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Meta-Analytic Methods of Pooling Correlation Matrices for Structural Equation Modeling Under Different Patterns of Missing Data

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Meta-Analytic Methods of Pooling Correlation Matrices

for Structural Equation Modeling Under

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by

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Meta-Analytic Methods of Pooling Correlation Matrices

for Structural Equation Modeling Under

Different Patterns of Missing Data

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This study compared the effects of different methods of synthesizing correlations for meta-analytic structural equation modeling (SEM) under various patterns of missingness on the estimation of correlation parameters and the resulting SEM parameters and fit indices. Univariate weighting methods for synthesizing correlations are frequently used. An alternative multivariate method for pooling correlation matrices involves using generalized least squares (GLS), where the dependencies of the correlations within the same matrix are taken into consideration (Becker, 1992). Since previous research has reported poor performance with GLS versus univariate weighting procedures, a revised GLS method, W-COV GLS, was used. Both the W-COV GLS procedure and univariate weighting were compared using correlations transformed with Fisher's *z* versus untransformed correlations.

There is frequently a problem when synthesizing correlation matrices due to the effects of missing data. One type of missing data scenario is the file-drawer problem

(Rosenthal, 1979) in which a potential selection bias may occur whereby correlations that are non-significant are not reported. The performance of the different synthesis methods were assessed under different degrees and types of missingness including an approximation of the file-drawer problem using listwise and pairwise deletion to handle missing data.

Results from this study indicated comparable performance of univariate weighting with the *z* transformation and W-COV GLS procedures, both with and without the transformation, for estimating the correlation parameters and ensuing parameters of the structural model. However, the W-COV GLS procedure performed slightly better in estimating the standard errors of the paths in the structural model and for the chi-squared test of data-model fit. When data were MCAR then there was almost no relative bias detected but when data were MNAR there were unacceptably high levels of relative bias in estimation of the correlation and SEM model parameters as well as high model rejection rates regardless of method used to synthesize correlations. Pairwise deletion resulted in higher incorrect rejection rates and larger bias in the standard error estimates for the SEM model than did listwise deletion. Inaccurate standard error estimates were found for several of the paths and attributed to the use of a correlation matrix with SEM.

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Chapter 1: Introduction

The term meta-analysis originated in 1976 when Glass published a study to assess the effectiveness of psychotherapy. Prior to Glass's study, research had been published with inconsistent findings regarding the effectiveness of psychotherapy. Glass proposed meta-analysis as a method of combining the often conflicting results from studies purporting to measure the same relationships between variables. Glass proposed taking the mean of the effect sizes (where each estimate represents the relationship between two variables) from each study in order to represent the typical effectiveness of psychotherapy.

Whereas meta-analytic researchers still compute an effect size to describe a relationship between variables, associated techniques and applications have progressed since Glass's original study. Researchers now typically weight effect sizes to account for study differences in sample sizes and have developed procedures to address other issues such as missing data and using fixed versus random-effects models. Meta-analytic techniques have also expanded to encompass synthesis of several effect sizes from each study. Whereas the most frequent method of summarizing these results involves use of univariate weighting procedures, multivariate weighting procedures have also been proposed to account for the dependence that arises from several outcomes reported in the same study.

More recently, meta-analysis has been combined with structural equation modeling techniques to promote theory building. Structural equation modeling (SEM) involves imposing a theoretical model on a set of variables to explain their relationships.

The use of meta-analysis with SEM involves identifying some type of theoretical model among a set of variables. Then studies are collected that examine the correlations among the relevant variables in the model. A meta-analysis is conducted to synthesize correlations across studies which are then used to test the fit of the model using SEM techniques.

Since its inception, meta-analysis has become an increasingly popular tool, with applications in varied areas such as the medical and social sciences, education, and business. Meta-analytic studies are frequently cited in the literature and have become a commonly used technique for summarizing results across studies focused on the same relationships. Structural equation modeling is also a widely used tool in various fields. The combination of these two statistical techniques provides a unique method for theory-building. Examples where researchers have combined these two methods can be seen in the fields of education, business, and the social sciences.

The purpose of this study is to extend the literature in this area by examining the performance of multivariate versus univariate meta-analytic methods of pooling correlations under various patterns of missing data for use in structural equation modeling. The performance of these two kinds of methods for synthesizing correlations will be examined in a simulation study. Conditions examined in previous studies, such as the number of studies in the meta-analysis, and using Fisher's *z* (1928) transformed correlations versus untransformed correlations will also be investigated. However, the current study will extend previous research by evaluating the performance of these methods under additional conditions. In particular, the degree of missing data has not been evaluated for its impact on meta-analytic SEM results. In addition, studies have only examined the effects of data that is missing completely at random and not the scenario where the data are missing not at random. This study should present evidence regarding the performance of meta-analysis with structural equation modeling under these realistic conditions and provide guidelines for applied researchers.

Chapter 2: Literature Review

The present study will examine the performance of multivariate versus univariate weighting techniques for synthesizing correlations in meta-analytic structural equation modeling under various patterns of missing data. Meta-analysis and structural equation modeling developed as separate techniques and therefore it is important to understand the use of each of these methods in order to better understand their use together and the various conditions that can affect their performance.

This chapter will begin with a clarification of meta-analysis, including a brief history and various applications. Univariate and multivariate methods for synthesizing correlations will then be introduced along with a description of transforming correlations using Fisher's *z* transformation (Fisher, 1928). This will be followed by an explanation of different scenarios in which correlations of interest to a meta-analyst may be missing from a study and how missing data have typically been handled in the literature. Finally, techniques for the use of meta-analysis with structural equation modeling will be explained.

Meta-Analysis

Meta-analysis is a methodological technique used to statistically combine results across studies to summarize the accumulated evidence in a specific research domain. Meta-analysts synthesize the results from a collection of relevant individual (also referred to as primary) studies to describe the significance and size of an effect (Rubin, 1992).

Specifically, meta-analytic procedures entail synthesizing one or more effect sizes from each primary study to give an overall estimate of a relationship in the population.

An effect size refers to the strength of an association. Larger values indicate a stronger relationship while smaller values (in terms of magnitude) indicate little or no relationship. An effect size is typically measured in two ways: as either the standardized difference between two means or the correlation between two variables. In order to implement the use of meta-analysis with SEM, researchers synthesize correlations from each primary study. This study will therefore focus only on the use of the correlation coefficient with meta-analysis.

The results from meta-analytic procedures provide several advantages over those from primary studies in terms of theory-building. Meta-analysis contributes to theory-building by summarizing the validity of theoretical relationships (Hall, Rosenthal, Tickle-Degnen, Mosteller, 1994). The use of meta-analysis enables synthesis of research across multiple replications and different operational definitions. Cooper and Hedges have commented that meta-analyses “attempt to integrate empirical research for the purpose of creating generalizations” (1994, p. 5). Advocates of meta-analysis note that because the summary statistics resulting from a meta-analysis are based on a larger sample size than each individual study within the meta-analysis, the results are assumed to be more accurate and precise (Hunter & Schmidt, 1990). Because multiple studies are combined in meta-analysis, the results of the analysis are typically more precise than those from a primary study. A short synopsis of the history of meta-analysis will be provided next followed by a brief review of the relevant meta-analytic techniques used currently.

Short History of Meta-Analysis

While Glass is considered to be the founder of meta-analysis, he was not the first researcher to quantitatively combine research results. Olkin (1990) noted that methods of effect size estimation have been around since the early 1900's. Pearson (1904) used five samples that described the rates of typhoid fever for people who were and were not inoculated. He computed a tetrachoric correlation to represent an index of the relationship between inoculation and infection. Pearson then averaged the correlations to obtain the typical value for this relationship. He used this average to better assess the relationship between inoculation and typhoid fever.

Rosenthal also began conducting quantitative reviews as far back as the early 1960's when he compared and combined results from studies that dealt with experimenter expectancies. Around the same time as Glass gave a name to meta-analysis, Rosenthal and Rubin (1978) synthesized findings from studies of interpersonal expectancies using a standardized mean difference between experimental and control groups.

Popularity and Increased Usage of Meta-Analysis

Since the development of the term meta-analysis, its popularity has been increasingly on the rise. A search of the term "meta-analysis" on the PsycInfo database in October, 2002 resulted in over 4,000 articles. In 1980 there were fewer than 20 articles published using meta-analysis while in the year 2001 alone more than 300 articles involving meta-analysis had been published. Meta-analysis is frequently used in various fields and the trend in the increased popularity of meta-analysis can be seen in areas such as business, education, psychology, and the medical sciences. Meta-analytic studies are also frequently cited in other articles. S. Cheung noted that “when compared with other articles published in the same journal, meta-analytic reviews seem to have a higher impact in terms of frequency of being cited” (2000, p. 7).

Examples of meta-analytic studies abound in the literature. In the field of education, meta-analysis has been used to assess the relation between classroom size and achievement (e.g., McGiverin, Gilman, & Tillitski, 1989) and to examine the efficacy of mainstreaming programs for special education students (e.g., Wang & Baker, 1985). In the medical sciences, meta-analysis has been used in multiple areas including, for example, an examination of the relationship between breast cancer risk and mammography screening (McCaul, Branstetter, Schroeder, Glasgow, 1996). In the social sciences, meta-analytic techniques have been applied to the study of ethnic differences in self-esteem among adolescents (e.g., Gray-Little, & Hafdahl, 2000).

Basic meta-analytic techniques still follow Glass et al.’s (1981) procedures. Meta-analytic techniques can be applied to a host of different test statistics from primary studies including t-tests, F-ratios, correlation coefficients, and the odds ratio. One or more effect size estimates are taken from multiple studies and combined across studies to estimate the average effect. Glass et al. (1981) proposed that studies examining the same relationship(s) should be considered a sample of study replicates gathered from a universe of studies and each study’s effect size estimate be used to estimate the population effect size. The model assumed typically for the population effect size is:

$$T_i = \theta + e_i \ , \qquad (1)$$

where T_i is the effect size estimate from study i;

θ is the population effect size;

and e_i is the random error assumed distributed normally with a mean of zero and common variance of σ_T^2 $\left(e_i \sim N\left[0, \sigma_T^2\right]\right)$.

Excessive heterogeneity can suggest that a single population correlation may not underlie the k correlation estimates and be interpreted as evidence that the observed correlations are more variable than expected given the model.

Fixed-Effects Model Versus Random-Effects Model

The possibility of heterogeneity necessitates the use of procedures for correlations that have not originated in a single population. Methods include modeling excessive correlation heterogeneity either by disaggregating studies into potentially homogeneous sub-groups based on categorical study characteristics and analyzing each sub-group separately or by incorporating specific study characteristics as predictors into the statistical model. These both represent cases of fixed-effects models. The fixed-effects model is the most commonly used model in meta-analytic studies (Hedges, 1994). In the fixed-effects model, it is assumed that the results of the meta-analysis will generalize to studies identical to those in the study sample. The effect size in the population is assumed to be constant for all of the studies included in the meta-analysis (Hedges, 1994).

Substantial heterogeneity can indicate that the effect varies with important between-study characteristics not accounted for in the model. In the random-effects model, the results are presumed to generalize to a population of studies from which the study sample is drawn. The population values vary randomly from study to study. The studies used in a meta-analysis are considered to be a sample of studies that could have been conducted and as being sampled from a universe of possible studies. Mixed-effects models incorporate both fixed and random effects and can also be used in meta-analytic procedures.

A chi-squared test of observed (residual) variation of effect size estimates can be used to assess the need to employ a random- or a fixed-effects model. When the test indicates a substantial amount of variation then a random-effects model should be considered. In this dissertation, only a fixed-effects model will be considered. However, future research should extend the research described in this study to the random-effects model.

Conventional Techniques and Correlational Studies

Shadish (1996) reported that the most common use of meta-analysis has been in summarizing the strength of a relationship between two variables. Sometimes this relationship takes the form of a correlation. One method of synthesizing correlations involves combining validity coefficients across studies to estimate the population validity coefficient and to examine its relationship with study characteristics (Hedges, 1988). In addition, this technique can be used to synthesize reliability coefficients across studies. Researchers also synthesize correlations when they are interested in causal models among variables as in structural equation modeling. Structural equation modeling is a technique used to examine the fit of hypothesized causal relationships among variables, including path analytic and confirmatory factor analytic models, to a sample correlation or covariance matrix (Bollen, 1989).

An example of a simple correlation coefficient of interest to a meta-analyst could describe the relationship between age and working memory. The correlation coefficient is represented by the symbol r. In a fixed-effects model:

$$r_i = \rho + e_i \tag{2}$$

where r_i is the observed correlation from study i;

ρ is the population correlation;

and e_i represents sampling error for study i.

In a univariate meta-analysis, the focus is on studies that examine only one correlation, such as the correlation between age and working memory. However, frequently researchers are interested in examining the relationships between more than two variables. A meta-analysis is considered multivariate when it synthesizes more than one effect, here correlation, from each study. For instance, a meta-analyst might be interested in examining not only the relationship between age and working memory, but also the two variables' relationship with a measure of perceptual speed in order to test a path-analytic model with SEM. The focus of this study is on the synthesis of correlations for use with structural equation modeling. The next section will mention some meta-analytic SEM studies that have been conducted. It will then present the techniques used to analyze correlations with meta-analytic structural equation modeling.

Two-Step Approach: General Overview of Meta-Analytic SEM

Among multivariate statistical modeling techniques, structural equation modeling (SEM) is rapidly increasing in popularity. SEM involves imposing a theoretical model onto a set of variables and assessing the fit of the data to the model. Path analysis and confirmatory factor analysis (CFA) are both considered to be special cases of SEM. The two-steps involved in meta-analytic SEM entail first pooling a correlation matrix across studies and second, analyzing the pooled matrix with SEM techniques. There have been a number of recent studies that have used this two-step meta-analytic SEM procedure. The use of meta-analytic structural equation modeling has been applied more frequently in the business literature (e.g., Brown & Peterson, 1993; Carson, Carson, & Roe, 1993; Hom, Caranikas-Walker, Prussia, & Griffeth, 1992; Verhaeghen & Salthouse, 1997; Viswesvaran & Ones, 1995) than in the social sciences literature (e.g., Becker, 1992a; Hafdahl, 2001). This approach has also been used most widely with path analytic models (e.g., Becker, 1992a; Hom, Caranikas-Walker, Prussia, & Griffeth, 1992; Hunter, 1983; Premack & Hunter, 1988; Schmidt, Hunter, & Outerbridge, 1986). However, the advent of latent-variable models with meta-analysis has also recently emerged (e.g., M. Cheung & Chan, 2002; Hafdahl, 2001).

The use of meta-analytic SEM has been noted as a useful approach for theory building (Becker & Schram, 1994; Viswesvaran & Ones, 1995). Theory-driven modeling with meta-analysis allows researchers to construct explanations by obtaining support for and refuting theoretical relationships. Researchers can also examine patterns across studies that are not readily apparent from a single study. The use of modeling with meta-analytic SEM allows more complex questions to be addressed than those of individual studies (Viswesvaran & Ones, 1995). A recent review of meta-analytic SEM for model building noted the importance of this technique and raised several practical concerns for meta-analytic SEM such as methods for the handling of missing data and suggestions regarding the appropriate sample size (Viswesvaran & Ones, 1995).

An example of meta-analytic SEM can be seen in a study investigating several models of the relationship between variables affecting male and female performance in school science (B. J. Becker, 1992a). The study examined both univariate and multivariate weighting methods of synthesizing correlations for use in a path analytic model. Becker (1992a) refers to this type of study as a model-driven synthesis. That is, the study proposed several models of interest to assess the variables that affect male and female science performance. Then, all studies examining the correlations between the variables of interest were collected from the literature and synthesized using both univariate and multivariate weighting methods to compare potential differences between the two methods. The resulting synthesized correlations were then analyzed with several different theoretically derived models using SEM techniques to determine the fit of the data to each model.

In the literature there are various other examples of meta-analytic SEM. Premack and Hunter (1988) used meta-analytic SEM to examine the research on the process of unionization using a theoretical model of that process. Verhaeghen and Salthouse (1997) examined a mediational model of the effects of age on several cognitive measures in adulthood. Brown and Peterson (1993) examined the antecedents and consequences of salesperson job satisfaction in a path analytic model. Harris and Rosenthal (1985) studied a path analytic model of the mediation of interpersonal expectancy effects. G. Becker (1996) described procedures for synthesizing the results from factor analytic studies examining the performance of the Buss-Durkee Hostility Inventory and used these synthesized results in a new factor analysis model. Manfredo, Driver, and Tarrant (1997) used meta-analytic SEM (specifically a confirmatory factor analysis model) to examine studies using the Recreational Experience Preference (REP) items to test the structure of the scale that had been determined in previous research.

These studies have employed different techniques for the first step of the meta-analytic SEM involving the synthesis of the correlation matrix. Some have used univariate weighting techniques, while others have used multivariate ones. Several of these techniques will be presented next starting with the univariate procedures.

Univariate Weighting Approaches to Synthesizing Correlations

Whereas Glass's original technique employed a simple average computed across the effect size(s) from each study in the meta-analysis, meta-analytic techniques have been enhanced to account for potential statistical artifacts associated with study differences. In order to illustrate relevant meta-analytic techniques for synthesizing correlation matrices, examples will be given using data from Verhaeghen and Salthouse (1997). Three variables were utilized from this study and thus the number of correlations between these variables is three. The correlations reported from this study can be seen in Table 1.

Table 1

Sample Correlations from Verhaeghen and Salthouse (1997)

		Correlations		
Study	Sample(*n*)	Age-Speed	Age-Memory	Speed-Memory
Botwinick & Storandt (1974)	120	-.57	-.31	.34
Park, et al. (1996)	301	-.64	-.31	.39
Salthouse (1992)	100	-.59	-.34	.36
Salthouse, et al. (1996)	197	-.46	-.26	.38

This example will demonstrate how the correlations between the three variables of interest (age, perceptual speed, and a measure of primary/working memory) can be pooled across the four studies using several different meta-analytic synthesis methods. (While the use of four studies is a rather small number, it has been used in the meta-analytic literature and this amount was used here for the sake of simplicity in explanation). The synthesized correlation matrix will first be computed using a univariate weighting method.

The most frequently implemented univariate approaches to synthesizing correlations use some type of weighting to account for statistical artifacts such as differing sample sizes per study. There are several univariate approaches to synthesizing correlations (e.g., Hedges & Olkin, 1985; Hunter & Schmidt, 1990). In addition to weighting correlations based on their sample size, Hunter and Schmidt (1990) procedures typically disattenuate correlations to correct for other statistical artifacts such as unreliability and range-restriction in their univariate analyses. However, the information necessary for this disattenuation, such as the reliability estimates, is not frequently reported in primary studies and statistical methods for simultaneously disattenuating an entire correlation matrix are not currently available. Hedges and Olkin's (1985) procedure for univariate weighting of correlations does not entail the individual corrections to correlations advocated by Hunter and Schmidt and is frequently used in meta-analytic SEM studies. The procedure for univariate weighting by Hedges and Olkin (1985) has been selected for use in this study.

Hedges and Olkin's (1985) method for synthesizing correlations involves weighting each correlation by the reciprocal of its estimated conditional variance, then averaging the weighted correlations across studies to obtain the synthesized population correlation estimate. Specifically, the equation for the estimated asymptotic conditional variance, *V*, for *r* is:

$$V_i = \left(1 - r_i^2\right)^2 / \left(n_i - 1\right), \tag{3}$$

The reciprocal of this conditional variance is then computed and used as the weight applied to each correlation. Because the conditional variance is affected by sample size, the correlation estimates from studies based on larger samples will have more influence on the resulting pooled estimate of the correlations than correlations from studies with smaller samples. The formula for the weighted average of correlation coefficients across studies is:

$$\hat{\rho}_{xy} = \frac{\sum_{i=1}^{k} w_i r_i}{\sum_{i=1}^{k} w_i} \qquad (4)$$

where $\hat{\rho}_{xy}$ is the estimated population correlation coefficient pooled across studies and w_i is the weight (the reciprocal of the conditional variance from Equation 3) applied to its corresponding observed study correlation r for study i and k is the number of studies.

For study i the correlations among the three variables are typically presented in matrix-form:

$$R_i = \begin{bmatrix} 1.0 & r_{ist} & r_{isv} \\ r_{its} & 1.0 & r_{itv} \\ r_{ivs} & r_{ivt} & 1.0 \end{bmatrix}$$

where s could represent age, t speed, and v memory. For analyses, the correlations are frequently re-organized so that they can be presented as a vector r_i for study i:

$$r_i = \begin{bmatrix} r_{its} \\ r_{ivs} \\ r_{ivt} \end{bmatrix}.$$

For the data in this example the following vectors of correlations from four studies will be used (see Table 1):

$$r_1 = \begin{bmatrix} -.57 \\ -.31 \\ .34 \end{bmatrix},\ r_2 = \begin{bmatrix} -.64 \\ -.31 \\ .39 \end{bmatrix},\ r_3 = \begin{bmatrix} -.59 \\ -.34 \\ .36 \end{bmatrix},\ r_4 = \begin{bmatrix} -.46 \\ -.26 \\ .38 \end{bmatrix}.$$

Each of these correlations is then weighted using the reciprocal of its conditional variance as presented in Equation 3. However, when synthesizing correlations the matter of transforming the correlations using Fisher's z transformation should also be considered.

