90	47	77	97	83	50	90
3	2	90	44	68	98	84	87	90
4	0	90	37	64	93	83	83	90
5	0	90	35	34	86	80	75	90
MS								
T	36	100	97	63	96	97	99	99
I	38	100	97	63	96	97	99	100
O	7	80	53	55	72	80	52	80
C	5	80	54	57	72	80	53	80

Note. N = 120. The following abbreviations have been used: χ^2 = Chi-square statistic; C = Combination; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; I = Inclusion; IND = Number of indicators per latent variable; MS = Model misspecifications; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; SS = Sample size; T = True.

Model	Index							
Complex								
	χ^2	CFI	CN	GFI	NFI	NNFI	RMSEA	RNI
SS								
100	12	71	1	13	57	68	73	72
200	8	78	16	22	69	69	77	77
500	2	78	40	35	70	70	79	78
1000	0	78	41	56	70	70	79	78
2000	0	78	41	58	70	70	79	78
5000	0	78	41	59	70	70	79	78
IND								
1	9	45	40	87	41	44	49	46
2	2	83	36	64	77	61	69	82
3	1	83	35	53	79	80	90	83
4	0	83	28	44	71	80	89	82
5	0	80	26	9	63	74	81	79
MS								
T	6	99	68	57	81	97	98	99
I	6	100	70	56	82	97	98	100
O	0	78	35	42	55	61	59	77
C	0	78	36	43	56	63	60	78

Note. N = 120. The following abbreviations have been used: χ^2 = Chi-square statistic; C = Combination; CFI = Comparative fit index; CN = Critical N; GFI = Goodness-of-fit index; I = Inclusion; IND = Number of indicators per latent variable; MS = Model misspecifications; NFI = Normed fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index; SS = Sample size; T = True.

APPENDIX S

Percentages of Model Acceptance as a Function of Model Complexity and Number of Indicators per Latent Variable for the CFI, NNFI, RMSEA, and RNI in the True and Omission Conditions

	Indicators				
Index: CFI	1	2	3	4	5
True					
Simple	95	100	100	100	100
Moderate	100	100	100	100	100
Complex	99	99	100	100	98
Omission					
Simple	84	97	100	100	100
Moderate	0	100	100	100	100
Complex	0	96	100	100	92
Index: NNFI	Indicators				
	1	2	3	4	5
True					
Simple	98	100	100	100	100
Moderate	91	100	100	100	100
Complex	30	99	100	100	95
Omission					
Simple	14	97	100	100	100
Moderate	0	99	100	100	100
Complex	0	24	100	100	87
Index: RMSEA	Indicators				
	1	2	3	4	5
True					
Simple	17	71	89	83	67
Moderate	92	98	100	100	99
Complex	98	100	100	100	100
Omission					
Simple	7	19	75	76	39
Moderate	0	2	100	100	96
Complex	0	41	98	100	100

Index: RNI	Indicators				
	1	2	3	4	5
True					
Simple	95	99	100	100	100
Moderate	100	100	100	100	100
Complex	99	99	100	100	98
Omission					
Simple	84	97	100	100	100
Moderate	0	100	100	100	100
Complex	0	96	100	100	92

Note. N = 360. The following abbreviations have been used: CFI = Comparative fit index; NNFI = Nonnormed fit index; RMSEA = Root mean square error of approximation; RNI = Relative noncentrality index.

APPENDIX T

Percentage of Model Acceptance Using Alternative Cutoff Values for the Fit Indices in the True and Omission Conditions for Single and Multiple Indicator Models

Table T.01

Percentage of Model Acceptance for the Chi-Square Statistic

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.05[a]	55	9	41	18
.06	60	9	45	18
.07	66	9	52	19
.08	70	10	58	19
.09	73	10	63	19
.10	80	10	67	19
.11	80	12	73	19
.12	82	14	74	22
.13	82	15	74	26
.14	82	18	75	30
.15	83	19	75	33

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.05	38	13	18	10
.06	39	14	19	12
.07	40	14	19	13
.08	40	15	20	13
.09	42	16	21	14
.10	42	17	23	14
.11	43	17	25	15
.12	43	17	25	16
.13	43	17	25	16
.14	44	17	25	17
.15	44	17	25	18

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.05	12	0	6	0
.06	12	0	6	0
.07	12	1	6	0
.08	13	1	7	0
.09	13	1	7	1
.10	14	2	8	1
.11	14	2	8	1
.12	14	2	8	2
.13	15	3	9	2
.14	15	3	9	3
.15	15	3	9	3

[a]Recommended cutoff value for all simulations.

Table T.02

Percentage of Model Acceptance for the Comparative Fit Index

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90[a]	95	80	100	98
.91	91	73	99	95
.92	91	67	98	90
.93	87	52	97	86
.94	80	35	95	83
.95	65	22	90	78
.96	56	13	67	55
.97	37	9	43	34
.98	22	5	24	7
.99	5	2	11	2
1.00	2	0	6	1

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	100	0	100	80
.91	100	0	98	79
.92	95	0	96	74
.93	94	0	95	69
.94	91	0	95	64
.95	88	0	94	60
.96	86	0	93	57
.97	81	0	93	50
.98	66	0	92	28
.99	36	0	57	27
1.00	2	0	18	5

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	98	0	97	78
.91	94	0	95	74
.92	92	0	94	70
.93	90	0	93	56
.94	87	0	91	39
.95	83	0	88	36
.96	76	0	80	29
.97	59	0	65	18
.98	38	0	42	7
.99	19	0	21	3
1.00	1	0	1	0

[a]Recommended cutoff value for all simulations.

Table T.03

Percentage of Model Acceptance for the Critical N

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
200[a]				
210	100	48	100	50
220	100	41	100	49
230	100	36	100	48
240	100	33	100	47
250	100	28	100	46
260	94	25	100	45
270	90	23	80	40
280	82	21	78	37
290	78	18	70	33
300	60	17	55	28

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
200	95	38	97	53
210	84	35	92	40
220	77	30	90	37
230	75	25	87	35
240	71	24	85	31
250	70	24	74	29
260	63	23	68	25
270	50	20	51	18
280	45	16	45	17
290	43	13	40	11
300	42	11	31	10

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
200	75	37	70	35
210	60	20	67	33
220	58	20	65	30
230	57	19	60	31
240	55	19	53	28
250	47	18	49	27
260	43	17	42	24
270	36	15	35	20
280	30	15	28	17
290	23	14	22	14
300	15	11	13	9

[a]Recommended cutoff value for all simulations.

Table T.04

Percentage of Model Acceptance for the Goodness-of-Fit Index

Model: Simple

Indicators Value	True Single	Omission Single	True Multiple	Omission Multiple
.90[a]				
.91	100	100	83	65
.92	100	99	63	57
.93	100	98	53	51
.94	100	97	50	46
.95	98	96	44	36
.96	95	89	34	29
.97	90	72	28	15
.98	73	44	15	4
.99	15	1	3	0
1.00	0	0	0	0

Model: Moderate

Indicators Value	True Single	Omission Single	True Multiple	Omission Multiple
.90	100	93	63	55
.91	100	90	61	53
.92	98	88	54	49
.93	94	80	51	46
.94	89	78	46	40
.95	83	74	42	38
.96	70	63	25	19
.97	56	45	16	10
.98	15	4	7	1
.99	0	0	0	0
1.00	0	0	0	0

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	85	82	60	40
.91	80	76	56	38
.92	73	67	53	32
.93	69	62	48	29
.94	62	55	44	24
.95	54	46	38	20
.96	35	29	23	15
.97	17	11	8	6
.98	9	5	3	2
.99	0	0	0	0
1.00	0	0	0	0

[a]Recommended cutoff value for all simulations.