Fisher's Z Transformation

When synthesizing correlations, some researchers (for example, Hedges & Olkin, 1985; B J. Becker & Farbach, 1994) advocate first transforming each correlation coefficient by using Fisher's (1928) normalizing and variance-stabilizing *z* transformation where:

$$z_r = .5\{\ln[(1+r)/(1-r)]\}. \quad (5)$$

While Equation 3 is used to compute the conditional variance to weight untransformed correlations, the formula for the conditional variance of the transformed correlation, z_r, simplifies to:

$$v = \frac{1}{(n_i - 3)}, \quad (6)$$

where n_i corresponds to the sample size from study *i*. The Fisher's *z* transformation is applied to each correlation in the matrix prior to the synthesis of the correlations, and the resulting synthesized (transformed) correlations may be transformed back to the correlation metric prior to ensuing analyses. The transformation necessary to convert z_r back to the correlation metric is given by:

$$r_z = (e^{2z} - 1)/(e^{2z} + 1). \quad (7)$$

One of the primary justifications for the use of this Fisher's *r*-to-*z* transformation is that it removes the dependence of the estimate of the correlation variance on the sample estimate of the correlation (B. J. Becker, 2000). The sampling distribution of *r*'s sampled from ρ tends to be more skewed as ρ moves away from zero (Hedges & Olkin, 1985). The use of Fisher's transformation is reported to result in a more normal distribution even when there are smaller sample sizes and the population correlation is an extremely large absolute value (Steiger, 1980). A comparison of the results between *z*-transformed and untransformed correlations (from Table 1) with Hedges-Olkin univariate weighting can be seen in Table 2.

Table 2

Synthesized Correlations Using Transformed and Untransformed Correlations

	Correlations		
Transformation	Age-Speed	Age-Memory	Speed-Memory
Fisher's *Z*	-.576	-.301	.375
None	-.588	-.301	.375

As can be seen in Table 2, there are minor differences between the synthesized correlations that have and have not been transformed. Other researchers have noted differences between transformed and untransformed correlations for univariate weighting analyses in several simulation studies (e.g., Becker & Fahrbach, 1994; Hafdahl, 2001).

Some researchers advocate using the *z* transformation when synthesizing correlations unless sample sizes are very large (e.g., Shaddish & Haddock, 1994). Correlations that have been transformed using Fisher's *z* have an asymptotic distribution that is multivariate normal. When the sample size for a correlation estimate is based on fewer than 100 observations and the population correlation is large in magnitude (typically around an absolute value of .5 or greater) then the untransformed correlation based on the asymptotic distribution approximation has been found to be negatively biased (Hedges, 1994).

Silver and Dunlap (1987) conducted a simulation study comparing transformed versus untransformed correlations for synthesizing correlations with small sample sizes of 30 or less. They concluded that the use of untransformed *r*s resulted in negatively biased estimates of population correlations and in the case of moderate sized correlations the negative bias was substantial for sample sizes of less than 30. The use of Fisher's *z* transformation led to slightly positively biased results but largely negligible. The authors concluded that *z* transformed *r*s were always less biased than *r* regardless of sample size. However, because the untransformed *r*s displayed only small bias when the sample size was 30 the authors debated the use of the Fisher's *z* transformation with larger sample sizes.

In a simulation study examining different synthesis methods for use with meta-analytic structural equation modeling, Hafdahl (2001) assessed the differences between transformed and untransformed correlations using univariate weighting for the resulting pooled correlation matrix. Hafdahl (2001) reported that univariate approaches worked well whether or not the transformation was used, but that when differences emerged between the two, it was the *z* transformed correlations that resulted in less bias.

Yet not all researchers advocate the use of the *z* transformation. Hunter and Schmidt (1990) argue that use of the *z* transformation can lead to positively biased results and instead are in favor of combining correlations without the *z* transformation. They noted that in an application with real data, the Fisher's *z* inflated the true correlations while *r* had only a small negative bias unless the sample size was less than 40 (Hunter & Schmidt, 1990). In a simulation study, Strube (1988) noted that only when three or fewer studies were included in a meta-analysis was the bias in estimation resulting from using transformed correlations less than when using untransformed *r*. He also reported that as the number of studies included in the meta-analysis increased then the overestimation of the meta-analytic outcomes based on the *z* transformation was almost equal to the underestimation of the results based on the untransformed *r*. Fisher (1928) noted that the *z* transformation resulted in a small positive bias but this bias was often negligible. However, when *n* is very small and the value of ρ is very large (.5 or greater) this positive bias should not be ignored (Strube, 1988).

In summary, there is still no consensus regarding whether or not to transform correlations before synthesizing correlation matrices. The methods for pooling correlation matrices discussed in this section apply to correlations that are synthesized with univariate weighting procedures, the next sections will describe methods used for synthesizing correlation matrices with multivariate procedures and will discuss the results from studies focused on comparisons of both univariate and multivariate synthesis methods.

Multivariate Approach to Synthesizing Correlation Matrices

As mentioned previously, the most common method for synthesizing multiple correlations per study is the univariate weighting approach. However, correlations that arise from the same study should not be considered independent as is assumed when using univariate weighting methods. The use of the univariate weighting approach when pooling multiple correlations from a single study could be inappropriate since possible within-study covariation is ignored.

Martinussen and Bjornstad (1999) conducted a simulation study to evaluate the performance of univariate weighting in synthesizing correlation matrices across studies. The authors reported that the true population standard deviation was underestimated (indicating less variability) when dependent correlations were treated as independent. Ignoring dependency can result in inflation of Type I error rates (B.J. Becker, 2000; Raudenbush, B. J. Becker, & Kalaian, 1988). Despite these cautions, applied meta-analytic SEM researchers typically treat related correlations as if they were independent (e.g., Brown & Peterson, 1993; Premack & Hunter, 1988).

Several authors have advocated the use of multivariate weighting techniques to model the dependence in study correlations when synthesizing multiple outcomes in meta-analyses (B. J. Becker, 2000; Shadish & Haddock, 1994). All of these methods require the incorporation of information about the degree of covariance between outcome variables (here, the correlations). Multivariate weighting techniques allow the correlations in each study's correlation matrix to be synthesized simultaneously unlike in univariate analyses where each correlation of interest is synthesized separately.

One technique proposed by B. J. Becker (1992b) involves the use of generalized least squares (GLS) to model the dependency between correlations when pooling correlation matrices. When the covariances among pairs of correlations are nonzero but very small, the use of univariate analysis is approximately correct (Hedges, 1992). However, when covariances differ substantively from zero then the results from a GLS analysis can be more accurate (B. J. Becker, 1992b) and can be very different from those of a weighted univariate analysis. B. J. Becker (1992b) advocates that the failure to incorporate this dependence into synthesis procedures can lead to biased estimation of the pooled correlation matrix.

Generalized Least Squares Synthesis of Correlations

If q is the total number of variables being summarized, then $q(q-1)/2$ provides the total number of unique correlations in the associated correlation matrix. To implement the GLS approach a variance-covariance matrix, Σ, is estimated for each study's correlation matrix. Each study's Σ is then used to weight the associated correlations in the computation of the resulting correlation matrix, R, pooled across studies. Olkin and Siotani (1976) derived the formulas for the estimation of the variance and covariance for the large-sample normal approximation to the distribution of a vector of correlation estimates. For study i, the population variance of the correlation estimate between variables s and t in study i, r_{ist}, with population correlation of ρ_{ist} is:

$$\sigma^2_{r_{ist}} \approx (1-\rho^2_{ist})^2 / n_i \tag{8}$$

where n_i represents the sample size for study i. The covariance, $\sigma_{ist,iuv}$, between population correlations ρ_{ist} and ρ_{iuv} was derived to be:

$$\begin{aligned}\sigma_{r_{ist},r_{iuv}} = [&0.5\rho_{ist}\rho_{iuv}(\rho^2_{isu}+\rho^2_{isv}+\rho^2_{itu}+\rho^2_{itv})+\rho_{isu}\rho_{itv}+\rho_{isv}\rho_{itu} - \\ &(\rho_{ist}\rho_{isu}\rho_{isv}+\rho_{its}\rho_{itu}\rho_{itv}+\rho_{ius}\rho_{iut}\rho_{iuv}+\rho_{ivs}\rho_{ivt}\rho_{ivu})]/n_i\end{aligned} \tag{9}$$

(Olkin & Siotani, 1976). Since the population parameters, ρ, are unknown, estimates of the variances and covariances for the correlations can be obtained by substituting sample estimates, r, for the corresponding values of ρ.

This variance-covariance matrix is then used to solve the equation:

$$\hat{\rho} = (X'\hat{\Sigma}^{-1}X)^{-1} X'\hat{\Sigma}^{-1} r \qquad (10)$$

where r is the k $px1$ stacked vector of studies' observed correlations (for a meta-analysis based on k studies with p correlations being synthesized). In the current example (see Table 1) the vector of all correlations to be synthesized would be denoted as $r' =$(-.57, -.31, .34, -.64, -.31, .39, -.59, -.34, .36, -.46, -.26, .38). In Equation 10, X is a stack of k pxp identity matrices when none of the k studies are missing any of the p correlation estimates. In the current example with three correlations and four studies X is a 12 x 3 matrix:

$$X= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \hline 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \hline 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \hline 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \qquad (11)$$

The large estimated sample variance-covariance matrix, $\hat{\Sigma}$, is a block-wise diagonal matrix consisting of each study's variance-covariance matrix ($\hat{\Sigma}_1$ through $\hat{\Sigma}_k$). For this four study example:

$$\hat{\Sigma} = \begin{bmatrix} \hat{\Sigma}_1 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & & & & & \vdots \\ 0 & & \hat{\Sigma}_2 & & & & 0 \\ \vdots & & & \ddots & & & \vdots \\ 0 & & & & \hat{\Sigma}_3 & & 0 \\ \vdots & & & & & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & \hat{\Sigma}_4 \end{bmatrix} \tag{12}$$

with $\hat{\sum}_i$ as a 3x3 variance-covariance matrix associated with study *i*'s correlation matrix. In this three variable example between variables *s*, *t*, and *v* (age, speed, and memory, respectively) the formula for the population covariance, $\sigma_{ist,isv}$, between population correlations ρ_{ist} and ρ_{isv} simplifies to:

$$\begin{aligned}\sigma_{r_{ist},r_{isv}} &= [0.5\rho_{ist}\rho_{isv}(1+\rho_{isv}^2+\rho_{ist}^2+\rho_{itv}^2)+\rho_{itv}+\rho_{ist}\rho_{isv} - \\ &(\rho_{ist}\rho_{isv}+\rho^2{}_{its}\rho_{itv}+\rho_{ist}\rho_{isv}+\rho^2{}_{ist}\rho_{ivt})]/n_i\end{aligned}.$$

The primary difference between computation using univariate weighting versus generalized least squares analyses is that under univariate weighting only the variances from study *i*'s correlations are reported along the main diagonal of the $\hat{\Sigma}_i$ s: the values for the covariances are assumed to be zero. Using Equations 8 and 9 and the information in Table 1 the variance-covariance matrices were calculated for each of the four studies. The covariance matrices computed from the correlations reported in Verhaeghen and Salthouse (1997) for the studies from Botwinick & Storindt (1974) and Park et al. (1996) were estimated to be, respectively:

$$\hat{\Sigma}_1 = \begin{bmatrix} .0038 & .0013 & -.0011 \\ .0013 & .0068 & -.0035 \\ -.0011 & -.0035 & .0065 \end{bmatrix} \text{ and } \hat{\Sigma}_2 = \begin{bmatrix} .0012 & .0005 & -.0003 \\ .0005 & .0027 & -.0015 \\ -.0003 & -.0015 & .0024 \end{bmatrix},$$

and those for the studies from Salthouse (1992) and Salthouse, et al. (1996) were, respectively:

$$\hat{\Sigma}_3 = \begin{bmatrix} .0042 & .0015 & -.0013 \\ .0015 & .0078 & -.0042 \\ -.0013 & -.0042 & .0076 \end{bmatrix} \text{ and } \hat{\Sigma}_4 = \begin{bmatrix} .0032 & .0012 & -.0006 \\ .0012 & .0044 & -.0017 \\ -.0006 & -.0017 & .0037 \end{bmatrix}.$$

Combining these matrices to obtain $\hat{\Sigma}$ resulted in a 12 x 12 blockwise diagonal matrix (see Equation 12) comprised of $\hat{\Sigma}_1$ through $\hat{\Sigma}_4$. This $\hat{\Sigma}$ was then used in Equation 10 to obtain the resulting pooled vector of correlations:

$$r = \begin{bmatrix} -.589 \\ -.306 \\ .378 \end{bmatrix}$$

To assess the performance of the *z* transformed correlation for GLS, B. J. Becker and Fahrbach (1994) modified Equation 9 for the computation of the population covariance among pairs of correlations such that:

$$\sigma_{z_{ist}, z_{iuv}} = \sigma_{r_{ist}, r_{iuv}} / [(1-\rho_{ist}^2)(1-\rho_{iuv}^2)] \,. \tag{13}$$

The variance computation is obtained using Equation 6. For further analyses with SEM, the *z* transformed pooled correlation is then transformed back to the *r* metric using Equation 7. A comparison of the results for using the *z* transformation versus untransformed correlations with GLS can be seen in Table 3.

Table 3

GLS Synthesized Correlations Using Transformed and Untransformed Correlations

	Correlations		
Transformation	Age-Speed	Age-Memory	Speed-Memory
Fisher's *Z*	-.577	-.302	.375
None	-.589	-.306	.378

As is apparent from Table 3, the use of transformed and untransformed correlations with GLS can result in fairly different estimates of the elements of the synthesized correlation matrix. In addition, when compared with the corresponding univariate weighted estimates presented in Table 2, it can be seen that all four methods' estimates differ. Several simulation studies have examined multivariate and univariate weighting (with transformed and untransformed correlations) to assess their performance of synthesizing correlations. These studies have reported somewhat varying results depending on the different conditions simulated.

In B. J. Becker and Fahrbach's (1994) simulation study the performance of multivariate versus univariate weighting techniques was compared under various manipulated conditions. These conditions included the number of studies, the sample size per study, and the use of transformed versus untransformed correlations. They examined how well the two methods estimated the population correlation matrix for correlations between three variables. They concluded that the traditional GLS procedure was unsatisfactory when compared to the univariate procedure in terms of the bias and standard errors of the estimates of the population correlations across all study conditions.

Hafdahl (2001) conducted a simulation study to assess the effects of GLS versus univariate weighting for the resulting pooled correlation matrix using 12 variables. The author reported that univariate weighting methods (including Fisher's *z* transformed correlations) outperformed GLS in terms of the estimates of bias, standard error, root mean squared error, and confidence intervals of the pooled correlation matrix under varying number of studies included. In the simulation study the sample size was varied within simulated meta-analyses. GLS produced a substantial positive bias and small standard errors of the synthesized correlation estimates, which created very inefficient pooled correlation estimates and confidence intervals. This bias for GLS increased when more studies were included in the meta-analyses.

Due to the poor performance of GLS in pooling correlation matrices several researchers proposed new methods for use with GLS. Becker and Fahrbach (1994) and S. Cheung (2000) both noted that it was most likely that the inefficient estimates of the covariance between correlations for the variance-covariance matrix, $\hat{\Sigma}$, that had resulted in the inadequate performance of GLS. Because each covariance was estimated using individual correlations containing measurement error, both studies proposed computing some type of average value to estimate the covariance and thus account for some of this measurement error. In Becker and Fahrbach's (1994) study the covariance was computed by using the average of the correlations for the estimates of each population correlation. In S. Cheung's (2000) study, instead of a direct average, a univariate weighting approach was used in which each correlation was weighted by its sample size. The correlations were then summed and divided by the total sample size to obtain the weighted correlation for each estimate of the population correlation. Then, these synthesized (or in Becker & Fahrbach's study, the mean) correlations were used to estimate each study's variance-covariance matrix along with the study's sample size, n_i. Equations 8 and 9 for computing the variances and covariances, respectively, for the *i*th study were modified in these approaches to be:

$$\hat{\sigma}^2_{r_{ist}} \approx (1-\bar{r}^2_{st})^2 / n_i \text{ , and} \tag{14}$$

$$\begin{aligned}\hat{\sigma}_{r_{ist},r_{iuv}} &= [0.5\bar{r}_{st}\bar{r}_{uv}(\bar{r}^2_{su}+\bar{r}^2_{sv}+\bar{r}^2_{tu}+\bar{r}^2_{tv})+\bar{r}_{su}\bar{r}_{tv}+\bar{r}_{sv}\bar{r}_{tu}- \\ &(\bar{r}_{st}\bar{r}_{su}\bar{r}_{sv}+\bar{r}_{ts}\bar{r}_{tu}\bar{r}_{tv}+\bar{r}_{us}\bar{r}_{ut}\bar{r}_{uv}+\bar{r}_{vs}\bar{r}_{vt}\bar{r}_{vu})]/n_i\end{aligned} \tag{15}$$

The traditional GLS procedures apply for the additional steps in the computation of the final pooled correlation matrix, $\hat{\rho}$ in Equation 10.

A slightly different approach than those of Becker and Fahrbach (1994) and S. Cheung (2000) of computing the variance-covariance matrix for each study could also be considered. Specifically, like S. Cheung (2000), a weighted estimate of the population correlation matrix is used to estimate the variance-covariance matrix. However, for this study, Hedges-Olkin's univariate weighting method for synthesizing correlations (see Equation 4) was used rather than the weighting procedure used by S. Cheung (2000) since it was the method used for the univariate weighting procedure for this study. These synthesized correlations were then used to compute the variances and covariances (see Equations 14 and 15, respectively). To differentiate this method from those used by Becker and Fahrbach (1994) and S. Cheung (2000), the procedure used in this study will be referred to as W-COV GLS.

To implement W-COV GLS for this study with transformed correlations, elements of each study's correlation matrix are first transformed using Fisher's z (see Equation 5). Each study's transformed correlation matrix is then synthesized using Hedges-Olkin univariate weighting procedures to result in a synthesized transformed correlation matrix. These synthesized correlations are then transformed back to the r metric using Equation 7 prior to the computation of the variance-covariance matrix. This synthesized transformed correlation matrix is then used to compute the variance-covariance matrix for each study along with the study's sample size, n_i using Equations 14 and 15. The correlations in the vector, r, for each study are z-transformed and then the traditional GLS procedures are used (see Equation 10) to calculate the final synthesized matrix. These pooled z-transformed correlations are then transformed back to the r metric (see Equation 7). Differences between the estimates of synthesized correlations (using the correlations from Table 1) with the procedures for W-COV GLS for transformed and untransformed correlations can be seen below in Table 4.

Table 4

W-COV GLS Synthesized Correlations Using Transformed and Untransformed Correlations

	Correlations		
Transformation	Age-Speed	Age-Memory	Speed-Memory
Fisher's Z	-.576	-.300	.375
None	-.572	-.300	.375

Becker and Fahrbach (1994) compared the performance of the traditional GLS method for computing the variance-covariance matrix with those computed via their method of using a direct average of the correlations on the pooled correlation matrix in their simulation study. They found that even for small study samples the bias was minimal when using average correlations to compute the variance-covariance matrix with GLS for computation of the covariances. In contrast, the pooled correlation matrices based on traditional GLS procedures yielded moderate to severe positive bias especially with small sample sizes. This bias was compounded by the addition of studies. The variability was also overestimated with this method. The study also indicated the superiority of Fisher's *z* transformation with the average-$\hat{\Sigma}$ over the traditional-$\hat{\Sigma}$ with GLS. They reported that this method reduced spurious variation in the covariance matrix and improved the overall results. The authors concluded that for the conditions examined in the study, the average-$\hat{\Sigma}$ GLS method with Fisher's transformation was superior to the univariate weighting analyses and traditional GLS procedures.

In S. Cheung's (2000) simulation study, the performance of univariate weighting with his weighted average-$\hat{\Sigma}$ and with traditional $\hat{\Sigma}$ for GLS procedures was compared. The study reported that use of the weighted average-$\hat{\Sigma}$ GLS method resulted in superior performance over the univariate weighting procedure. The parameter estimates for the pooled correlation matrix with this procedure were estimated without bias for both listwise and pairwise deletion (in contrast with those for the traditional $\hat{\Sigma}$ GLS procedure). Thus, whereas the use of traditional $\hat{\Sigma}$ GLS procedures does not seem to be appropriate for synthesizing correlations, results from some type of GLS procedure involving use of an average-$\hat{\Sigma}$ have produced more accurate estimates.

Neither Hafdahl (2001) nor B. J. Becker and Fahrbach's (1994) meta-analytic studies investigated the impact of missing correlations on the synthesis techniques being compared. There are several reasons why correlations of interest might be missing from a study. The next section will describe sources of possible missingness as well as how univariate weighting and GLS synthesis methods address missing data.

Reasons for Missing Data within a Research Synthesis

When conducting a meta-analytic synthesis, the problem of missing correlations frequently arises. This missingness can be the result of several types of scenarios. Missing data mechanisms can be classified into three groups: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR) (Little & Rubin, 1987). Data are called MCAR if missingness occurs purely by chance. With MCAR data the value of a variable is independent of both the variable itself and the other variables in the model. Graham, Hofer, Donaldson, MacKinnon and Schafer (1997) have noted that data are rarely missing completely at random unless the missingness was planned by the researcher. Data are MAR when the values of the variable do not depend on the values of data that are missing but depend on some characteristic of the data that is observed. MNAR data, or non-ignorable missingness, is the term used for the scenario where missingness is related to the value of the variable itself (Little & Rubin, 1987; Pigott, 1994).

While studies are frequently designed to investigate more than one outcome, it is uncommon for all studies in a meta-analysis to report all of the correlations of interest. Missingness can occur as the result of several different causes. There may not be room in an article to include all correlations, researchers do not always report nonsignificant correlations (file-drawer problem), or the variables of interest for the meta-analysis may not have been examined in the study. Studies such as dissertations allow more room for relevant correlations than what is permissible in a published article. Second, the individual study may not have analyzed all of the variables of interest in the meta-analysis. An individual study may focus on one aspect of relevance to the meta-analysis but not on another. For example, a meta-analyst might be interested in synthesizing correlations between the variables age, speed, and working memory. However, an individual study might only be concerned with the relationship between age and working memory and only report the correlation between these two variables. Data can also be missing as a result of the file-drawer problem (Rosenthal, 1979) in which a potential selection bias may occur whereby correlations that are non-significant or not in the predicted direction are not reported. This type of missing data is considered MNAR because the missingness is contingent on the values of the data missing.

A study by Premack and Hunter (1988) where meta-analytic SEM was performed will be used as an example to illustrate a common problem with missing data in applied meta-analytic SEM research. The authors were interested in the relationship between six different variables in their study (they later combined two of these variables). Premack and Hunter (1988) examined the variables predicting an individual's decision to vote for or against union representation. They used 14 different studies in their meta-analysis, of which there were none that reported all six of the variables of interest. Of the six variables, there was no one variable that all of the studies reported. In total, for all of the variables the researchers were interested in, only about 55% of the correlations between variables needed for the meta-analysis were present in all of the studies.

Because researchers are more interested in certain relationships, the situation regularly arises where some correlations are reported more often than others in the literature. This results in the scenario where some correlations are more commonly missing than others because they have not been studied as frequently. Harris and Rosenthal (1985) conducted a meta-analytic study using path analysis on the pooled correlations to examine a model of the mediation of interpersonal expectancy effects. They noted that some correlations had been reported more often than others. For example, the correlation between expectancy and output was reported 48 times out of 50 in the primary studies collected for the meta-analysis, while the correlation between output and outcome was only reported six times. Other researchers have also pointed out that certain relationships of interest for the meta-analysis are studied more often than others. B. J. Becker (1992a) noted in an analysis of a model of social and psychological factors in achievement behaviors that out of 32 studies the relationship between aptitude and achievement was well studied in the literature with 100 correlations reported while the relationship between achievement and a measure of self-concept was only represented by 12 correlations.

While missing correlations affect the estimation of both GLS procedures and univariate procedures for synthesizing correlations, missing correlations provide a particular problem for the use of GLS procedures. Missing correlations have an impact on the estimation of GLS results because the computation of the covariance between two *r*s (see Equation 9) requires all other correlations that share subscripts with the two covarying correlations of interest. For example, if r_{ist} and r_{isv} were reported in a study and not r_{itv} then $\sigma_{r_{ist},r_{isv}}$ could not be calculated. Some estimate of r_{itv} is needed and therefore, methods for dealing with missing data must be employed. Several of these methods will be described in the next section.

Strategies for Dealing with Missing Data

For the univariate weighted synthesis of a correlation matrix, a common method for dealing with missing data involves using only studies that provide the entire correlation matrix of interest. This method, known as listwise deletion, results in the analysis of studies with only complete data. However, when large amounts of data are missing across studies, this may lead to a much smaller sample of studies that will be analyzed. The researcher makes the assumption that the complete cases are representative of the original sample of studies (Pigott, 1994). The information from the missing data are ignored in listwise deletion. Pigott (1994) has noted that when there are small amounts of data missing and the data are MCAR then using listwise deletion in meta-analysis is appropriate but if the data are MAR or MNAR then listwise deletion can result in biased results. However, the use of listwise deletion is not always a realistic alternative for multivariate meta-analysis, particularly when the researcher is interested in a large number of variables. For example, if listwise deletion had been employed with Premack and Hunter's (1988) study, all studies would have been deleted (since each study had some missingness).

To avoid dropping all cases with missing data, some researchers have advocated the use of pairwise deletion for univariate weighted analyses. This method involves using each correlation reported in studies. Pairwise deletion maximizes the amount of data available for the variables of interest. In applied research on meta-analytic SEM, pairwise deletion is the method most frequently used to address missing data with univariate weighting analyses (e.g., Brown & Peterson, 1993; Premack & Hunter, 1988; Verhaeghen & Salthouse, 1997). However, there are problems involved with using pairwise deletion as well. The use of pairwise deletion means that the pooled correlation between variables *s* and *t* might be based on a different number of studies than the synthesized correlation between variables *u* and *v*. Along with the problem of determining which sample size to use for ensuing analyses of the resulting synthesized correlation matrix, pairwise deletion can also result in non-positive definite correlation matrices because each element of the correlation matrix is computed from a different subset of the cases (Arbuckle, 1996). A non-positive definite correlation matrix occurs when the determinant of the correlation matrix (or any principal submatrix) is zero or negative. A non-positive matrix is a problem for SEM analyses because estimation procedures involve inverting the correlation matrix. The process of inverting the matrix involves dividing by the matrix determinant, which when zero results in a non-positive definite correlation matrix.

When pairwise deletion is used with GLS procedures then the matrices, X and $\hat{\Sigma}$, as well as the vector, r, are modified for the computation of the synthesized correlation matrix. The vector of correlations, r, and the matrix, X, in Equation 10 are reduced by removing the rows corresponding to missing correlations. In addition, rows and columns corresponding to the missing observations are deleted from the covariance matrix, $\hat{\Sigma}_i$ corresponding to the study i with missingness. However, as has been mentioned and is evident in Equation 9, for the computation of the covariance between two correlations, say r_{ist} and r_{isv}, the value of r_{itv} is still needed. Researchers have avoided this problem when calculating $\hat{\Sigma}$ by substituting a pooled estimate for r_{itv} (for example, S. Cheung, 2000; B.J. Becker & Schram, 1994). This estimate has typically been computed using one of the univariate weighting methods. This method first involves computing the weighted univariate average across studies using listwise or pairwise deletion. Then this resulting estimate of the population correlation is substituted for the missing correlation in the computation of the covariance between the two non-missing correlations. A GLS analysis can then be performed.

The adequacy of the methods listed above for dealing with missing data also depend on the reasons why the data are missing from the study. Listwise deletion for univariate weighting and GLS procedures may work well when correlations are MCAR and when there is not a large amount of missingness. However, when the data are MNAR or MAR and/or there is a large degree of missing data then the values of the synthesized correlations may be seriously biased when using listwise deletion for univariate weighting and GLS procedures (Pigott, 1994). With MNAR or MAR data and large amounts of missingness, pairwise deletion can also result in large bias estimates (Pigott, 1994), however, because pairwise deletion uses more of the available information it is expected that the results would be less biased than those from listwise deletion.

Using the previous real data example (see Table 1), listwise deletion and pairwise deletion for univariate weighting, GLS, and W-COV GLS will be illustrated when one of the variables (memory) is randomly missing from one study. Table 5 lists the correlations and indicates the missing correlations corresponding to the missing variable.

Table 5

Sample Correlations with Missingness

		Correlations		
Study	Sample(n)	Age-Speed	Age-Memory	Speed-Memory
Botwinick & Storandt (1974)	120	-.57	--	--
Park, et al. (1996)	301	-.64	-.31	.39
Salthouse (1992)	100	-.59	-.34	.36
Salthouse, et al. (1996)	197	-.46	-.26	.38

In Table 6 below, the results can be seen for univariate weighting, GLS, and W-COV GLS for the correlations contained in Table 5 using pairwise and listwise deletion.

Table 6

Synthesized Untransformed Correlations Using Listwise and Pairwise Deletion

Method of Deletion	Relationship	Univariate Weighting	GLS	W-COV GLS
Listwise	Age-Speed	-.591	-.593	-.572
	Age-Memory	-.300	-.306	-.299
	Speed-Memory	.382	.384	.382
Pairwise	Age-Speed	-.589	-.589	-.572
	Age-Memory	-.300	-.304	-.298
	Speed-Memory	.382	.383	.382

As can be seen in Table 6, when there are missing correlations then the estimates of the pooled correlations can be somewhat different depending on whether listwise or pairwise deletion is used. In a simulation study, M. Cheung and Chan (2002) examined the performance of traditional GLS versus univariate weighting (including the use of Fisher's *z*) in a Monte Carlo study. The study included MCAR data that were handled with the use of pairwise deletion and also manipulated sample size across simulated meta-analyses. Specifically, the study examined these methods for synthesizing correlations based on their performance in the homogeneity test. The homogeneity test is a goodness-of-fit test (measured by a chi-squared statistic with a null hypothesis of homogeneity) based on the amount of variation in the correlations across studies (B. J. Becker, 2000). A large amount of variation (greater than would be expected given sampling error) signifies that the correlations may be derived from more than one population and that a random-effects model may be more appropriate. M. Cheung and Chan (2002) concluded that traditional GLS was unsatisfactory in estimating the homogeneity of the correlations with sample sizes less than 500 while both univariate weighting methods (*r* and *z* transformed) produced more accurate results. However, the conclusion of the inferior performance of GLS was based only on the estimates from the test of homogeneity of the correlation matrix and not the bias present in the estimates of the synthesized correlations and their corresponding standard error estimates.

S. Cheung's (2000) simulation study compared the performance of traditional GLS, the weighted average method for computing $\hat{\Sigma}$ with GLS, and univariate weighting procedures on the pooled correlation matrix. Data was designated to be MCAR and missingness was handled with both pairwise and listwise deletion. Similar to M. Cheung and Chan's (2002) study, the resulting pooled correlation matrix was only evaluated in terms of its performance for the test of homogeneity of the correlation matrix. The study reported that both listwise and pairwise GLS had chi-squared rejection rates substantially above the nominal level of 5% with pairwise deletion resulting in much larger values than listwise. The univariate approach demonstrated better rates closer to 5% for both listwise and pairwise deletion. The performance of the weighted average-$\hat{\Sigma}$ GLS procedure showed superior performance over traditional GLS and was comparable to that of univariate weighting.

In summary, the research indicates that univariate methods seem to perform better than traditional GLS for pooling of correlation matrices in the presence of missingness according to the test of homogeneity of the correlation matrix while the weighted average method for computing the variance-covariance matrix for GLS appears to perform comparably to univariate weighting. However, these two studies (M. Cheung & Chan, 2002; S. Cheung, 2000) have not indicated how GLS procedures performed relative to univariate weighting in the presence of missing data with criteria other than the test of homogeneity (i.e., bias of the synthesized correlation estimates). The next section in this paper will address the use of meta-analysis with structural equation modeling in the presence of missing data.

Meta-Analysis and Structural Equation Modeling

Missing data initially affects not only the first step in meta-analytic SEM, the computation of the synthesized correlation matrix, but also has implications for the second step, the resulting structural equation modeling (SEM). In the context of theory building with SEM, researchers typically encounter the scenario where numerous studies do not report all of the correlations of interest. Viswesvaran and Ones (1995) report several options for dealing with missingness when incorporating synthesized correlation matrices into structural equation modeling. Researchers have in some cases limited themselves to studying the theoretical relationships only for constructs for which a full matrix of correlations is present in the literature (e.g., Hom et al., 1992). As mentioned earlier, this use of listwise deletion can create biased results, particularly when there are a large number of studies that have only examined a subset of the variables of interest and are therefore deleted from further analyses. Others have used pairwise deletion to incorporate studies with missing data when computing their synthesized correlation matrix (e.g., Hunter, 1983; Verhaeghen & Salthouse, 1997). Pairwise deletion is typically more popular in meta-analytic SEM partly because it makes use of all the relevant correlations of interest with little loss of information. However, pairwise deletion has several implications for when the matrix is then used in a structural equation modeling analysis. First, pairwise deletion can result in a non-positive definite correlation matrix that might produce non-convergence for the SEM solution. In addition, there is the problem of determining which sample size to use for estimation of the resulting model.

While the possibility of a non-positive definite correlation matrix has been noted with meta-analytic SEM, it has not been supported with empirical evidence (e.g., M. Cheung & Chan, 2002; Viswesvaran & Ones, 1995). Because the correlations used in meta-analytic SEM have been meta-analytically derived, they are typically based on large sample sizes and thus non-positive definiteness should be less of a problem. Marsh (1988) conducted a simulation study to examine the performance of pairwise deletion under various degrees of missingness with covariance structures. The study found that only when the sample size was as small as 200 and the percent of MCAR data was equal to 50 that a problem existed with non-positive definite matrices.

Sample size is also a relevant concern in structural equation modeling. Larger sample sizes are necessary in order to ensure stable estimation, particularly when the structural model is more complex (i.e., a large number of variables and/or paths). Kline (1998) noted that studies involving sample sizes of fewer than one hundred should not use SEM to analyze data because the estimation of the model parameters is not appropriate. A potential role for the use of meta-analytic techniques lies in increasing the sample size for the resulting SEM by combining results from multiple studies.

When not every study contributes all necessary correlations then determining the sample size for use as input into the SEM analysis becomes more complicated. If listwise deletion is used then the total sample size is obtained by summing together the sample sizes associated with each study included in the meta-analysis (those without missing data). However, if pairwise deletion is used then typically either the median or mean sample size of the correlations in the pooled correlation matrix has been employed (for example, Brown & Peterson, 1993; Carson, Carson, & Roe, 1993). Using the data in Table 4 with pairwise deletion for missingness, the synthesized correlation between age and speed is based on a sample size of 718, age and memory is 598, and speed and memory is 598. By taking the average of these sample sizes the resulting input SEM sample size is now 638 and the median value is 598.

In Marsh's (1998) simulation study, the performance of different sample sizes with pairwise deletion under various degrees of missingness was examined for bias estimates of the chi-squared statistic with covariance matrices in SEM. The study assessed the performance of pairwise deletion using the minimum, mean, and maximum sample size associated with each covariance term. Using the previous example, the equivalent for meta-analytic SEM would be to use 598 for the minimum sample size, 638 for the mean, and 718 for the maximum. Marsh (1998) reported that use of the minimum sample size was the most adequate estimator of the chi-squared statistic among the three but that use of this sample size did not fully eliminate the bias in the chi-squared statistic, particularly when 50% of the data were missing.

A potential problem for meta-analytic SEM is the use of the synthesized *correlation* matrix for SEM techniques. Ideally researchers should use covariance matrices for structural modeling due to potential problems with the resulting estimation of the standard errors and test statistics when correlation matrices are used (Cudeck, 1989; Kline, 1998). Cudeck (1989) reported that some standard errors are incorrect in almost all studies using correlation matrices. If a model is not scale-invariant then all the standard error estimates will be incorrect (Browne, 1982; Cudeck, 1989). However, studies reporting correlations typically do not report the standard deviations needed to compute the covariances. In addition, meta-analytic techniques for synthesizing covariance matrices have not yet been fully developed. Widely used SEM programs have also not developed techniques to appropriately analyze correlation matrices. There are several programs such as SEPATH (Steiger, 1999) and RAMONA (Browne, 1997) which will produce more accurate standard error estimates with correlation matrices. However, these programs are typically not used by applied researchers. Therefore, in conducting meta-analysis with structural equation modeling the correlation matrix has only been used for analysis in both applied and simulation studies (e.g., S. Cheung, 2001; Hafdahl, 2001; Premack and Hunter, 1988). It should not however be assumed that the results of the SEM with use of a correlation matrix would be the same as if a covariance matrix has been used.

In a simulation study, Hafdahl (2001) examined a comparison of multivariate versus univariate weighting techniques for recovering factor loadings using exploratory factor analysis with varying numbers of studies. It was reported that the estimated factor loadings and global factor-pattern recovery based on synthesized correlation matrices from both univariate-*r* and univariate-*z* approaches were almost always more accurate and efficient than those based on the traditional method of GLS synthesis. These findings were also more pronounced for meta-analyses as sample size increased (particularly when 100 or 200 studies were combined).

When data are MCAR then both listwise and pairwise deletion should result in unbiased SEM parameter estimates for large sample sizes (Bollen, 1989). In a simulation study to examine the performance of pairwise deletion with covariance matrices for SEM, Marsh (1988) determined that when data are MCAR and pairwise deletion was used there was no impact of the percent missingness (from 1% to 50%) on parameter estimation bias with varying sample sizes of 200, 500, and 1000. However, the study also reported that use of pairwise deletion resulted in positive bias in the estimation of the chi-squared test statistic of the data-model fit and the size of this bias became larger with increasing amounts of missingness. While Marsh (1998) pointed out that investigating MCAR data (since it is frequently seen as implausible in applied meta-analysis) was a major limitation of the study there is currently no known information on the impact of pairwise deletion on data that are MNAR.

Several recent simulation studies have examined the performance of meta-analytic SEM using a correlation matrix under various conditions with missing data. S. Cheung (2000) conducted a simulation study with MCAR data and examined the performance of both pairwise and listwise deletion using meta-analysis for use with path analytic models. S. Cheung (2000) evaluated the performance of GLS, weighted average-

$\hat{\Sigma}$ GLS, and univariate weighting while manipulating several conditions and using different criteria for assessing the performance of each. Some of the main criteria evaluated in the study included the SEM parameter estimate bias, the confidence intervals for these estimates, and the goodness-of-fit of the path-analytic model using the chi-squared test of goodness-of-fit. Using both listwise and pairwise deletion for the methods of synthesizing correlations, the model parameter estimates were reported to have negligible bias. In evaluating the goodness of fit for the path model, S. Cheung reported that listwise deletion for univariate weighting, weighted-$\hat{\Sigma}$ GLS, and GLS produced chi-squared rejection rates at the expected level of 5%. However, when pairwise deletion was used, all synthesis methods demonstrated rejection rates above the nominal level. Whereas the chi-squared value for the fit of the model with weighted average-$\hat{\Sigma}$ GLS resulted in inflated rejection rates with pairwise deletion, the over-rejection rates was smaller than with the univariate pairwise deletion procedure.

M. Cheung and Chan (2002) conducted a meta-analytic SEM simulation study examining the performance of traditional GLS versus univariate weighting with MCAR data using pairwise deletion. In evaluating the synthesis methods' performance in terms of model fit, they reported that both GLS and the univariate procedures resulted in inflated chi-squared values for the test of the fit of the model. This positive bias for the chi-squared values decreased for GLS when the sample sizes per study increased. M. Cheung and Chan (2002) also reported that the SEM parameter estimates for GLS were generally biased except when the sample size was large (500 or 1,000) while the parameter estimates for univariate weighting were typically unbiased. The relative bias for the standard errors of the SEM parameter estimates in GLS was very large with small sample sizes (50 or 100) but decreased dramatically as the sample sizes increased. The bias of the standard errors of the paths for the univariate weighting methods was also relatively large. These researchers concluded that using traditional GLS with meta-analytic SEM may not be appropriate due to its poor performance in the study.

Statement of the Problem

This section will begin by summarizing the findings concerning the performance of GLS, W-COV GLS, and univariate weighting for meta-analytic SEM. Whereas the use of GLS for synthesizing correlation matrices, in theory, should result in more accurate estimates because it accounts for the dependency between correlations, a series of simulation studies have instead reported the poor performance of GLS in comparison with univariate techniques. Researchers have indicated that GLS has performed poorly in estimating the pooled correlation matrix (B. J. Becker & Fahrbach, 1994; Hafdahl, 2001), the path parameters for the ensuing structural equation model, the standard errors of the paths, and the chi-squared test of the fit of the model (M. Cheung & Chan, 2002 S. Cheung, 2000; Hafdahl, 2001) in comparison with univariate weighting procedures. However, when the GLS procedure was enhanced so that some type of average $\hat{\Sigma}$ was used for the computation of the variance-covariance matrix, then GLS has been found to outperform both traditional GLS and univariate weighting procedures (Becker & Fahrbach, 1994; S. Cheung, 2000). Therefore, this study will examine the performance of GLS using the W-COV GLS procedure described earlier for computing the variance-covariance matrix.

Whereas researchers have examined the performance of weighted average-$\hat{\Sigma}$ GLS procedures and univariate weighting with missing correlations (S. Cheung, 2000), the amount of missing data has not yet been manipulated. Additional research is needed that compares the performance of synthesis methods when there are varying degrees of missing data. Missing data are frequently a problem with multivariate meta-analysis, particularly when researchers are interested in the relationship between large numbers of variables. Therefore, it is necessary to examine how the performance of W-COV GLS and univariate weighting procedures affect estimation of the pooled correlation matrix and ensuing SEM parameters in scenarios with varying amounts of missing data.

In addition, previous simulation studies that have examined the effects of missing data have only investigated the condition where the data are MCAR but have not included the condition where data are MNAR or MAR. As noted earlier, it is more realistic for certain correlations to have been reported more frequently than others and to have correlations that are smaller in magnitude not reported due to the file-drawer problem. In particular, correlations that are not reported due to the magnitude of the correlation are MNAR. The assumption of completely random missingness is often unrealistic in applied research. Therefore, it is unlikely that correlations are MCAR as has been assumed in previous simulation studies. Additional research is needed to examine the condition where certain correlations have been reported less frequently than others and are therefore missing not at random. The absence of these correlations could result in inadequate estimation of the synthesized correlations and the ensuing structural model's parameters.