Table T.05

Percentage of Model Acceptance for the Normed Fit Index

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90[a]	95	80	96	93
.91	91	73	94	87
.92	89	58	91	81
.93	83	41	86	72
.94	75	25	80	65
.95	60	14	69	57
.96	45	7	56	32
.97	29	3	34	18
.98	11	1	18	1
.99	1	0	1	0
1.00	1	0	0	0

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	99	4	99	69
.91	94	0	95	69
.92	83	0	86	57
.93	68	0	69	26
.94	57	0	60	21
.95	45	0	47	35
.96	33	0	39	23
.97	18	0	26	11
.98	9	0	12	4
.99	3	0	5	0
1.00	0	0	0	0

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	80	0	83	58
.91	71	0	75	47
.92	63	0	69	18
.93	55	0	60	13
.94	48	0	53	11
.95	37	0	41	9
.96	28	0	33	6
.97	18	0	23	4
.98	6	0	9	1
.99	1	0	1	0
1.00	0	0	0	0

[a]Recommended cutoff value for all simulations.

Table T.06

Percentage of Model Acceptance for the Nonnormed Fit Index

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90[a]	30	19	86	83
.91	26	12	85	82
.92	23	9	84	81
.93	20	8	83	80
.94	17	6	80	76
.95	14	4	71	62
.96	13	4	42	29
.97	12	3	19	7
.98	3	1	5	2
.99	2	0	3	0
1.00	1	0	1	0

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	98	0	100	79
.91	97	0	100	79
.92	94	0	100	76
.93	90	0	100	73
.94	86	0	97	66
.95	83	0	95	63
.96	79	0	93	56
.97	74	0	92	50
.98	56	0	91	24
.99	35	0	55	21
1.00	4	0	14	8

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	93	0	95	59
.91	88	0	94	49
.92	81	0	92	43
.93	75	0	90	38
.94	68	0	85	33
.95	56	0	79	29
.96	38	0	73	25
.97	15	0	65	19
.98	2	0	43	15
.99	0	0	19	3
1.00	0	0	1	0

[a]Recommended cutoff value for all simulations.

Table T.07

Percentages of Model Acceptance for the Root Mean Square Error of Approximation

Model: Simple

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.01	0	0	0	0
.02	0	0	0	0
.03	0	0	4	1
.04	3	0	8	2
.05	4	1	11	3
.06	7	3	13	4
.07	15	4	38	7
.08[a]	45	10	79	71
.09	47	13	84	80
.10	52	17	87	82

Model: Moderate

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.01	3	0	5	1
.02	6	0	11	5
.03	8	0	20	12
.04	31	0	46	25
.05	48	0	63	44
.06	65	0	79	35
.07	86	0	95	42
.08	91	0	100	58
.09	98	5	100	67
.10	100	12	100	70

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.01	26	0	40	0
.02	43	0	54	0
.03	71	1	75	2
.04	82	4	90	4
.05	95	6	95	10
.06	95	31	100	35
.07	96	56	100	58
.08	96	61	100	64
.09	97	70	100	74
.10	97	79	100	83

[a]Recommended cutoff value for all simulations.

Table T.08

Percentages of Model Acceptance for the Relative Noncentrality Index

Model: Simple

Indicators Value	True Single	Omission Single	True Multiple	Omission Multiple
.90[a]	94	80	100	98
.91	91	73	98	95
.92	91	67	98	91
.93	87	52	97	86
.94	80	24	95	83
.95	65	22	90	78
.96	44	18	67	53
.97	26	14	43	34
.98	22	5	24	7
.99	5	2	11	3
1.00	1	0	7	2

Model: Moderate

Indicators Value	True Single	Omission Single	True Multiple	Omission Multiple
.90	100	0	100	79
.91	99	0	99	79
.92	94	0	96	73
.93	93	0	95	70
.94	90	0	94	65
.95	89	0	94	59
.96	87	0	93	55
.97	80	0	93	51
.98	65	0	91	26
.99	37	0	53	25
1.00	3	0	17	6

Model: Complex

Indicators	True Single	Omission Single	True Multiple	Omission Multiple
Value				
.90	97	0	97	78
.91	93	0	94	73
.92	91	0	94	70
.93	90	0	93	56
.94	88	0	90	38
.95	85	0	86	37
.96	77	0	79	27
.97	54	0	67	19
.98	36	0	40	8
.99	17	0	20	4
1.00	1	0	1	0

[a]Recommended cutoff value for all simulations.