Additional research is also necessary to assess the performance of W-COV GLS procedures versus univariate weighting with listwise and pairwise deletion under various patterns and types of missingness. S. Cheung (2000) evaluated the performance of a weighted average-$\hat{\Sigma}$ with GLS, traditional GLS, and univariate weighting using listwise and pairwise deletion and reported that listwise deletion was superior over pairwise deletion for all synthesis methods in all conditions. S. Cheung also reported that the use of GLS with the weighted average-$\hat{\Sigma}$ resulted in unbiased results for both listwise and pairwise deletion. However, the performance of these synthesis methods using listwise and pairwise deletion is not known under varying degrees of missing data and when data are MNAR.

Researchers have also reported conflicting findings regarding the performance of traditional GLS procedures versus univariate weighting with Fisher's transformed and untransformed correlations. Becker and Fahrbach (1994) reported that use of Fisher's transformation resulted in more accurate estimates for the pooled correlation matrix for both univariate weighting and GLS. Hafdahl (2001) also reported that transforming correlations using Fisher's *z* resulted in superior estimation of the synthesized correlation matrix over the use of untransformed correlations. However, other researchers (i.e., Hunter & Schmidt, 1990) have concluded that transforming correlations results in synthesized correlations that are positively biased and therefore should not be used. The performance of W-COV GLS with transformed and untransformed correlations is unknown and should be investigated.

Varying sample size across studies within a simulated meta-analysis is another area not always examined in simulated meta-analytic SEM research. Only S. Cheung (2000) and Hafdahl (2001) have examined this. Two simulation studies (B. J. Becker & Fahrbach 1994; M. Cheung & Chan, 2002) did not vary sample size across studies within each simulated meta-analysis. Instead, sample size was held constant within simulated meta-analyses and only varied across meta-analyses. Both studies noted, however, that future research should address the more authentic scenario where sample size varies within a meta-analysis. In primary studies, correlations are based on sample sizes that can range from less than 20 to several thousand people. Additional research is needed to assess the impact of missing variables in meta-analytic SEM while reflecting this variability in sample sizes typically found in a meta-analysis.

The effect of the number of studies included in the meta-analysis on the estimation of the pooled correlation matrix and the resulting SEM analysis is an area of additional research interest. Hafdahl (2001) reported that the bias in the pooled correlation estimates for traditional GLS procedures increased when more studies were included in the meta-analyses thus indicating an effect of the number of studies synthesized in meta-analytic SEM. In reviewing the applied research on meta-analytic SEM, the number of studies included have ranged anywhere from as small as four (Schmidt, Hunter, & Outerbridge, 1986) to 155 studies (Tett & Meyer, 1993) with an average value of around 30 studies included. Research should reflect this variability in number of studies included in meta-analyses found in the literature.

Researchers have also suggested examining indices other than the chi-squared statistic when interpreting the goodness-of-fit of structural equation models with meta-analysis (Cheung & Chan, 2002). Because the chi-squared statistic is influenced by sample size it may indicate a significant value (lack of model fit) when it is really an artifact of the large sample size and the model should not be rejected. Studies using meta-analytic SEM in the applied literature have reported fit statistics other than the chi-squared value among them the Goodness of Fit Index (GFI), the Comparative Fit Index (CFI) and the Normed Fit Index (NFI) (e.g., Hom et al., 1993; Verhaeghen & Salthouse, 1997). Hu and Bentler (1997) have recommended the use of joint criteria with fit indices when selecting a model. In fact, applied researchers frequently reject the use of the chi-squared statistic for meta-analytic SEM since the pooled correlations are typically based on large sample sizes. Whereas fit indices other than the chi-squared statistic are frequently evaluated in the applied literature, to date, no simulation study for meta-analytic SEM has examined the performance of goodness-of-fit tests other than the sample-sensitive chi-squared test.

Purpose

The purpose of this simulation study is to extend the research concerning the performance of the GLS procedure (specifically the W-COV adaptation) versus univariate weighting for meta-analytic SEM of observed variables under various patterns of missing data. The performance of these methods for synthesizing correlations and in estimating the ensuing structural model parameters will be examined while manipulating conditions examined in previous studies, such as the number of studies in the meta-analysis, and using Fisher's (1928) transformed versus untransformed correlations. However, the current study will extend previous research by investigating additional conditions, including the degree of missingness, and the type of missingness (MCAR versus MNAR). The results of this study will have applications to both multivariate meta-analysis and meta-analytic SEM.

Chapter 3: Method

A Monte Carlo simulation study was conducted to assess the performance of univariate weighting and W-COV GLS for synthesis of correlations for use with meta-analytic SEM under different patterns and types of missingness. Of additional interest in this study was the performance of these methods with *z*-transformed and untransformed correlations as well as with listwise versus pairwise deletion. The results were evaluated in terms of estimation of the pooled correlation matrix as well as the resulting structural equation model parameter estimation. Several conditions were varied, including the number of studies, the degree of missingness (both in terms of number of studies and number of variables with missingness), and the type of missing data. The performance of these methods for synthesizing correlations was assessed through the resulting synthesized correlation estimate relative bias and the relative bias of the SEM path coefficients and their standard errors. In addition, the conclusions concerning model fit associated with four SEM fit indices were also investigated.

Study Design

The SEM model parameters used to generate data for all study conditions were taken from Hunter and Premack's (1988) meta-analytic SEM study using real data in order to approximate authentic meta-analytic SEM conditions. This path analytic model (SEM of observed variables) includes five variables and can be seen in Appendix A along with the standardized path values. This model was also selected because it had a variety of characteristics frequently found in models from applied meta-analytic SEM studies. These characteristics include the presence of mediating variables, path coefficients and model-implied correlations that reflect a variety of magnitudes from small to moderate, including both positive and negative relationships.

Number of Studies. The data generated were varied across several design factors. First, the number of studies included in the meta-analysis was varied. To determine reasonable values for the number of studies included, a review of applied as well as simulation meta-analytic SEM studies in the literature was conducted. In the applied literature, the number of studies included varied anywhere from four studies (Schmidt, Hunter, & Outerbridge, 1986) to 155 studies (Tett & Meyer, 1993) and typically involved around 30 studies. In the simulation studies, typical values examined included small numbers as low as five as well as more moderate levels such as 20 or 50 (Becker & Fahrbach, 1994; M. Cheung & Chan, 2002; S. Cheung, 2001; Hafdahl, 2001). Two values were therefore chosen to represent small, 10, and moderate, 30, numbers of studies included in meta-analyses.

Percentage of Studies with Missingness. The second design factor chosen to vary was the amount of studies with missing variables. Based on a review of the meta-analytic SEM literature, the number of studies with missing variables was manipulated to reflect scenarios found in applied research (for example, Verhaeghen & Salthouse, 1997). Three levels of missingness were used in this study to reflect these authentic scenarios including: none, 20%, and 40% of studies with missing data.

Percentage of Variables Missing. The third design factor varied was the percentage of missing variables within the studies that were selected to have missing data. Researchers have reported as much as 45% of the correlations of interest missing for a meta-analytic SEM study (for example, Premack & Hunter, 1988). Two levels were chosen to reflect varying degrees of missingness based on reviewing applied meta-analytic SEM research. Within studies designated to have missingness, these two conditions included scenarios where 20% and 40% of the variables were missing.

Type of Missingness. The fourth design factor selected to vary was the type of missing data. Previous meta-analytic SEM simulation studies investigating synthesis of correlation matrices have involved data missing completely at random (MCAR). In the current study results for MCAR data were investigated. However, applied researchers have noted that typically some correlations of interest are studied more frequently than others (Becker, 1992a; Harris & Rosenthal, 1985) and that some correlations are not reported as often because of non-significance (Rosenthal, 1979). To reflect these scenarios, results for data missing not at random (MNAR) were also evaluated. In conditions with MCAR data, every variable had an equal probability of being designated as missing. In the MNAR case, certain variables were selected to have missingness contingent on certain values of their corresponding correlations. Specifically, to replicate the file drawer problem correlations sampled from population correlations that were smaller in magnitude were selected to be missing. This process will be elaborated on later in this chapter.

Sample Size. The within-study sample size was varied by sampling from a distribution of sample sizes. It should be noted that this is not a design condition for this study because the degree of the variation was constant. The sample sizes used in this approach were adapted from Verhaeghen and Salthouse's (1997) meta-analytic SEM analysis of 91 studies. These sample sizes can be seen in Appendix B and range in value from 35 to 1680. Each study within the simulated meta-analysis was associated with a different sample size randomly sampled with replacement from this distribution. The use of this method was chosen to approximate authentic meta-analytic conditions where correlations across studies are based on varying sample sizes.

Synthesis Methods Compared. The primary purpose of this study was to assess the performance of univariate weighting versus W-COV GLS methods under different patterns and types of missingness. Therefore, univariate weighting and W-COV GLS methods for pooling correlation matrices were evaluated (as described below) in terms of the estimation of the synthesized correlation matrices and the resulting SEM parameters for each condition and with the baseline condition of no missing data. These methods for pooling correlation matrices were assessed when used with *z* transformed and untransformed correlation coefficients. Both pairwise and listwise deletion were used with each synthesis method to compare their performances for handling missingness.

Study Design Overview

The four design factors examined in this study were fully crossed [2 (number of studies) x 2 (percentage of studies with missing variables) x 2 (percentage of missing variables) x 2 (type of missing data)]. Each of these 16 conditions were compared for their performance using eight different methods for synthesizing the pooled correlation matrix (see Table 7): univariate weighting (Univariate-*r)* combined with listwise and pairwise deletion, univariate weighting with *z* transformation (Univariate-*z*) combined with listwise and pairwise deletion, W-COV GLS (W-COV GLS-*r*) combined with listwise and pairwise deletion and W-COV GLS with z transformation (W-COV GLS-z) combined with listwise and pairwise deletion. These conditions were compared with the baseline condition of no missingness.

Data Generation

SAS/IML (SAS Institute, 2001) version 8.2 was used to generate data according to the number of studies included, percent of studies with variables missing, percent of variables missing, and type of missingness. Using the correlation matrix implied by the model parameters (see Table 8) SAS/IML was programmed to generate a sample of data at the subject level assuming a normal distribution. For each study, k, a sample size, n, was randomly selected with replacement from the distribution of numbers in Appendix B. For study k there were then n rows of normally distributed data. The raw data for a study was then multiplied by the square root of the population matrix in Table 8. This scaling process through the Cholesky decomposition results in data that is from a population characterized by the correlation matrix from Table 8. Correlations were then computed from the study's generated raw data to produce each study's correlation matrix.

Table 7

Conditions of the Study Design

Synthesis Methods Compared 1. Univariate-*r* Listwise 2. Univariate-*r* Pairwise 3. Univariate-*z* Listwise 4. Univariate-*z* Pairwise 5. W-COV GLS-*r* Listwise 6. W-COV GLS-*r* Pairwise 7. W-COV GLS-*z* Listwise 8. W-COV GLS-*z* Pairwise
Number of Studies 1. 10 2. 30
Percentage of Studies with Missing Variables 1. 20% 2. 40%
Percentage of Variables Missing 1. 20% 2. 40%
Type of Missing Data 1. MCAR 2. MNAR

Table 8

Generating Population Correlation Matrix

Variable	1	2	3	4	5
1. Wage level	1.000	.110	.065	-.038	-.121
2. Extrinsic job satisfaction	.110	1.000	.590	-.348	-.474
3. Satisfaction with administration	.065	.590	1.000	-.590	-.629
4. Union instrumentality	-.038	-.348	-.590	1.000	.632
5. Unionization	-.121	-.474	-.629	.632	1.000

For each iteration this procedure was done *k* times, thereby resulting in *k* correlation matrices providing data for one simulated meta-analysis. For each of the 16 conditions, these steps were done 1,000 times, resulting in 1,000 simulated meta-analyses per condition. In each simulated meta-analysis there were ten correlations per study. To illustrate, for conditions with 10 studies included, there were 10,000 correlations generated (10 studies x 10 correlations x 1,000 replications). For each simulated meta-analysis missingness was built into the data according to the associated condition being simulated. In Table 9, the impact of the missingness can be seen for each level of number of studies included and on the number of variables designated to be missing. The procedures for the implementation of the missing data will be elaborated upon below. After each condition had been manipulated to meet the appropriate design characteristics, the eight different methods of synthesizing correlations were applied to each dataset. Following the computation of the synthesized correlation matrix, each of the eight sets of synthesized correlation matrices were used to estimate the SEM model presented in Appendix A.

Table 9

Patterns of Missingness Simulated

		Missingness	
	Type of Missingness	Percent (Number) of Studies with Missingness	Percent (Number Per Study) of Variables Missing
Number of Studies			
$K = 10$	MCAR	20% (2)	20% (1)
			40% (2)
		40% (4)	20% (1)
			40% (2)
$K = 30$	MCAR	20% (6)	20% (1)
			40% (2)
		40% (12)	20% (1)
			40% (2)
$K = 10$	MNAR	20% (2)	20% (1)
			40% (2)
		40% (4)	20% (1)
			40% (2)
$K = 30$	MNAR	20% (6)	20% (1)
			40% (2)
		40% (12)	20% (1)
			40% (2)

When the data were MCAR, each variable had an equal probability of being missing. Either 20% or 40% of the studies were randomly selected to have missing variables. Then, within these studies, either 20% or 40% of the variables were randomly designated as missing. This resulted in either four or seven of the study's correlations being designated as missing in either 20% or 40% of the studies, respectively, within a simulated meta-analysis.

In the MNAR condition, the missingness was contingent on the value of the correlations involving Variable 1 and Variable 2. In the population generating correlation matrix, Variable 1 (Wage Level) and Variable 2 (Extrinsic Job Satisfaction) had the lowest and second lowest average correlations with the other variables, respectively. To approximate the file drawer problem these two variables were the ones selected to have missingness. Several examples will be given to illustrate how variables were selected to be missing in the MNAR condition. In the first example, the condition had 10 studies, 20% of the variables were missing, and 20% of the studies had missing variables. In each study within a simulated meta-analysis the absolute values for Variable 1's four correlations (r_{21}, r_{31}, r_{41}, and r_{51}) were summed together. Then these summed values were rank ordered and the studies with the smallest two values were designated to have Variable 1 missing (and thus the four correlations corresponding to the variable). In the second example under the same conditions but when 40% of the variables were missing, the additional three correlations that include Variable 2 were summed together along with the four correlations involving Variable 1 (r_{21}, r_{31}, r_{41}, r_{51}, r_{32}, r_{42}, and r_{52}) for each study. The two studies with the smallest summed value for the seven correlations were set such that any correlations involving Variables 1 and 2 were missing for those studies. This procedure was the same in the condition where 40% of the studies had missing variables except that instead of the two smallest values being selected, the studies with the four smallest values were designated to have missing variables (and associated correlations).

In the conditions where 30 studies were used then the smallest 6 (20%) or 12 (40%) of the studies' summed values had variables missing.

Following the use of listwise or pairwise deletion to handle the missing data, the four pooling methods (univariate-*r*, univariate-*z*, W-COV GLS-*r*, and W-COV GLS-*z*) were then used to synthesize the correlations. The procedure for the univariate-*z* and univariate-*r* weighting used in this study followed the steps explained in Chapter Two for both transformed and untransformed correlations. To implement W-COV GLS-*r*, untransformed correlations were synthesized across studies within each simulated meta-analysis using the Hedges-Olkin univariate weighting procedure with listwise or pairwise deletion for computation of the variance-covariance matrix. Each study's variance-covariance matrix, $\hat{\Sigma}_i$, was then calculated using this synthesized correlation matrix along with the study's sample size, n_i (see Equations 14 and 15). The variance-covariance matrix, $\hat{\Sigma}$, comprised of each study's $\hat{\Sigma}_i$ was then substituted into Equation 10 and the synthesized correlation matrix computed.

To implement W-COV GLS-*z* the elements of each study's correlation matrix were first transformed using Fisher's *z* (see Equation 5). Each study's transformed correlation matrix was then synthesized using Hedges-Olkin univariate weighting procedure to result in a synthesized transformed correlation matrix. These synthesized correlations were then transformed back to the *r* metric using Equation 7 prior to the computation of the variance-covariance matrix. This synthesized correlation matrix was then used to compute the variance-covariance matrix for each study along with the study's sample size, n_i using Equations 14 and 15. The correlations in the vector, *r*, for each study were z-transformed and then the traditional GLS procedures were calculated (see Equation 10). The W-COV GLS synthesized correlations were then transformed back to the *r* metric (see Equation 7).

Studies with missing correlations were simply deleted when listwise deletion was implemented for the W-COV GLS procedure. However, with pairwise deletion the computation of the variance-covariance matrix was more complicated. First, the correlations were synthesized with univariate weighting using pairwise deletion. Then, each synthesized correlation matrix was used to estimate $\hat{\Sigma}_i$ for each study. The rows in the vector, *r*, and the matrix, *X*, corresponding to the missing correlations were removed and the rows and columns in $\hat{\Sigma}$ were also removed for the computation of the pooled correlation matrix, *R*.

The basis for the SAS/IML program used to synthesize the correlations came from a program developed by M. Cheung (2003) designed to synthesize correlations using Hedges-Olkin procedures for univariate weighting with the *z* transformation and traditional GLS procedures. However, the program was modified for this study in order to employ the W-COV GLS procedure with transformed and untransformed correlations as well as to implement the Hedges-Olkin procedure with untransformed correlations.

SAS's (SAS Institute, 2001) Proc Calis was used to estimate the model depicted in Appendix A with each of the synthesized correlation matrices for each iteration and in each condition. The model was estimated using maximum likelihood estimation. With listwise deletion the sample size for use with the SEM analyses was just the sum total of the sample sizes from each of the studies that had no missing data. However, for pairwise deletion the computation of the sample size for SEM was more complicated because each synthesized correlation was based on a different total sample size. The sample size used in this study for estimation of the structural model was determined by computing the mean of the total sample sizes associated with each synthesized correlation. While Marsh's (1989) simulation study on the optimal sample size for use with pairwise deletion in SEM indicated the minimum (or smallest) sample size used in the computation of the elements of a covariance matrix resulted in less bias than the mean sample size, using the mean value was chosen for this study because it reflected the computation of the sample size applied researchers have typically used in meta-analytic SEM studies (e.g., Premack & Hunter: 1988; Verhaeghen & Salthouse, 1997).

Data Analysis

Forming the Pooled Correlation Matrix

The estimated pooled correlation matrices were summarized and compared across the 1,000 iterations for each condition. The recovery of the pooled correlations was evaluated using the percentage relative bias (Hoogland & Boomsma, 1998). Specifically, the percentage relative bias was calculated for each of the ten synthesized correlation estimates using the formula:

$$B(\hat{r}_p) = \left(\frac{\overline{r}_p - \rho_p}{\rho_p} \right) 100 \tag{16}$$

where $\overline{r_p}$ is the average of the estimates for the *p*th correlation parameter for the 1,000 replications and ρ_p is the corresponding, generating parameter value (Hoogland & Boomsma, 1998). In their robustness study, Hoogland and Boomsma (1998) recommended that bias estimates be within 5 percent of the corresponding population value.

Fitting the Structural Equation Model

Several methods were used to compare the performance of the eight different methods for pooling correlation matrices in terms of the resulting structural equation model parameter estimates. First, the parameter estimates of the seven paths in the model were compared with the population values (see Appendix A) under each condition using the following equation to compute the percentage relative bias:

$$B(\hat{\theta}_p) = \left(\frac{\overline{\theta}_p - \theta_p}{\theta_p} \right) 100 \tag{17}$$

where $\overline{\theta}_p$ is the average of the estimate for the p_{th} parameter for the 1,000 replications and θ_p is the corresponding parameter value (Hoogland & Boomsma, 1998). Second, the accuracy of the estimates of the standard errors of the corresponding seven paths using the percentage relative bias:

$$B(\hat{se}_{\hat{\theta}_p}) = \left(\frac{\overline{\hat{se}}_{\hat{\theta}_p} - \hat{se}_{\theta_p}}{\hat{se}_{\theta_p}} \right) 100 \tag{18}$$

where $\overline{\hat{se}}_{\hat{\theta}_p}$ is the mean of the estimated standard errors of the corresponding $\hat{\theta}_p$ and $\hat{se}_{\theta_p}$ is an estimate of the population value of the standard error of $\hat{\theta}_p$ for the 1000 iterations (Hoogland & Boomsma, 1998). The path estimates are considered acceptable when they are within 5 percentage points from their corresponding parameter value, while an acceptable standard error bias level is within 10 percent of the standard deviation of the corresponding path estimate (Hoogland & Boomsma, 1998).

Third, tests of the goodness-of-fit of the model were evaluated across the 16 conditions. Specifically, the proportion of model rejection rates based on the chi-squared test with an α level of .05 were tallied. Rejection rates based on Hu and Bentler's (1999) joint criteria for assessing data-model fit were also calculated. Their criteria include: a Comparative Fit Index (CFI) greater than or equal to .96 with a Standardized Root Mean-Square Residual (SRMR) less than or equal to .10. An alternative criterion also investigated involved a Root Mean-Square Error of Approximation (RMSEA) less than .06 with a SRMR less than or equal to .10.

In addition to the descriptive analyses, a factorial Analysis of Variance (ANOVA) was conducted for each of the eight methods of synthesizing correlations with relative bias measures as the dependent measure using the 16 study conditions. This was done for each of the 10 synthesized correlation bias estimates, seven path bias estimates, and seven path standard error bias estimates. The levels of the study design included the type of missingness (2) x number of studies included (2) x percent of studies missing (2) x percent of variables missing (2). An η^2 statistic was computed providing an effect size measure representing the proportion of variance of the relative bias explained by each design factor and their 2-way interactions. The formula for computing η^2 is:

$$\eta^2 = \frac{SS_{effect}}{SS_{total}} \qquad (17)$$

where SS_{effect} is the Sum of Squared deviations that corresponds to the main or interaction effect of interest, and SS_{total} is the Sum of Squared deviations for the total model. A conservative α-level of 0.01 was used along with a minimal cutoff of .10 for the associated η^2 that qualified the effect size as moderate.