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Meredith Award - Outstanding Graduate Student
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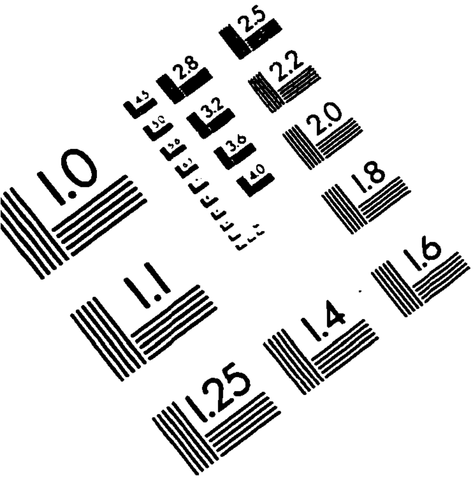

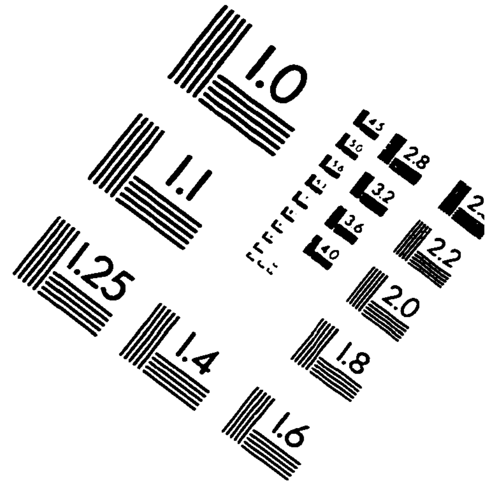

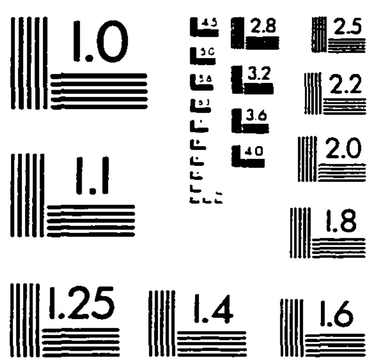

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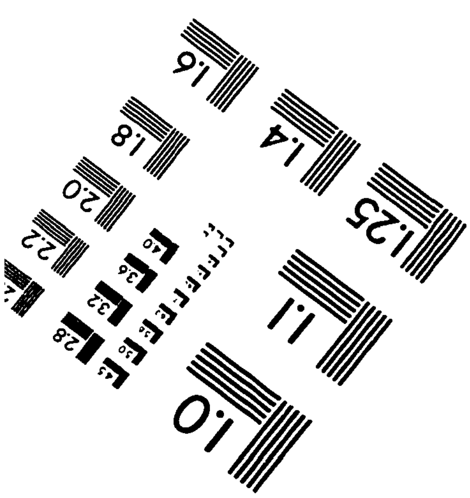

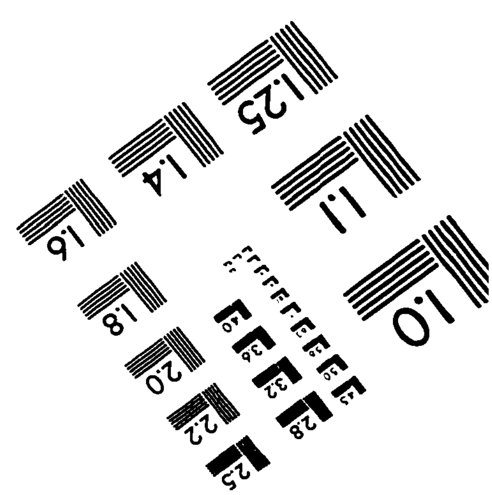

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