Chapter 4: Results

Non-Positive Definite Correlation Matrices

In all simulated meta-analyses there were no inadmissible solutions, that is, no synthesized correlation matrix was non-positive definite. This is similar to the findings of Marsh (1998) where non-positive definite cases did not result for sample sizes greater than 200 even with up to 50% of the data missing. The sample size on which the synthesized correlation matrix was based and used for the estimation of the structural model were all much greater than 200 and can be seen in Table 10.

Synthesized Correlation Estimates

The percentage relative bias in the synthesized correlation estimates from the eight methods of synthesizing correlation matrices across the 16 study conditions and the baseline condition (of no missingness) are summarized in Table 11 through Table 20. The results of the ANOVAs for parameter estimates with substantial bias can be seen in Appendix C. Descriptive information about each of these synthesis methods across the conditions is provided in the following sections as well as the ANOVA results.

When the data were MCAR all 10 of the synthesized correlation estimates were within five percent of the population value regardless of the number of studies, amount of missingness, type of deletion, and method used to synthesize the correlations. These relative bias estimates for MCAR data were comparable to the estimates from the baseline condition with no missing data.

Table 10

Comparison of Sample Size Descriptives for Pairwise Versus Listwise Deletion Used in SEM

	Missingness			Method							
				Pairwise				Listwise			
K	Type	% Studies	% Variables	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
10	NO MISSING			2421.9	899.3	1001	6357				
	MCAR	20	20	2231.4	836.0	959	6629	1921.2	796.2	751	6505
			40	2091.9	798.8	698	5478	1945.5	794.0	643	5384
		40	20	2032.4	744.6	844	6270	1461.7	660.7	493	5004
			40	1762.5	678.0	695	4692	1478.5	658.3	506	4510
	MNAR	20	20	2243.7	831.2	939	5670	1953.4	806.0	693	5478
			40	2139.1	829.8	884	6146	2004.6	827.2	776	6078
		40	20	2036.2	754.7	722	5735	1380.1	671.0	391	4761
			40	1713.1	658.2	695	4886	1396.7	637.0	364	4602
30	NO MISSING			7287.2	1507.0	3785	13931				
	MCAR	20	20	6697.9	1380.9	3559	12067	5817.4	1319.6	3195	10785
			40	6387.1	1389.6	3418	11615	5940.1	1364.2	3122	10816
		40	20	6226.3	1275.2	3391	10632	4478.9	1156.6	2176	9219
			40	5257.1	1184.3	2985	9711	4373.7	1156.7	2148	8670
	MNAR	20	20	6738.3	1449.2	3628	13159	5878.4	1419.7	2916	12230
			40	6454.0	1417.3	3475	11877	6071.9	1414.7	3220	11507
		40	20	6016.4	1226.1	3149	10799	4103.3	1084.7	1862	8690
			40	5210.8	1203.9	2531	10566	4286.0	1176.8	1765	9517

Table 11

Relative Percentage Bias of Synthesized Estimates for ρ_{21} =.110

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			2.04		0.67		0.27		0.68	
	MCAR	20	20	2.21	2.34	0.87	0.95	0.51	0.54	0.92	0.95
			40	1.86	1.81	0.56	0.52	-0.04	0.12	0.36	0.52
		40	20	1.16	0.85	-0.20	-0.43	-0.69	-0.86	-0.24	-0.43
			40	1.07	0.70	-0.25	-0.59	-0.76	-0.99	-0.38	-0.60
	MNAR	20	20	15.23	15.23	13.92	13.92	13.26	13.51	13.68	13.92
			40	10.31	10.31	9.09	9.09	8.38	8.71	8.82	9.10
		40	20	27.71	27.71	26.37	26.37	25.34	25.94	25.79	26.38
			40	20.75	20.75	19.31	19.31	18.10	18.86	18.57	19.31
30	NO MISSING			1.83		0.55		0.12		0.55	
	MCAR	20	20	1.93	1.66	0.61	0.36	0.18	-0.07	0.58	0.37
			40	1.13	1.03	-0.13	-0.24	-0.54	-0.66	-0.15	-0.24
		40	20	1.56	1.52	0.31	0.27	-0.07	-0.11	0.34	0.28
			40	1.32	1.58	-0.08	0.20	-0.18	-0.22	0.22	0.19
	MNAR	20	20	14.37	14.37	13.06	13.06	12.56	12.69	12.91	13.06
			40	10.05	10.05	8.75	8.75	8.08	8.37	8.49	8.77
		40	20	27.62	27.62	26.23	26.23	25.53	25.84	25.91	26.24
			40	21.35	21.35	19.36	19.36	18.82	19.48	19.31	19.95

Table 12

Relative Percentage Bias of Synthesized Estimates for ρ_{31} = .065

Missingness				Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			2.50		1.13		0.66		1.13	
	MCAR	20	20	1.69	1.25	0.36	-0.06	-0.31	-0.47	0.08	-0.05
			40	-0.02	0.64	-1.29	-0.62	-1.63	-1.04	-1.23	-0.64
		40	20	1.67	2.14	0.38	0.87	-0.26	0.47	0.02	-0.02
			40	2.68	2.55	1.42	1.31	0.82	0.88	1.23	1.31
	MNAR	20	20	23.91	23.91	22.57	22.57	21.91	22.10	22.39	22.60
			40	17.35	17.35	15.95	15.95	14.57	15.54	15.05	15.96
		40	20	47.29	47.29	45.95	45.95	44.79	45.48	45.22	45.98
			40	37.55	37.55	35.96	35.96	33.19	35.45	33.74	36.00
30	NO MISSING			1.30		0.03		-0.39		0.02	
	MCAR	20	20	1.13	1.48	-0.20	0.14	-0.46	-0.29	-0.04	0.14
			40	0.86	0.66	-0.40	-0.56	-0.76	-0.95	-0.34	-0.57
		40	20	1.18	1.08	-0.11	-0.18	-0.49	-0.58	-0.08	-0.19
			40	1.62	0.79	0.33	-0.53	-0.14	-0.90	0.27	-0.52
	MNAR	20	20	22.64	22.64	21.34	21.34	20.72	20.93	21.21	21.42
			40	16.11	16.11	14.74	14.74	13.37	14.34	13.86	14.79
		40	20	49.46	49.46	47.98	47.98	47.04	47.51	47.52	48.04
			40	39.24	39.24	37.65	37.65	35.20	37.17	35.74	37.67

Table 13

Relative Percentage Bias of Synthesized Estimates for ρ_{32} = .590

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	%Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.97		0.14		-0.13		0.14	
	MCAR	20	20	1.01	1.04	0.16	0.20	-0.13	-0.08	0.15	0.20
			40	0.84	0.85	0.01	0.01	-0.26	-0.26	0.01	0.01
		40	20	0.87	0.81	0.01	-0.02	-0.26	-0.28	0.02	-0.02
			40	0.95	0.97	0.13	0.15	-0.17	-0.12	0.10	0.15
	MNAR	20	20	1.02	1.11	0.18	0.26	-0.09	-0.02	0.18	0.26
			40	2.11	2.11	1.38	1.38	0.92	1.16	1.15	1.38
		40	20	0.95	1.15	0.13	0.30	-0.14	0.02	0.13	0.30
			40	3.01	3.01	2.27	2.27	1.55	2.04	1.77	2.27
30	NO MISSING			0.97		0.12		-0.15		0.12	
	MCAR	20	20	0.96	0.97	0.12	0.13	-0.16	-0.14	0.11	0.13
			40	0.93	0.95	0.11	0.12	-0.16	-0.14	0.11	0.12
		40	20	0.97	0.96	0.13	0.12	-0.16	-0.15	0.12	0.12
			40	0.93	0.94	0.06	0.07	-0.20	-0.22	0.08	0.07
	MNAR	20	20	0.91	0.97	0.09	0.14	-0.18	-0.12	0.09	0.15
			40	2.04	2.04	1.31	1.31	0.87	1.09	1.10	1.32
		40	20	1.00	1.23	0.17	0.32	-0.10	0.03	0.16	0.32
			40	3.13	3.13	2.36	2.36	1.69	2.13	1.93	2.37

Table 14

Relative Percentage Bias of Synthesized Estimates for ρ_{41} = -.038

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	%Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			1.51		0.32		-0.03		0.35	
	MCAR	20	20	2.53	2.58	1.16	1.14	0.72	0.69	1.18	1.15
			40	0.00	0.77	-1.30	-0.54	-1.95	-0.98	-1.55	-0.49
		40	20	-1.52	0.76	-2.74	-0.58	-2.81	-1.03	-2.43	-0.61
			40	2.97	3.29	1.73	2.13	1.69	1.72	2.11	2.15
	MNAR	20	20	29.82	29.82	28.45	28.45	27.83	27.91	28.38	28.43
			40	24.87	24.87	23.38	23.38	21.28	22.92	21.83	23.45
		40	20	67.08	67.08	65.51	65.51	64.26	64.90	64.76	65.58
			40	54.55	54.55	52.87	52.87	48.85	52.22	49.52	52.92
30	NO MISSING			1.93		0.63		0.21		0.68	
	MCAR	20	20	3.00	2.74	1.62	1.35	1.01	0.93	1.42	1.40
			40	1.16	1.02	-0.07	-0.21	-0.30	-0.66	0.11	-0.22
		40	20	1.99	2.66	0.63	1.33	0.26	0.92	0.68	1.35
			40	0.06	-0.29	-1.21	-1.54	-1.49	-1.96	-1.06	-1.50
	MNAR	20	20	28.48	28.48	27.00	27.00	26.49	26.54	27.01	27.11
			40	23.13	23.13	21.7	21.7	19.74	21.26	20.30	21.78
		40	20	68.97	68.97	67.27	67.27	66.46	66.69	66.94	67.41
			40	56.56	56.56	54.69	54.69	50.91	54.15	51.58	54.81

Table 15

Relative Percentage Bias of Synthesized Estimates for ρ_{42} = -.348

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			1.28		0.12		-0.26		0.12	
	MCAR	20	20	1.38	1.44	0.28	0.31	-0.14	-0.06	0.22	0.31
			40	1.06	1.08	-0.08	-0.06	-0.43	-0.43	-0.08	-0.06
		40	20	0.92	0.79	-0.20	-0.29	-0.48	-0.64	-0.13	-0.29
			40	1.58	1.45	0.41	0.32	-0.08	-0.04	0.29	0.33
	MNAR	20	20	1.01	1.09	-0.09	-0.03	-0.44	-0.39	-0.08	-0.03
			40	4.05	4.05	3.04	3.04	1.91	2.75	2.24	3.06
		40	20	1.37	1.81	0.28	0.66	-0.07	0.29	0.29	0.66
			40	7.28	7.28	6.15	6.15	4.30	5.84	4.61	6.16
30	NO MISSING			1.13		-0.01		-0.37		0.00	
	MCAR	20	20	1.41	1.42	0.26	0.27	-0.12	-0.09	0.24	0.28
			40	1.45	1.49	0.32	0.36	-0.05	-0.01	0.32	0.36
		40	20	1.25	1.34	0.13	0.22	-0.24	-0.14	0.12	0.23
			40	1.29	1.29	0.15	0.15	-0.23	-0.22	0.12	0.15
	MNAR	20	20	1.25	1.30	0.13	0.16	-0.23	-0.19	0.13	0.17
			40	3.97	3.97	2.96	2.96	1.88	2.67	2.22	2.97
		40	20	1.28	1.48	0.15	0.26	-0.21	-0.13	0.15	0.26
			40	6.80	6.80	5.70	5.70	3.86	5.39	4.20	5.72

Table 16

Relative Percentage Bias of Synthesized Estimates for ρ_{43} = -.590

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.96		0.13		-0.13		0.13	
	MCAR	20	20	1.10	1.08	0.26	0.24	-0.04	-0.03	0.23	0.24
			40	0.81	0.81	-0.04	-0.03	-0.31	-0.31	-0.04	-0.03
		40	20	0.81	0.67	-0.02	-0.14	-0.30	-0.41	-0.04	-0.14
			40	1.02	1.03	0.16	0.19	-0.15	-0.08	0.13	0.19
	MNAR	20	20	0.91	0.93	0.06	0.10	-0.21	-0.18	0.07	0.10
			40	0.86	1.42	0.04	0.64	-0.23	0.38	0.04	0.64
		40	20	1.18	1.14	0.36	0.28	0.09	0.00	0.36	0.28
			40	0.89	1.98	0.06	1.17	-0.21	0.90	0.06	1.17
30	NO MISSING			0.93		0.09		-0.18		0.09	
	MCAR	20	20	1.04	1.06	0.20	0.22	-0.09	-0.06	0.19	0.22
			40	1.08	1.06	0.24	0.23	-0.04	-0.05	0.23	0.23
		40	20	0.89	0.88	0.07	0.08	-0.22	-0.19	0.05	0.08
			40	0.93	0.93	0.07	0.06	-0.19	-0.22	0.08	0.06
	MNAR	20	20	0.97	0.93	0.14	0.10	-0.13	-0.17	0.14	0.10
			40	0.98	1.50	0.14	0.68	-0.14	0.43	0.14	0.69
		40	20	0.90	0.97	0.06	0.06	-0.22	-0.23	0.06	0.06
			40	1.00	2.12	0.15	1.26	-0.12	0.99	0.15	1.26

Table 17

Relative Percentage Bias of Synthesized Estimates for ρ_{51} = -.121

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			2.43		1.07		0.66		1.07	
	MCAR	20	20	0.76	0.88	-0.50	-0.38	-0.83	-0.79	-0.43	-0.37
			40	1.05	1.14	-0.22	-0.11	-0.84	-0.53	-0.44	-0.12
		40	20	1.43	1.60	0.20	0.44	-0.43	0.05	-0.03	0.42
			40	2.11	1.90	0.87	0.68	0.34	0.29	0.78	0.69
	MNAR	20	20	13.23	13.23	11.97	11.97	11.41	11.56	11.80	11.95
			40	10.89	10.89	9.62	9.62	9.04	9.21	9.45	9.62
		40	20	27.21	27.21	25.91	25.91	25.05	25.53	25.42	25.89
			40	20.50	20.50	19.09	19.09	18.19	18.66	18.61	19.08
30	NO MISSING			1.88		0.60		0.20		0.59	
	MCAR	20	20	2.04	2.11	0.72	0.81	0.32	0.39	0.73	0.82
			40	1.43	1.37	0.18	0.10	-0.19	-0.30	0.21	0.11
		40	20	1.90	1.83	0.59	0.53	0.16	0.12	0.57	0.55
			40	1.52	1.37	0.22	0.05	-0.22	-0.39	0.19	0.04
	MNAR	20	20	13.89	13.89	12.62	12.62	12.15	12.27	12.52	12.64
			40	9.00	9.00	7.73	7.73	7.19	7.36	7.59	7.76
		40	20	27.02	27.02	25.66	25.66	25.05	25.27	25.42	25.66
			40	21.20	21.20	19.78	19.78	18.91	19.36	19.37	19.79

Table 18

Relative Percentage Bias of Synthesized Estimates for ρ_{52} = -.474

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			1.09		0.07		-0.27		0.07	
	MCAR	20	20	1.39	1.37	0.38	0.35	0.02	0.00	0.34	0.35
			40	0.90	0.84	-0.10	-0.15	-0.42	-0.47	-0.10	-0.15
		40	20	0.81	0.73	-0.19	-0.24	-0.48	-0.56	-0.15	-0.24
			40	1.11	1.17	0.12	0.21	-0.22	-0.11	0.09	0.21
	MNAR	20	20	1.13	1.40	0.13	0.40	-0.20	0.07	0.13	0.39
			40	3.21	3.21	2.35	2.35	1.57	2.09	1.85	2.35
		40	20	1.26	2.00	0.26	0.98	-0.06	0.64	0.27	0.98
			40	4.84	4.84	3.97	3.97	2.68	3.71	2.94	3.98
30	NO MISSING			1.15		0.13		-0.19		0.13	
	MCAR	20	20	1.18	1.20	0.18	0.19	-0.15	-0.13	0.18	0.19
			40	1.25	1.26	0.26	0.27	-0.08	-0.05	0.25	0.27
		40	20	1.14	1.19	0.13	0.18	-0.20	-0.14	0.12	0.18
			40	1.12	1.14	0.01	0.00	-0.21	-0.19	0.11	0.14
	MNAR	20	20	0.89	0.95	0.12	0.17	-0.14	-0.08	0.12	0.17
			40	2.91	2.91	2.03	2.03	1.26	1.77	0.13	0.71
		40	20	1.20	1.67	0.21	0.59	-0.10	0.25	0.22	0.60
			40	4.77	4.77	3.85	3.85	2.63	3.59	2.92	3.86

Table 19

Relative Percentage Bias of Synthesized Estimates for ρ_{53} = -.629

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.91		0.14		-0.11		0.14	
	MCAR	20	20	0.89	0.92	0.12	0.14	-0.12	-0.11	0.13	0.15
			40	0.79	0.76	0.01	-0.02	-0.25	-0.27	0.00	-0.01
		40	20	0.70	0.58	-0.08	-0.18	-0.32	-0.43	-0.07	-0.18
			40	0.78	0.85	0.01	0.08	-0.27	-0.17	-0.03	0.08
	MNAR	20	20	0.95	1.04	0.17	0.24	-0.08	-0.02	0.17	0.25
			40	0.89	1.44	0.13	0.72	-0.12	0.50	0.13	0.72
		40	20	1.05	1.30	0.28	0.51	0.03	0.24	0.28	0.51
			40	0.76	1.97	-0.03	1.20	-0.28	0.96	-0.03	1.20
30	NO MISSING			0.92		0.16		-0.09		0.16	
	MCAR	20	20	0.96	0.97	0.18	0.19	-0.08	-0.07	0.17	0.19
			40	0.95	0.97	0.18	0.19	-0.08	-0.06	0.18	0.19
		40	20	0.90	0.87	0.11	0.09	-0.16	-0.16	0.09	0.09
			40	0.80	0.80	0.01	0.00	-0.23	-0.25	0.02	0.00
	MNAR	20	20	0.89	0.95	0.12	0.17	-0.14	-0.08	0.12	0.17
			40	0.90	1.45	0.12	0.71	-0.13	0.48	0.13	0.71
		40	20	0.79	1.02	0.02	0.19	-0.23	-0.08	0.02	0.20
			40	0.95	2.07	0.19	1.31	-0.06	1.07	0.19	1.32

Table 20

Relative Percentage Bias of Synthesized Estimates for ρ_{54} = .632

Missingness				Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.86		0.09		-0.17		0.09	
	MCAR	20	20	0.97	1.04	0.19	0.26	-0.07	0.00	0.18	0.26
			40	0.90	0.92	0.12	0.14	-0.14	-0.12	0.11	0.14
		40	20	0.81	0.73	0.03	-0.03	-0.23	-0.27	0.02	-0.03
			40	0.84	0.89	0.06	0.11	-0.22	-0.13	0.03	0.11
	MNAR	20	20	0.87	0.90	0.06	0.08	-0.20	-0.10	0.06	0.07
			40	0.83	1.23	0.04	0.46	-0.22	0.21	0.13	0.72
		40	20	0.96	1.09	0.20	0.29	-0.05	0.02	0.20	0.29
			40	0.73	1.56	-0.03	0.78	-0.28	0.54	-0.03	0.78
30	NO MISSING			0.88		0.11		-0.14		0.11	
	MCAR	20	20	0.86	0.87	0.11	0.11	-0.15	-0.14	0.10	0.11
			40	0.95	0.96	0.18	0.19	-0.07	-0.06	0.18	0.19
		40	20	0.90	0.91	0.14	0.17	-0.12	-0.08	0.12	0.16
			40	0.85	0.83	0.09	0.07	-0.15	-0.18	0.09	0.06
	MNAR	20	20	0.87	0.85	0.09	0.07	-0.17	-0.18	0.09	0.07
			40	0.95	1.29	0.17	0.54	-0.08	0.30	0.17	0.54
		40	20	0.80	0.89	0.04	0.07	-0.21	-0.20	0.04	0.07
			40	0.85	1.60	0.09	0.83	-0.16	0.60	0.09	0.84

When the data were MNAR then certain synthesized correlation estimates displayed substantial amounts of positive bias depending on the design condition. Estimates of the four correlations corresponding to Variable One ($\rho_{21}, \rho_{31}, \rho_{41}, \rho_{51}$), demonstrated substantial relative bias under all conditions with MNAR data (Table 11, Table 12, Table 14, and Table 17, respectively). The ANOVA results for all synthesis methods for each of the four correlations indicated that this overestimation bias was primarily due to the type of missing data (η^2 ranged from .72 to .77). This relative bias for all synthesis methods was also related to the interaction between the type of missingness and the number of studies with missing correlations (η^2 ranged from .10 to .13). The MNAR conditions where 40% of the studies had missing correlations displayed larger amounts of relative bias than conditions where only 20% of studies had missing correlations. However, the opposite was true for the percentage of variables missing, that is, there was more relative bias present when 20% of the variables were missing than when 40% of the variables were missing.

The only other synthesized correlation to demonstrate relative bias greater than 5% for MNAR data was ρ_{42} (Table 15) and only when 40% of the studies and variables had missingness. ANOVA results for all synthesis methods indicated that the bias was related to the type of missingness (η^2 ranged from .28 to .31), percent of the variables that were missing (η^2 ranged from .29 to .31) and their interaction (η^2 ranged from .26 to .29). Neither the use of listwise nor pairwise deletion nor the method of synthesis was significantly related to the bias in any of the correlations. It should also be noted that listwise and pairwise deletion resulted in the same relative bias estimates with univariate weighting (and very similar estimates for W-COV GLS) for the correlations set to missing in the MNAR procedure (e.g., see Table 17). This was because when listwise deletion removed a study with missing data it always removed the studies with the lowest generated values so the estimates for listwise and pairwise deletion were always the same for only the correlations that were set to missing.

Model Path Estimates

The percentage relative bias of the parameter path estimates from the eight methods of synthesizing correlation matrices across the 16 design conditions and the baseline condition of no missingness are summarized in Table 21 through Table 27. Descriptive information about each of these synthesis methods across the conditions is provided in the following sections as well as the ANOVA results. The ANOVA results for each synthesis method on each path parameter with substantial bias present can be seen in Appendix C.

Similar to the synthesized correlation estimates, there was no substantial relative bias (greater than 5%) in the parameter path estimates when the data were MCAR regardless of synthesis method, number of studies, type of deletion, and degree of missingness and were also comparable to the relative bias found in the baseline condition. However, also consistent with the relative bias present in the synthesized correlation estimates, there were specific patterns to the relative bias present when the data were MNAR.

Table 21

Relative Percentage Bias of Path Estimates for Parameter $V1 \rightarrow V5$ = -.07

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			2.24		1.09		0.76		1.07	
	MCAR	20	20	-0.93	-0.61	-1.89	-1.55	-2.02	-1.86	-1.71	-1.53
			40	0.98	0.81	-0.04	-0.18	-0.69	-0.53	-0.36	-0.21
		40	20	1.72	1.48	0.75	0.64	0.01	0.34	0.31	0.60
			40	1.60	1.18	0.61	0.18	0.02	-0.13	0.42	0.18
	MNAR	20	20	5.80	5.56	4.90	4.65	4.49	4.39	4.71	4.62
			40	5.08	5.05	4.11	4.08	4.33	3.76	4.61	4.06
		40	20	12.76	12.11	11.89	11.24	11.33	11.07	11.52	11.18
			40	7.23	7.10	6.20	6.06	6.94	5.79	7.20	6.03
30	NO MISSING			1.44		0.40		0.11		0.39	
	MCAR	20	20	1.56	1.69	0.49	0.68	0.17	0.33	0.51	0.67
			40	1.08	1.08	0.07	0.03	-0.24	-0.27	0.08	0.05
		40	20	1.61	1.35	0.54	0.28	0.14	-0.06	0.47	0.30
			40	1.31	1.26	0.24	0.17	-0.24	-0.23	0.10	0.14
	MNAR	20	20	7.83	7.67	6.91	6.76	6.59	6.54	6.80	6.73
			40	2.77	2.76	1.83	1.81	2.08	1.53	2.34	1.82
		40	20	11.39	11.03	10.51	10.19	10.15	9.98	10.35	10.11
			40	7.23	7.12	6.26	6.14	6.87	5.86	7.17	6.12

Table 22

Relative Percentage Bias of Path Estimates for Parameter V2 → V5 = -.15

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.03		-0.31		-0.43		-0.32	
	MCAR	20	20	1.70	1.33	1.30	0.90	0.99	0.71	1.13	0.88
			40	-0.17	-0.33	-0.42	-0.56	-0.47	-0.63	-0.37	-0.58
		40	20	0.00	0.16	-0.29	-0.14	-0.32	-0.22	-0.23	-0.13
			40	0.46	0.65	0.21	0.48	0.25	0.40	0.33	0.49
	MNAR	20	20	-0.31	0.52	-0.66	0.27	-0.75	0.18	-0.63	0.24
			40	4.61	3.22	4.61	3.11	3.55	3.08	3.54	3.10
		40	20	-0.84	0.91	-1.21	0.56	-1.29	0.44	-1.14	0.58
			40	7.21	3.80	7.50	4.08	5.14	4.13	5.04	4.10
30	NO MISSING			0.46		0.08		-0.02		0.08	
	MCAR	20	20	0.28	0.31	0.00	0.03	-0.04	-0.04	0.06	0.04
			40	0.74	0.61	0.44	0.40	0.30	0.32	0.40	0.39
		40	20	0.33	0.53	0.05	0.27	-0.02	0.21	0.06	0.26
			40	0.67	0.77	0.45	0.52	0.35	0.46	0.42	0.55
	MNAR	20	20	-0.44	0.14	-0.68	-0.07	-0.74	-0.15	-0.66	-0.06
			40	3.52	2.14	3.49	1.99	2.40	1.97	2.40	1.99
		40	20	-0.36	0.58	-0.65	0.23	-0.71	0.14	-0.60	0.26
			40	6.70	3.84	6.58	3.74	4.54	3.77	4.53	3.69

Table 23

Relative Percentage Bias of Path Estimates for Parameter V3 $\rightarrow$ V5 = -.30

	Missingness			Method							
				Univariate-r		*Univariate-z*		*W-COV GLS-r*		*W-COV GLS-z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.24		0.14		0.10		0.15	
	MCAR	20	20	-0.55	-0.48	-0.60	-0.52	-0.50	-0.53	-0.49	-0.52
			40	0.02	-0.08	-0.11	-0.20	-0.17	-0.25	-0.14	-0.19
		40	20	-0.24	-0.40	-0.36	-0.52	-0.35	-0.58	-0.31	-0.52
			40	-0.29	-0.22	-0.38	-0.35	-0.45	-0.40	-0.42	-0.36
	MNAR	20	20	0.08	0.01	0.03	-0.08	0.01	-0.12	0.04	-0.06
			40	-1.39	-0.33	-1.52	-0.36	-1.28	-0.36	-1.22	-0.35
		40	20	-0.12	-0.08	-0.22	-0.14	-0.24	-0.18	-0.22	-0.15
			40	-2.57	0.06	-2.97	-0.27	-2.36	-0.34	-2.23	-0.27
30	NO MISSING			0.16		0.09		0.05		0.10	
	MCAR	20	20	0.33	0.33	0.16	0.15	0.09	0.08	0.14	0.15
			40	0.00	0.11	-0.12	-0.07	-0.16	-0.13	-0.11	-0.07
		40	20	0.12	-0.03	-0.09	-0.24	-0.16	-0.32	-0.10	-0.23
			40	-0.22	-0.22	-0.43	-0.40	-0.46	-0.46	-0.39	-0.41
	MNAR	20	20	-0.03	0.00	-0.18	-0.15	-0.24	-0.20	-0.17	-0.16
			40	-1.23	-0.07	-1.46	-0.20	-1.23	-0.23	-1.14	-0.19
		40	20	-0.66	-0.49	-0.77	-0.60	-0.80	-0.65	-0.77	-0.59
			40	-2.26	0.01	-2.41	-0.12	-1.92	-0.19	-1.83	-0.09

Table 24

Relative Percentage Bias of Path Estimates for Parameter V4 → V5 = .40

Missingness				Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.67		0.06		-0.13		0.06	
	MCAR	20	20	0.91	1.04	0.29	0.41	0.07	0.21	0.27	0.41
			40	0.98	1.06	0.37	0.44	0.17	0.24	0.37	0.44
		40	20	0.95	0.95	0.34	0.35	0.09	0.17	0.29	0.35
			40	0.78	0.77	0.14	0.16	-0.07	-0.02	0.12	0.16
	MNAR	20	20	0.63	0.59	-0.04	-0.11	-0.25	-0.33	-0.04	-0.12
			40	0.23	0.33	-0.45	-0.37	-0.54	-0.60	-0.33	-0.38
		40	20	0.44	0.37	-0.14	-0.28	-0.35	-0.49	-0.15	-0.27
			40	-0.46	-0.32	-0.99	-0.90	-0.93	-1.10	-0.74	-0.91
30	NO MISSING			0.71		0.11		-0.08		0.11	
	MCAR	20	20	0.54	0.54	-0.01	-0.01	-0.19	-0.18	-0.01	-0.01
			40	0.75	0.74	0.17	0.17	-0.02	-0.02	0.17	0.17
		40	20	0.78	0.83	0.24	0.29	0.05	0.12	0.23	0.29
			40	0.80	0.76	0.28	0.22	0.09	0.04	0.25	0.22
	MNAR	20	20	0.63	0.53	0.03	-0.08	-0.17	-0.28	0.02	-0.08
			40	0.48	0.46	-0.12	-0.14	-0.20	-0.34	-0.01	-0.14
		40	20	0.50	0.39	-0.08	-0.24	-0.28	-0.44	-0.09	-0.25
			40	-0.32	-0.25	-0.90	-0.83	-0.84	-1.02	-0.65	-0.85

Table 25

Relative Percentage Bias of Path Estimates for Parameter V3 → V4 = -.59

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.96		0.13		-0.13		0.13	
	MCAR	20	20	1.10	1.08	0.26	0.24	-0.04	-0.03	0.23	0.24
			40	0.81	0.81	-0.04	-0.03	-0.31	-0.31	-0.04	-0.03
		40	20	0.81	0.67	-0.02	-0.14	-0.30	-0.41	-0.04	-0.14
			40	1.02	1.03	0.16	0.19	-0.15	-0.08	0.13	0.19
	MNAR	20	20	0.91	0.93	0.06	0.10	-0.21	-0.18	0.07	0.10
			40	0.86	1.42	0.04	0.64	-0.23	0.38	0.04	0.64
		40	20	1.18	1.14	0.36	0.28	0.09	0.00	0.36	0.28
			40	0.89	1.98	0.06	1.17	-0.21	0.90	0.06	1.17
30	NO MISSING			0.93		0.09		-0.18		0.09	
	MCAR	20	20	1.04	1.06	0.20	0.22	-0.09	-0.06	0.19	0.22
			40	1.08	1.06	0.24	0.23	-0.04	-0.05	0.23	0.23
		40	20	0.89	0.88	0.07	0.08	-0.22	-0.19	0.05	0.08
			40	0.93	0.94	0.06	0.07	-0.20	-0.22	0.08	0.07
	MNAR	20	20	0.97	0.93	0.14	0.10	-0.13	-0.17	0.14	0.10
			40	0.98	1.50	0.14	0.68	-0.14	0.43	0.14	0.69
		40	20	0.90	0.97	0.06	0.06	-0.22	-0.23	0.06	0.06
			40	1.00	2.12	0.15	1.26	-0.12	0.99	0.15	1.26

Table 26

Relative Percentage Bias of Path Estimates for Parameter V2 → V3 = .59

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			0.97		0.14		-0.13		0.14	
	MCAR	20	20	1.01	1.04	0.16	0.20	-0.13	-0.08	0.15	0.20
			40	0.84	0.85	0.01	0.01	-0.26	-0.26	0.01	0.01
		40	20	0.87	0.81	0.01	-0.02	-0.26	-0.28	0.02	-0.02
			40	0.95	0.97	0.13	0.15	-0.17	-0.12	0.10	0.15
	MNAR	20	20	1.02	1.11	0.18	0.26	-0.09	-0.02	0.18	0.26
			40	2.11	2.11	1.38	1.38	0.92	1.16	1.15	1.38
		40	20	0.95	1.15	0.13	0.30	-0.14	0.02	0.13	0.30
			40	3.01	3.01	2.27	2.27	1.55	2.04	1.77	2.27
30	NO MISSING			0.97		0.12		-0.15		0.12	
	MCAR	20	20	0.96	0.97	0.12	0.13	-0.16	-0.14	0.11	0.13
			40	0.93	0.95	0.11	0.12	-0.16	-0.14	0.11	0.12
		40	20	0.97	0.96	0.13	0.12	-0.16	-0.15	0.12	0.12
			40	0.93	0.94	0.06	0.07	-0.20	-0.22	0.08	0.07
	MNAR	20	20	0.91	0.97	0.09	0.14	-0.18	-0.12	0.09	0.15
			40	2.04	2.04	1.31	1.31	0.87	1.09	1.10	1.32
		40	20	1.00	1.23	0.17	0.32	-0.10	0.03	0.16	0.32
			40	3.13	3.13	2.36	2.36	1.69	2.13	1.93	2.37

Table 27

Relative Percentage Bias of Path Estimates for Parameter V1 → V2 = .11

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			2.04		0.67		0.27		0.68	
	MCAR	20	20	2.21	2.34	0.87	0.95	0.51	0.54	0.92	0.95
			40	1.86	1.81	0.56	0.52	-0.04	0.12	0.36	0.52
		40	20	1.16	0.85	-0.20	-0.43	-0.69	-0.86	-0.24	-0.43
			40	1.07	0.70	-0.25	-0.59	-0.76	-0.99	-0.38	-0.60
	MNAR	20	20	15.23	15.23	13.92	13.92	13.26	13.51	13.68	13.92
			40	10.31	10.31	9.09	9.09	8.38	8.71	8.82	9.10
		40	20	27.71	27.71	26.37	26.37	25.40	25.94	25.79	26.38
			40	20.75	20.75	19.31	19.31	18.10	18.86	18.57	19.31
30	NO MISSING			1.83		0.55		0.12		0.55	
	MCAR	20	20	1.93	1.66	0.61	0.36	0.18	-0.07	0.58	0.37
			40	1.13	1.03	-0.13	-0.24	-0.54	-0.67	-0.15	-0.24
		40	20	1.56	1.52	0.31	0.27	-0.07	-0.11	0.34	0.28
			40	1.32	1.58	-0.08	0.20	-0.18	-0.22	0.22	0.19
	MNAR	20	20	14.37	14.37	13.06	13.06	12.56	12.69	12.91	13.06
			40	10.05	10.05	8.75	8.75	8.08	8.37	8.49	8.77
		40	20	27.62	27.62	26.23	26.23	25.53	25.85	25.91	26.24
			40	21.35	21.35	19.94	19.94	18.82	19.48	19.31	19.95

When the data were MNAR then three path estimates displayed substantial amounts of positive bias. In the path from Variable One to Variable Five (Table 21) ANOVA results indicated that the bias was attributable to the type of missing data (η^2 ranged from .67 to .74) and the percentage of studies having missing data (η^2 ranged from .09 to .11). In the path from Variable Two to Variable Five (Table 22) there was relative bias only slightly above the 5% level and only when 40% of the studies and 40% of the variables had missingness and pairwise deletion was used. The path from Variable One to Variable Two (Table 27) displayed the greatest degree of relative bias for the MNAR conditions with amounts as large as 27.6%. ANOVA results indicated that a large proportion of this bias was attributable to the type of missing data ($\eta^2 = .77$ for all synthesis methods) and its interaction with the percentage of studies with missing data ($\eta^2 = .10$ for all synthesis methods). Similar to the relative bias found in the estimates of the correlation parameters, there was larger bias present when more studies had missing data and larger bias when fewer variables were missing with MNAR data.

Standard Error Estimates of Paths

The percentage relative bias of the standard error estimates of the paths from the eight methods of synthesizing correlation matrices across the 16 design conditions and the no missingness baseline condition are summarized in Table 28 through Table 34. Descriptive information about each of these synthesis methods across the conditions is provided in the following sections as well as results from the ANOVAs. The ANOVA results for the bias estimates from all standard errors can be seen in Appendix C.

Table 28

Relative Percentage Bias of Standard Error Estimates for Path V1 → V5

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			-3.75		-1.25		-0.67		-1.40	
	MCAR	20	20	-7.76	-3.81	-5.53	-1.66	-3.27	-1.28	-3.65	-1.70
			40	-9.16	-6.00	-7.21	-3.74	-3.17	-3.06	-3.85	-3.69
		40	20	-13.48	-7.47	-11.54	-5.20	-5.60	-4.55	-6.13	-5.13
			40	-13.38	-4.20	-11.44	-1.82	-3.37	-1.03	-4.35	-1.73
	MNAR	20	20	-8.30	-0.62	-6.08	1.85	-5.35	2.41	-5.99	1.80
			40	-9.95	-6.65	-7.74	-4.35	-7.47	-3.64	-7.91	-8.35
		40	20	-26.96	-9.91	-25.62	-8.21	-25.26	-7.56	-25.84	-8.35
			40	-13.64	-3.57	-11.79	-1.46	-12.20	-0.89	-12.82	-1.66
30	NO MISSING			0.81		2.89		3.20		2.82	
	MCAR	20	20	-5.95	-3.95	-3.80	-1.91	-1.31	-1.14	-1.73	-1.66
			40	-2.66	0.20	-0.65	2.45	2.82	3.03	2.22	2.22
		40	20	-13.38	-7.76	-11.63	-5.53	-5.36	-5.03	-5.93	-5.66
			40	-12.85	-4.79	-10.83	-2.22	-4.70	-1.66	-5.22	-2.26
	MNAR	20	20	-8.82	-2.16	-6.54	0.20	-5.78	1.06	-6.38	0.32
			40	-7.71	-4.96	-5.07	-2.27	-4.91	-1.60	-5.79	-2.34
		40	20	-22.92	-5.61	-21.05	-3.28	-20.38	-2.91	-20.89	-3.49
			40	-14.16	-5.31	-12.13	-3.04	-12.39	-2.48	-13.02	-3.09

Table 29

Relative Percentage Bias of Standard Error Estimates for Path V2 → V5

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-z	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			-8.81		-3.03		-2.38		-3.18	
	MCAR	20	20	-10.44	-5.65	-7.19	-1.58	-4.12	-0.89	-4.66	-1.65
			40	-12.21	-1.55	-9.71	1.73	-4.09	1.70	-4.06	1.78
		40	20	-7.95	-4.00	-3.71	-0.15	-1.13	-0.12	-1.41	-0.24
			40	-14.98	-7.20	-12.00	-3.46	-8.12	-3.02	-8.27	-3.41
	MNAR	20	20	-0.98	-4.79	3.40	-1.05	4.01	-0.68	3.49	-0.97
			40	-7.46	-2.47	-4.07	1.62	-1.42	1.99	-1.82	-4.12
		40	20	1.82	-9.59	6.29	-4.04	6.76	-3.20	6.37	-4.12
			40	-21.06	-6.36	-17.97	-1.66	-12.13	-1.02	-12.78	-1.62
30	NO MISSING			-7.43		-1.99		-0.42		-1.71	
	MCAR	20	20	-9.59	-6.22	-5.87	-2.73	-1.37	-2.54	-1.42	-2.87
			40	-8.04	-2.92	-4.23	0.30	-1.84	0.70	-2.07	0.34
		40	20	-13.00	-4.45	-8.76	0.95	-4.05	1.34	-4.44	1.18
			40	-14.81	-6.28	-11.18	-1.96	-4.47	-1.30	-5.36	-2.01
	MNAR	20	20	-1.85	-5.49	1.83	-2.36	2.10	-2.22	1.91	-2.40
			40	-9.78	-4.35	-6.51	-0.47	-3.62	-0.37	-4.30	-0.43
		40	20	4.86	-5.12	9.99	-0.49	10.15	0.16	10.01	-0.59
			40	-16.37	-4.43	-13.17	0.25	-8.84	0.74	-9.22	0.37

Table 30

Relative Percentage Bias of Standard Error Estimates for Path V3 → V5

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			-10.09		-5.20		-5.09		-5.31	
	MCAR	20	20	-7.75	-4.33	-3.20	1.29	-1.06	2.00	-1.48	1.32
			40	-11.15	-6.07	-5.72	-1.20	-2.57	-0.81	-3.03	-1.20
		40	20	-13.28	-6.59	-9.80	-1.59	-4.96	-1.10	-5.09	-1.61
			40	-15.90	-9.38	-12.75	-5.08	-9.18	-4.92	-9.15	-4.99
	MNAR	20	20	-3.89	-6.71	1.85	-1.95	2.53	-1.86	2.01	-1.82
			40	-2.66	-7.15	2.40	-1.15	4.04	-0.60	3.37	-5.09
		40	20	-2.28	-11.79	4.47	-5.06	5.31	-4.37	4.33	-5.09
			40	-0.19	-3.47	5.30	2.58	10.79	2.98	9.94	2.53
30	NO MISSING			-3.67		1.59		2.30		1.65	
	MCAR	20	20	-6.49	-2.30	-0.55	3.99	3.22	4.81	2.62	3.98
			40	-7.05	-3.55	-2.48	-0.19	-0.78	0.13	-0.88	-0.22
		40	20	-12.30	-4.69	-7.62	0.70	-4.68	0.55	-4.63	0.75
			40	-13.99	-6.99	-9.07	-0.30	-3.11	1.00	-4.04	-0.44
	MNAR	20	20	-3.21	-5.83	2.10	0.04	2.51	0.59	2.31	0.13
			40	0.50	-2.15	5.64	3.25	6.95	3.33	6.81	2.90
		40	20	5.97	-4.40	10.75	1.40	10.80	1.83	10.91	1.28
			40	-0.74	-5.18	2.97	-0.06	6.04	0.54	5.94	0.10

Table 31

Relative Percentage Bias of Standard Error Estimates for Path V4→V5

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			-1.42		2.81		3.09		2.85	
	MCAR	20	20	-3.00	-1.38	0.97	3.76	2.27	4.08	2.31	3.88
			40	-9.78	-4.84	-6.39	0.32	-3.43	0.76	-3.60	0.25
		40	20	-6.87	-4.48	-1.00	1.18	0.60	1.81	0.17	1.39
			40	-9.49	-3.53	-6.74	0.17	-5.44	0.03	-5.19	0.18
	MNAR	20	20	2.62	-2.45	7.25	2.68	7.43	2.85	7.35	2.77
			40	3.21	-5.27	9.41	1.55	10.60	2.42	9.82	-2.26
		40	20	0.34	-7.50	4.98	-2.35	5.58	-1.82	4.95	-2.26
			40	11.51	-4.17	16.59	-0.57	17.89	-0.61	17.57	-0.61
30	NO MISSING			-1.15		2.81		3.36		2.74	
	MCAR	20	20	-2.57	-1.12	1.93	3.89	3.14	4.13	3.08	3.79
			40	-3.03	-0.02	1.06	3.15	1.95	3.41	1.90	3.33
		40	20	-4.62	0.62	-2.36	3.40	-0.74	3.60	-0.76	3.42
			40	-3.23	-2.01	-0.28	1.74	2.36	2.35	2.06	1.73
	MNAR	20	20	3.17	-1.03	8.41	4.56	8.91	5.09	8.57	4.53
			40	6.96	0.24	11.89	4.63	12.06	4.84	11.90	4.34
		40	20	9.24	-2.04	13.17	2.88	13.05	2.85	13.24	2.92
			40	16.91	-0.91	21.44	3.51	22.06	4.25	22.13	3.71

Table 32

Relative Percentage Bias of Standard Error Estimates for Path V3 → V4

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			19.40		23.27		23.34		23.30	
	MCAR	20	20	16.33	18.00	19.76	21.42	21.39	21.31	21.48	21.37
			40	12.56	15.37	14.20	16.72	17.67	16.18	18.00	16.65
		40	20	12.51	12.30	15.48	15.38	18.74	15.26	18.69	15.42
			40	9.84	10.91	13.53	14.11	15.92	14.06	15.99	14.15
	MNAR	20	20	23.68	17.37	26.09	20.38	25.88	20.06	26.16	20.35
			40	31.49	22.64	33.00	25.12	32.10	25.05	32.92	15.41
		40	20	23.44	11.08	28.49	15.42	29.44	15.88	28.54	15.41
			40	41.48	16.62	44.91	20.60	44.86	21.23	45.00	20.60
30	NO MISSING			18.12		22.65		22.53		22.59	
	MCAR	20	20	20.92	21.13	24.16	24.29	24.94	24.02	25.28	24.33
			40	17.71	17.89	20.86	20.91	22.58	21.03	22.87	21.16
		40	20	17.95	18.40	20.23	21.05	22.64	20.80	23.11	20.95
			40	16.37	17.03	19.74	20.86	23.04	20.38	23.32	20.87
	MNAR	20	20	29.07	25.44	33.22	28.45	33.28	28.05	33.07	28.42
			40	26.31	15.71	29.59	19.66	29.39	19.89	29.66	19.86
		40	20	33.73	16.22	37.59	21.17	37.74	21.51	37.53	21.13
			40	44.23	17.56	48.19	23.49	48.05	24.18	48.29	23.34

Table 33

Relative Percentage Bias of Standard Error Estimates for Path V2 → V3

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			13.91		17.35		17.29		17.31	
	MCAR	20	20	19.11	17.75	21.92	20.96	22.79	21.27	23.05	21.00
			40	14.34	17.25	17.93	21.10	19.33	21.30	19.13	21.07
		40	20	16.02	18.08	21.58	22.74	24.79	23.23	24.18	22.80
			40	10.70	13.77	13.46	17.45	16.30	17.73	16.29	17.48
	MNAR	20	20	22.39	15.87	23.90	18.18	23.36	17.37	23.95	18.13
			40	14.13	18.63	19.10	23.79	20.77	24.59	19.92	17.57
		40	20	35.88	15.48	37.87	17.38	37.28	16.98	37.90	17.57
			40	2.69	15.81	6.47	20.07	9.08	20.84	8.78	20.14
30	NO MISSING			20.16		23.99		24.17		23.88	
	MCAR	20	20	20.02	18.63	23.37	21.64	24.12	21.57	24.61	21.71
			40	17.64	17.35	23.15	22.43	25.45	23.02	24.46	22.47
		40	20	18.30	18.54	20.35	19.64	21.58	18.82	22.03	19.72
			40	16.69	19.21	19.55	21.92	22.99	21.36	23.17	21.87
	MNAR	20	20	22.58	16.53	25.77	18.99	25.36	18.69	25.84	19.07
			40	9.92	13.65	14.42	18.23	15.73	19.04	15.02	18.14
		40	20	28.91	14.06	34.79	18.40	35.52	18.50	34.91	18.42
			40	3.65	15.21	10.24	22.54	14.48	24.21	13.58	22.48

Table 34

Relative Percentage Bias of Standard Error Estimates for Path V1→V2

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			1.31		3.16		3.60		3.20	
	MCAR	20	20	-4.09	-2.06	-2.66	-0.38	-0.45	0.18	-1.00	-0.34
			40	-6.96	-6.86	-5.60	-5.29	-3.05	-4.87	-4.32	-5.32
		40	20	-3.02	-2.74	-1.23	-1.36	0.84	-0.95	0.34	-1.42
			40	-3.95	-0.70	-2.62	0.61	1.39	0.98	0.96	0.55
	MNAR	20	20	-12.84	-5.55	-11.25	-3.82	-10.39	-3.28	-10.86	-3.83
			40	-7.35	-3.70	-5.89	-2.17	-5.43	-1.93	-5.73	-1.81
		40	20	-22.95	-3.78	-21.30	-1.72	-20.93	-1.41	-21.14	-1.81
			40	-12.89	-1.74	-11.27	0.10	-10.92	0.45	-11.18	0.09
30	NO MISSING			2.39		4.00		4.51		4.05	
	MCAR	20	20	-0.84	-1.34	0.64	0.07	1.48	0.62	0.88	0.05
			40	-3.48	-2.74	-2.01	-1.28	-0.46	-1.00	-0.91	-1.34
		40	20	-3.26	-3.94	-1.82	-2.75	0.91	-2.22	0.30	-2.74
			40	-5.49	-6.07	-3.74	-4.14	-1.27	-3.75	-1.46	-4.31
	MNAR	20	20	-10.20	-3.46	-8.40	-1.51	-8.03	-1.18	-8.38	-1.65
			40	-2.78	0.46	-1.11	2.18	-0.72	2.60	-1.02	2.20
		40	20	-20.54	-2.77	-18.85	-0.71	-17.99	-0.29	-18.41	-0.75
			40	-13.91	-4.30	-12.14	-2.33	-11.67	-1.92	-12.13	-2.50

While there was no substantial relative bias in the synthesized correlation estimates and path estimates for MCAR data, there was substantial relative bias present in the standard error estimates under varying conditions with MCAR data. However, the relative bias in the standard error estimates was for the most part not consistent across estimates. The only pattern that emerged was that the relative bias present was larger when using pairwise versus listwise deletion for all standard error estimates. There was more relative bias present when the data were MNAR than with MCAR data. Similar to the relative bias present in the estimates of the correlation and path parameters, the relative bias for the standard error estimates was typically larger when more studies had missing data for both MCAR and MNAR data. When the relative bias was negative then the standard error estimates for the two paths from Variable One had the largest bias estimates. However, two of the standard errors of the paths displayed substantial positive relative bias across all conditions.

In the standard error estimates of the path from Variable One to Variable Five (Table 28) substantial negative relative bias was present when 40% of the studies had missing variables for the univariate methods of synthesis with pairwise deletion and MCAR data. When the data were MNAR the substantial bias occurred in the same conditions, but also when multivariate methods were used to synthesize the correlations. The ANOVA results related this underestimation to the percentage of studies with missing variables for both univariate methods (with and without transformed correlations) of synthesis with pairwise deletion (η^2 = .56 and .57) and both multivariate methods of synthesis with pairwise deletion (η^2 = .31 and .31).

In the standard error estimates of the path from Variable Two to Variable Five (Table 29) substantial negative relative bias was present when 40% of the studies and the variables had missingness with pairwise deletion and MNAR data. This same pattern of negative relative bias was present with MCAR data but only with the univariate methods of synthesizing correlations. The ANOVA results related this underestimation to the percent of variables missing (η^2 = .29 to .34) and the interaction of the percentage of variables missing with the type of missing data (η^2 ranged from .28 to .30) for synthesis methods with pairwise deletion.

In the standard error estimates of the path from Variable Three to Variable Five (Table 30) the negative relative bias was only slightly greater than 10% in several conditions (ranging from -10.75% to -15.90%). This relative bias only occurred in conditions with pairwise deletion and was more prevalent with MCAR data and univariate weighting with untransformed correlations. The ANOVA results related this underestimation to the type of missing data (η^2 ranged from .66 to .73) for synthesis methods using pairwise deletion.

In the standard error estimates of the path from Variable Four to Variable Five (Table 31) the negative relative bias was present when 40% of the variables and studies had missingness for pairwise deletion with MNAR data (except with 30 studies and only 20% of the variables had missingness). The ANOVA results related this underestimation to the type of missing data (η^2 ranged from .67 to .71) for synthesis methods using pairwise deletion.

In the standard error estimates of the path from Variable One to Variable Two (Table 34) the negative relative bias was present in all conditions with MNAR data except when 20% of the studies and 40% of the variables had missingness. The ANOVA results related this underestimation to the type of missing data (η^2 ranged from .50 to .58), its interaction with the percent of studies with missing data (η^2 ranged from .13 to .15) and its interaction with the percent of variables missing (η^2 ranged from .10 to .14) for all synthesis methods using pairwise deletion.

Across all study conditions and synthesis methods and even when there was no missingness, positive relative bias greater than 10 percent was present for the standard errors of the paths from Variable Three to Variable Four and from Variable Two to Variable Three (Table 32 and Table 33). This overestimation was also present across conditions when the data were MNAR and reached as high as 44.91%. The ANOVA results related the relative bias in the standard error of the path from Variable Three to Variable Four to the type of missing data (η^2 ranged from .61 to .68) for all synthesis methods with pairwise deletion. The ANOVA results related the relative bias in the standard error of the path from Variable Two to Variable Three to the percentage of missing variables (η^2 ranged from .45 to .51) for all synthesis methods with pairwise deletion.

Goodness of Fit Indices for the Structural Model

The percentage rejection rates of the chi-squared test for the fit of the data to the structural model across study conditions and synthesis methods can be seen in Table 35. (It should be noted that the model tested replicated the generating model and thus the correct decision is not to reject the model). Even with no missingness the rejection rates were slightly above the expected 5% level across all eight methods for synthesizing correlations. In addition, Hu and Bentler's (1999) joint criteria for the goodness of fit of a model was examined across all design factors and synthesis methods. The joint criteria of a Comparative Fit Index (CFI) greater than or equal to .96 and a Standardized Root Mean-Square Residual (SRMR) less than or equal to .10 resulted in selecting the model in every design factor and synthesis method. The joint criteria of a Root Mean-Square Error of Approximation (RMSEA) less than .06 and a SRMR less than or equal to .10 also resulted in selecting the model across every design factor and synthesis method.

Listwise Versus Pairwise Deletion for the Chi-Squared Test

Pairwise deletion resulted in higher rejection rates for the chi-squared test than did listwise deletion across all design factors and synthesis methods except when W-COV GLS was used with MCAR data then the chi-squared rejection percentages were comparable for pairwise and listwise deletion. In particular, when data were MNAR the pairwise rejection rates were in some cases twice that of rates when using listwise deletion and reached as high as 31.8%. The degree of missing data negatively impacted the results for both methods of deletion when the data were MNAR. The performance of pairwise deletion was unacceptably high in almost every condition with MNAR data.

Z Transformed Versus Untransformed Correlations

Transformed and untransformed correlations produced fairly comparable rejection rates across conditions with perhaps a slight positive bias for the univariate-*r* method with listwise deletion and MCAR data.

Table 35

Rejection Percentages for the Chi-Squared Test of Model Fit

	Missingness			Method							
				Univariate-*r*		Univariate-*z*		W-COV GLS-*r*		W-COV GLS-*z*	
K	Type	% Studies	% Variables	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise	Pairwise	Listwise
10	NO MISSING			7.1		5.7		5.8		6.1	
	MCAR	20	20	9.6	7.0	8.4	5.5	6.2	5.3	6.9	5.5
			40	8.5	6.2	7.3	5.5	6.2	5.6	6.6	5.5
		40	20	9.1	6.2	7.9	5.2	4.8	5.0	5.4	5.2
			40	10.2	6.5	8.9	5.3	5.6	5.2	5.5	5.5
	MNAR	20	20	10.2	7.5	8.8	6.5	8.3	6.5	8.7	6.7
			40	9.6	6.8	9.4	6.6	8.5	6.7	8.0	6.5
		40	20	19.7	9.9	18.4	9.8	18.4	9.4	18.1	9.6
			40	18.2	8.2	18.2	7.3	14.8	7.2	14.7	7.4
30	NO MISSING			7.1		5.2		4.8		5.1	
	MCAR	20	20	8.2	5.7	6.6	5.1	4.3	5.0	5.0	5.1
			40	7.8	6.1	6.5	5.9	5.6	5.6	5.7	5.8
		40	20	9.8	7.3	8.2	5.6	5.6	5.1	5.7	5.6
			40	9.5	7.7	8.3	5.8	5.3	5.4	5.7	5.8
	MNAR	20	20	11.6	7.8	10.8	7.0	11.0	7.0	10.4	7.3
			40	10.0	7.6	11.1	7.1	8.8	7.6	8.5	7.3
		40	20	31.8	16.9	31.0	16.9	30.7	16.6	31.3	16.7
			40	26.4	13.0	29.5	13.6	22.0	13.9	21.5	13.5

Univariate Versus Multivariate Methods

The univariate methods produced the largest chi-squared rejection rates across all conditions. The multivariate methods resulted in rejection rates close to the five percent expected rate across all design factors with MCAR data. However, with MNAR data the rejection rates reached as high as 31.3% with pairwise deletion. In addition, the number of studies with missingness impacted the rejection rates when data were MNAR. When 30 studies were combined then the rejection rates were higher than when 10 studies were combined. This difference is more apparent when 40% of the studies contained MNAR data.

Implementation of the MNAR Procedure

In order to understand why when relative bias was present in the MNAR conditions it was larger with fewer variables missing, an examination of which study had variables selected to be missing within a simulated meta-analysis was conducted. This deviation from the expected linear trend (of more missingness corresponding to more bias) was believed to be the result of the procedures used to select variables to be missing in the MNAR condition described in Chapter Three. In the MNAR conditions, the absolute values of each study's correlations involving either Variable One or Variable One and Variable Two were summed together and the smallest values were derived to be missing. In the example used in Chapter Three with 10 studies, 20% of the studies had missing variables and 40% of the variables were missing, the three correlations that include Variable 2 were summed together along with the four correlations involving Variable 1 ($r_{21}, r_{31}, r_{41}, r_{51}, r_{32}, r_{42},$ and r_{52}) for each study. The two studies with the smallest summed values for the seven correlations were set such that any correlations involving Variables 1 and 2 were missing for those studies. However, using these same conditions but when only 20% of the variables were missing, only the four absolute values for the correlations involving Variable One were summed together for each study. To illustrate this process, the summed absolute values from one simulated meta-analysis for just Variable One and for Variable One and Two together can be seen in Table 36.

Table 36

Correlations' Summed Absolute Values Used to Select Studies with Missingness Under MNAR Condition

	Summed Absolute Values of Correlations Involving	
Study	Variable One	Variable One and Variable Two
Study One	.32	1.82
Study Two	.46	1.60
Study Three	.69	2.00
Study Four	.31	1.59
Study Five	.73	1.96
Study Six	.16	1.59
Study Seven	.42	1.96
Study Eight	.51	1.90
Study Nine	.42	1.86
Study Ten	.20	1.89

In the condition with 20% of the variables missing, Variable One would be missing in Studies Six and Ten. However, if the condition had been the one with 40% of the variables missing, then Study Four and Study Six would have would have been the ones designated to have missing correlations involving Variable One and Variable Two missing. So different studies would have Variable One set to missing depending on the level of variables with missingness. In the 40% condition sometimes the study associated with the smallest absolute value for correlations involving Variable One was not set to have missingness because the Variable One correlations were combined with those of Variable Two. This admitted smaller correlations into the simulated meta-analysis and less bias in the estimation of the correlation parameters for studies with higher levels of missingness (the 40% versus 20% conditions). The same was also true for studies with the smallest correlations involving Variable Two.

Correlation Versus Covariance Matrix

In order to understand why even with no missing correlations there was still a substantial amount of bias for most of the standard error estimates of the paths (and in particular why two of the standard error estimates of the paths had substantial positive bias across all conditions) several additional conditions were run and examined. Since using a correlation matrix instead of a covariance matrix can result in inaccurate standard error estimates and thereby affect the chi-squared test of model fit in SEM (Cudeck, 1989), it was of interest in this study to determine if the large standard error bias and rejection rates for the chi-squared test were attributable to the use of the correlation matrix. To assess this, data were generated for a 10 study meta-analysis and then scaled with the Cholesky decomposition using the data generation procedures discussed in Chapter 3. This was done for 1,000 iterations and with no missing data. However, correlations were not computed from the data and then synthesized as before, instead, the raw data were used to estimate the model in Appendix A. The raw data were then analyzed in one of two ways, as either a covariance or a correlation matrix. The results from the path estimate bias and standard error bias can be seen in Table 37 for both methods. In examining these results it is readily apparent that the large standard error bias is attributable to the use of the correlation matrix as input to the structural model. When covariance matrices were analyzed then all of the standard error estimates were within 10 percent and the path estimates were within five percent of their corresponding parameter values. The rejection rates for the chi-squared test of model-data fit was also 4%. When correlation matrices were used to estimate the structural model then the results were very similar to those produced by the synthesized correlations with no missingness. The rejection rates for the chi-squared test of model-data fit was also 4.1%.

Table 37

Relative Percentage Bias for Path Estimates and Their Standard Errors with Covariance and Correlation Matrices

	Parameter						
Type of Matrix	$V1 \rightarrow V5$	$V2 \rightarrow V5$	$V3 \rightarrow V5$	$V4 \rightarrow V5$	$V3 \rightarrow V4$	$V2 \rightarrow V3$	$V1 \rightarrow V2$
Path Estimates							
Correlation	-0.49	0.66	-0.13	-0.14	-0.10	-0.08	0.82
Covariance	-0.20	0.18	0.06	0.04	-0.05	-0.08	-1.06
Standard Error Estimates							
Correlation	-2.59	-0.56	-0.71	3.78	23.82	24.49	0.40
Covariance	-1.89	-4.09	2.10	-1.46	-1.45	-5.57	3.04

Chapter 5: Discussion

The results from this study support some previous findings and extend current understanding of meta-analytic SEM procedures. This chapter summarizes the findings from this study and compares them with the results from other meta-analytic SEM studies. Limitations and future directions of this study are provided. Finally, implications from the results of this study for future meta-analytic SEM work are given.

Framework

The purpose of this study was to compare several methods for synthesizing correlations with various patterns and types of missing data. Specifically, of interest in this study was a comparison of the multivariate weighting procedure (W-COV GLS) with univariate weighting with and without Fisher's *z* transformation and using listwise and pairwise deletion for handling missing data. In applied meta-analytic SEM analyses, it is typical for primary studies to have missing correlations of interest. Researchers often do not report all of the relevant correlations in their study. Data can also be missing as a result of the file-drawer problem (Rosenthal, 1979) in which a potential selection bias may occur whereby correlations that are non-significant or not in the predicted direction are not reported and are considered to be MNAR. To date, simulation studies have not examined the performance of different methods for synthesizing correlations with MNAR data. Therefore, of concern in this study was the performance of univariate versus multivariate weighting methods for synthesizing correlations with various degrees and types of missing data on recovery of the true correlations and path coefficients in the associated structural equation model. Recovery was assessed using the relative bias estimates of the synthesized correlations, path parameters of the structural model and standard errors of the paths, as well as the data-model fit rejection rates resulting from using several goodness-of-fit indices.

Summary of Results and Comparison with Previous Research

There was no substantial relative bias present in the estimates of the synthesized correlations or the paths in the structural model when data were MCAR, even in the condition with the largest degree of missing data. These findings are similar to previous meta-analytic SEM simulation research where data with no missingness produced accurate estimates of the population correlations (Becker and Fahrbach, 1994; Hafdahl, 2001) and MCAR data did not result in substantial relative bias for the SEM parameter estimates (M. Cheung & Chan, 2002; S. Cheung, 2001). However, in this study when data were MNAR then relative bias was found for estimation of the synthesized correlations and path estimates affected by the missing data. The bias in the MNAR condition for the synthesized correlation estimates involving Variable One led to bias in the parameter estimates and the standard error estimates for the paths corresponding to Variable One. Specifically, the synthesized correlations and path estimates associated with Variable One demonstrated the largest degree and amounts of relative bias with MNAR data. Because these correlation parameters were small in magnitude then the use of relative bias versus absolute bias could have led to larger bias estimates and future research should examine the difference between the two methods for estimating bias.

This positive relative bias in the four synthesized correlations involving Variable One and the paths from Variable One to Variable Two and from Variable One to

Variable Five (see Appendix A) was on average larger in the condition when more (40%) of the studies had missingness than when fewer (20%) studies had missing data. This overestimation was not surprising considering that the smallest generated correlations were designated as missing in each simulated meta-analysis, thereby inflating the final synthesized estimates. However, unexpectedly, when 40% of the variables were missing then the relative bias was smaller than when only 20% of the variables were missing for both levels of number of studies with missing data. In order to understand these unanticipated results, an examination of the generated correlations designated to be missing in the MNAR condition was compared for both levels of the percentage of variables missing. It was found that differences in this bias could be attributed to the procedures used to implement the MNAR condition in this study. Specifically, in the MNAR condition with 40% of the variables missing it was not always the smallest correlations associated with Variable One and Variable Two that were set to missing, thus the synthesized correlation estimate was not as inflated as when the smallest correlations were always set to missing in the 20% of variables missing condition. This would also explain why the relative bias that was present in every condition for the correlations involving Variable One when the data were MNAR was not present in every condition for Variable Two. It is believed that if a different procedure had been used to replicate patterns of MNAR data such as if the correlations involving Variable One and Variable Two were summed and averaged separately instead of together that the linear trend of more relative bias present with larger degrees of missing variables might have been found.

Of additional interest in this study was the presence of substantial relative bias in the estimates of the standard errors of the paths. While there was no substantial relative bias for the estimates of the population correlations and path parameters with MCAR data, the standard error estimates did demonstrate relative bias in certain conditions, although not consistently, for some paths with MCAR data. There was also substantial relative bias present when the data were MNAR for certain conditions. The ANOVA results only consistently related the bias to the use of pairwise deletion. This bias was frequently unacceptable reaching magnitudes as high as 48.3% and was negative for all paths except for the paths from Variable Two to Variable Three and Variable Three to Variable Four. In these two paths on average there was extensive positive relative bias present in all conditions for both MCAR and MNAR data.

Because Cudeck (1989) reported that use of a correlation matrix with SEM can result in biased standard error estimates, raw data generated from the population correlations was analyzed as both a correlation and a covariance matrix in order to ascertain if the positive relative bias present in these two paths was related to the use of the correlation matrix with SEM. The standard error estimates of the paths in the structural model using a correlation matrix were very comparable to the standard error estimates from the baseline condition of no missingness with large amounts of positive relative bias for the two paths with the synthesized correlation estimates. However, an examination of the standard error estimates from analyzing the covariance matrix revealed no substantial relative bias, thereby indicating that this relative bias found in all conditions for these two paths was related to the use of a correlation matrix with SEM.

There was no difference in the relative bias of the synthesized correlations, path estimates, and standard errors whether 10 or 30 studies were combined for the meta-analysis. This is similar to previous meta-analytic SEM simulation research, where the number of studies included in the meta-analysis did not impact the estimation of the path and standard error estimates (S. Cheung, 2000).

Of further concern in this study was the performance of several goodness-of-fit indices under various conditions and synthesis methods. Interestingly, both sets of the joint criteria proposed by Hu and Bentler (1999) resulted in selecting the model for every design factor and synthesis method. The chi-squared test for the fit of the data to the model resulted in a slightly higher than nominal rates of model rejection with MCAR data for all synthesis methods. However with MNAR data this over-rejection rate was unacceptable and reached as high as 31.8%. While the number of studies included was not seen to impact parameter estimation the number of studies was seen to influence the rejection rates for the chi-squared test with larger degrees of missing data. Specifically, a higher rejection rate was found when more studies had missingness and when 30 studies were included.

Comparison of Methods for Synthesizing Correlations

In this study, the W-COV GLS procedure performed similarly to the univariate weighting method in synthesizing correlations and estimating the paths of the structural model across all conditions. This finding is similar to those of S. Cheung (2000) and Becker and Fahrbach (1994) in which the use of some type of average method for computing the variance-covariance matrix for GLS resulted in results similar to those of univariate weighting. The use of the W-COV GLS procedure avoided the problems found with traditional GLS procedures such as the substantial bias found in parameter estimation and the over-rejection of the model using the chi-squared test with no missingness or when data were MCAR (S. Cheung, 2001; M. Cheung & Chan, 2002; Becker & Fahrbach, 1994; Hafdahl, 2001). However, differences in the performance of W-COV GLS and univariate weighting were present in the estimates of the standard errors and in the rejection rates for the chi-squared test of the fit of the model. When these differences emerged, it was typically the W-COV GLS procedure that produced more accurate estimates of the standard error estimates and model rejection rates closer to the expected 5% level for the chi-squared test. This matched S. Cheung's (2001) finding of the superior performance of his weighted average method for computing the variance-covariance matrix for use with GLS on the chi-squared test over univariate and traditional GLS procedures. However, it should be noted that regardless of the synthesis method used, the bias present in the correlations and parameters involving Variable One when 20% of the variables were MNAR was always substantial.

A second difference to materialize among the methods for synthesizing correlations was detected between the results for the transformed and untransformed correlations. With univariate weighting, the transformed correlations on average produced smaller relative bias estimates in almost every case where bias was present and had model rejection rates closer to the nominal 5% rate than the untransformed correlations. This replicated the findings of Becker and Fahrbach (1994) and Hafdahl (2001) where *z* transformed correlations resulted in more precise estimation for synthesized correlations and estimation of the structural model than untransformed correlations. These findings suggest that the *z* transformation does normalize the distribution of correlations and result in less biased estimates for univariate weighting. However, a comparison of transformed and untransformed correlations using the W-COV GLS procedure did not result in any differences across all relative bias estimates and for rejection rates for the chi-squared statistic. Further research should investigate why this difference did not emerge for the W-COV GLS procedure.

The biggest difference among methods used in synthesizing correlations emerged in the comparison of listwise and pairwise deletion. There was no difference found between listwise and pairwise deletion in the relative bias of the synthesized correlations and the path estimates with MCAR and MNAR data. However, in the estimation of the standard errors and in the rejection rates for the chi-squared model fit test, pairwise deletion resulted in far more inaccurate results than did listwise deletion for W-COV GLS and univariate weighting. S. Cheung (2000) also found higher rejection rates of the model when pairwise deletion was used than with listwise deletion. M. Cheung and Chan (2002) also reported slight over-rejection rates with univariate weighting and traditional GLS procedures for synthesizing correlations with pairwise deletion. In addition, when more studies were used in the meta-analysis the use of pairwise deletion produced even higher rejection rates. In Marsh's (1998) simulation study for the optimal sample size with pairwise deletion in SEM, the chi-squared test statistic was estimated with less bias when the minimum sample size was used rather than the mean sample size for the estimation of the structural model. Perhaps the inadequate performance from pairwise deletion in this study was related to the use of the mean sample size rather than the minimum sample size. When more studies were used then the use of the mean sample size seems to produce even larger inaccurate rejection rates for the data-model fit.

Limitations and Future Directions

While several characteristics of this study are potential limitations (i.e., the mean sample size for pairwise deletion with SEM, the use of a fixed-effects model, and the use of a correlation matrix with SEM), these characteristics were chosen because they are frequently used by applied meta-analytic SEM researchers. Therefore, while their use might not be optimal, their performance should be assessed, and the results used to inform ensuing practice.

First, the use of the mean sample size for the estimation of the structural model with pairwise deletion is potentially a limitation of this study. Future research examining the appropriate sample size for use with meta-analytic SEM should be assessed, with a focus on examining estimation of the standard errors and chi-squared model rejection rates resulting from different sample sizes currently used with pairwise deletion.

Second, the generating correlation parameters used in this study were based on a fixed-effects model. Applied meta-analytic SEM studies frequently are estimated using a fixed-effects model and therefore the performance of the conditions in this study with a fixed-effects model is important. However, a random-effects model might be more appropriate in many meta-analytic SEM studies, particularly when important between-study characteristics impact the variability of the model. Future research should examine whether the findings from this study are consistent for a random-effects model. The homogeneity test to determine if the correlations significantly vary thus indicating that a random-effects model should be used was also not evaluated in terms of the performance of the different methods for synthesizing correlations under different conditions.

An additional limitation of this study was the analysis of a correlation matrix for estimation of the structural model. As noted in Cudeck (1989), use of correlation matrices as covariance structures with SEM can result in biased standard error estimates and test statistics. In this study, the use of a correlation matrix did result in two extremely inaccurate path standard error estimates. However, typically meta-analytic SEM researchers only have correlation matrices available for SEM. Some applied meta-analytic SEM researchers have noted the potential problems arising from the use of correlation matrices with SEM (Hom, et. al, 1992; Verhaeghen & Salthouse, 1997), however the majority has not. Currently, widely used programs for the estimation of structural models have not made available corrections for using correlation matrices with SEM. There are several programs such as SEPATH (Steiger, 1999) and RAMONA (Browne, 1997) which will produce more accurate standard error estimates with correlation matrices. However, these programs are not widely used nor available to applied researchers. Future research should explore new methods for producing accurate standard error estimates when correlation matrices are analyzed.

This study also examined fairly small to moderate amounts of missing data. In applied meta-analytic SEM some models (particularly those with a large number of variables) have larger percentages of missing data than those used in this study. It could be interesting to determine in future research the impact of conditions with larger overall percentages of missingness as well as other types of missingness mechanisms, such as MAR and different patterns used to define MNAR data.

It was also noted earlier that a potential limitation of this study was the procedure used to replicate patterns of MNAR data. If the procedure had been implemented such that the correlations involving Variable One and Variable Two were summed and averaged separately instead of together then the linear trend of more relative bias present with larger degrees of missing variables might have been found. However, while this linear pattern across levels of missing variables was not replicated in this study, the relative bias, when present, was unacceptably high.

Lastly, both sets of the joint criteria proposed by Hu and Bentler (1999) for assessing data-model fit resulted in selecting the model across every design factor and synthesis method. Future research should investigate their use with misspecified models to assess the performance of these criteria for rejecting an incorrect model.

Implications for Meta-Analytic SEM Research

In this study, when correlations were MNAR then inaccurate estimates of the synthesized correlation matrix, the path parameters, the standard error estimates, and the chi-squared test of the goodness-of-fit of the model were reported regardless of method used to synthesize correlations. Applied meta-analytic SEM researchers should attempt to retrieve all correlations of interest by contacting researchers who may have additional data available though unreported. Fortunately, technology has enhanced accessibility to dissertations and associated data that are not always presented in published articles.

There are several practical procedures for assessing whether a file drawer problem exists among the studies collected for a meta-analysis. Cooper and Hedges' (1994) text entitled *The Handbook of Research Synthesis* provides several techniques for detection of the file-drawer problem including an examination of a funnel plot and Rosenthal's "file-drawer" method (Rosenthal, 1979). Meta-analytic researchers should always assess whether the correlations from studies collected seem representative of those in the population.

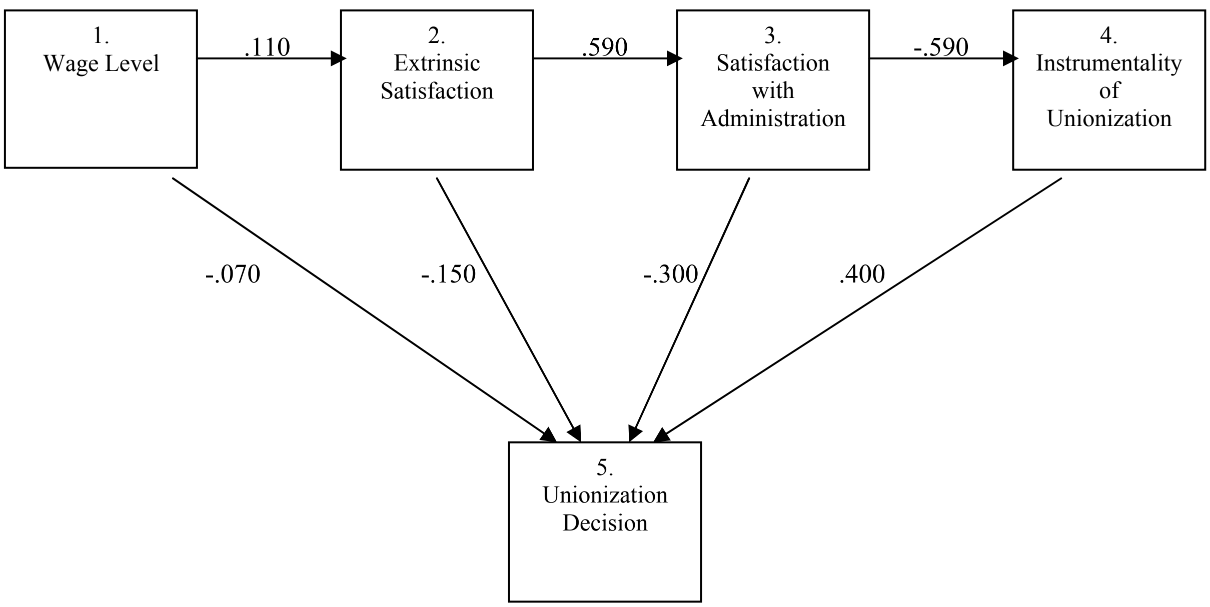
Another important finding to come out of this study was the inferior performance of pairwise deletion over listwise deletion with larger rejection rates of the chi-squared test and substantial bias present in the standard error estimates. While S. Cheung (2000) also noted that when data were MCAR pairwise deletion over-rejects the correct model, it is interesting that the model was over-rejected with pairwise deletion when data were MNAR. This is a very important matter to consider since most applied meta-analytic SEM researchers use pairwise deletion and listwise deletion is not an option in scenarios where most studies contain some missing data. While this is not certain until more research has been conducted, the estimation of the structural model with a smaller sample size such as the minimum sample size from synthesized correlations with pairwise deletion may produce more accurate results.

This study has also indicated the slightly superior performance of the W-COV GLS procedure over univariate weighting for synthesizing correlations. It is recommended based on these findings that the W-COV GLS procedure be implemented in multivariate meta-analytic procedures to account for the dependence between correlations arising from the same study. Interestingly, there was no difference for the W-COV GLS procedure with transformed and untransformed correlations. However, if univariate procedures are implemented then this study has identified that use of the *z* transformation for synthesizing correlations is superior to use of untransformed correlations. While the W-COV GLS procedure outperformed the univariate weighting method, it is still somewhat questionable whether the complexity involved in implementing this procedure outweighs its slightly superior performance. Additional research is necessary to determine whether the benefits of the W-COV procedure are substantially larger than with univariate weighting under other conditions. As a final note, researchers should also use caution in interpreting standard errors when using correlation matrices with standard SEM software packages.

Appendix A

Path Model with Standardized Path Values

from Premack and Hunter (1988)



Appendix B

Sample Sizes Reported for Studies Summarized in

Verhaeghen and Salthouse's (1997) Meta-Analysis

35	96	128	200	259
45	96	129	211	289
50	96	131	213	300
58	96	132	221	301
60	100	137	223	305
60	100	147	223	316
63	100	160	227	383
67	100	163	228	477
70	102	164	233	477
72	105	164	233	558
75	108	165	233	567
77	116	171	239	611
80	117	172	240	628
80	120	173	240	708
80	120	180	240	828
80	120	193	240	933
90	125	197	242	1205
90	127	198	246	1480
90	127	200	258	1680

Appendix C

Table C1

Analysis of Variance for ρ_{21} =.110

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	3309.1*	.77	3225.0*	.77	3406.8*	.77	3169.0*	.77
Number of Studies (S)	1	0.2	.00	0.1	.00	0.2	.00	0.1	.00
Percent Studies (PS)	1	366.0*	.08	353.1*	.08	385.4*	.08	351.7*	.09
Percent Variables (PV)	1	104.5*	.02	99.0*	.01	107.0*	.02	96.6*	.01
T x S	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
T x PS	1	438.5*	.10	423.6*	.10	456.6*	.10	423.2*	.10
T x PV	1	80.3*	.02	79.1*	.02	82.3*	.02	77.2*	.02
S x PS	1	2.0	.00	3.6	.00	2.0	.00	3.7	.00
S x PV	1	0.1	.00	0.3	.00	0.1	.00	0.3	.00
PV x PS	1	2.4	.00	2.0	.00	1.9	.00	1.5	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C2

Analysis of Variance for ρ_{21} =.110 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	2652.7*	.77	3178.3*	.77	2514.4*	.77	3121.6*	.77
Number of Studies (S)	1	0.0	.00	0.1	.00	0.0	.00	0.0	.00
Percent Studies (PS)	1	294.3*	.08	347.4*	.08	277.5*	.08	339.7*	.08
Percent Variables (PV)	1	92.6*	.03	97.5*	.02	89.4*	.02	96.3*	.02
T x S	1	0.1	.00	0.1	.00	0.0	.00	0.1	.00
T x PS	1	343.5*	.10	417.6*	.10	325.4*	.10	406.5*	.10
T x PV	1	70.9*	.02	77.2*	.02	69.5*	.02	77.0*	.02
S x PS	1	2.4	.00	3.6	.00	2.2	.00	3.6	.00
S x PV	1	0.1	.00	0.3	.00	0.1	.00	0.2	.00
PV x PS	1	1.9	.00	2.1	.00	1.8	.00	2.1	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C3

Analysis of Variance for ρ_{31} = .065

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	1587.5*	.75	1829.7*	.75	1601.0*	.75	1829.1*	.75
Number of Studies (S)	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
Percent Studies (PS)	1	253.0*	.12	285.5*	.12	255.8*	.12	286.0*	.12
Percent Variables (PV)	1	31.3*	.01	37.7*	.01	30.7*	.01	36.6*	.01
T x S	1	0.2	.00	0.5	.00	0.2	.00	0.5	.00
T x PS	1	217.3*	.10	255.6*	.10	220.2*	.10	256.6*	.10
T x PV	1	29.9*	.01	32.8*	.01	28.7*	.01	31.2*	.01
S x PS	1	0.5	.00	0.3	.00	0.6	.00	0.3	.00
S x PV	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
PV x PS	1	0.4	.00	1.0	.00	0.3	.00	0.9	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C4

Analysis of Variance for ρ_{31} = .065 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	1276.8*	.74	1843.8*	.75	1250.1*	.74	1827.5*	.75
Number of Studies (S)	1	0.1	.00	0.1	.00	0.1	.00	0.0	.00
Percent Studies (PS)	1	200.1*	.12	287.3*	.12	196.3*	.12	285.0*	.12
Percent Variables (PV)	1	33.8*	.02	38.2*	.02	33.5*	.02	37.7*	.02
T x S	1	0.1	.00	0.5	.00	0.1	.00	0.5	.00
T x PS	1	173.7*	.10	256.7*	.10	171.0*	.10	254.6*	.10
T x PV	1	33.0*	.02	33.0*	.01	32.9*	.02	32.9*	.01
S x PS	1	0.5	.00	0.3	.00	0.5	.00	0.3	.00
S x PV	1	0.0	.00	0.1	.00	0.0	.00	0.0	.00
PV x PS	1	0.7	.00	1.0	.00	0.7	.00	1.1	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C5

Analysis of Variance for ρ_{41} = -.038

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	880.6*	.74	1151.3*	.73	891.8*	.74	1188.5*	.73
Number of Studies (S)	1	0.1	.00	0.0	.00	0.1	.00	0.0	.00
Percent Studies (PS)	1	141.7*	.12	196.1*	.12	143.5*	.12	202.0*	.12
Percent Variables (PV)	1	10.4	.01	15.3	.01	10.4	.01	15.8	.01
T x S	1	0.0	.00	0.0	.00	0.0	.00	0.1	.00
T x PS	1	154.4*	.12	198.4*	.13	157.0*	.12	206.1*	.13
T x PV	1	8.8	.00	10.5	.01	8.5	.00	10.1	.01
S x PS	1	0.2	.00	0.2	.00	0.3	.00	0.3	.00
S x PV	1	0.3	.00	0.3	.00	0.3	.00	0.3	.00
PV x PS	1	0.5	.00	1.4	.00	0.5	.00	1.4	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C6

Analysis of Variance for ρ_{41} = -.038 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	674.4*	.72	1144.8*	.72	662.5*	.72	1126.8*	.72
Number of Studies (S)	1	0.1	.00	0.0	.00	0.1	.00	0.0	.00
Percent Studies (PS)	1	110.3*	.12	194.7*	.12	109.0*	.12	191.7*	.12
Percent Variables (PV)	1	12.6	.01	15.2	.01	12.7	.01	15.0	.01
T x S	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
T x PS	1	116.6*	.13	197.2*	.13	115.0*	.13	193.5*	.13
T x PV	1	11.3	.01	10.4	.01	11.4	.01	10.2	.01
S x PS	1	0.2	.00	0.2	.00	0.2	.00	0.2	.00
S x PV	1	0.2	.00	0.4	.00	0.2	.00	0.3	.00
PV x PS	1	0.7	.00	1.4	.00	0.7	.00	1.4	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* p < .01.

Table C7

Analysis of Variance for ρ_{42} = -.348

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	64.1*	.29	72.1*	.31	57.1*	.28	70.2*	.31
Number of Studies (S)	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
Percent Studies (PS)	1	7.8	.03	8.8	.04	7.8	.04	9.4	.04
Percent Variables (PV)	1	69.1*	.31	67.3*	.29	63.7*	.31	64.6*	.29
T x S	1	0.2	.00	0.5	.00	0.2	.00	0.5	.00
T x PS	1	9.4	.04	11.7	.05	9.2	.04	13.0	.06
T x PV	1	63.9*	.29	63.4*	.27	57.8*	.28	59.7*	.26
S x PS	1	0.2	.00	0.2	.00	0.3	.00	0.2	.00
S x PV	1	0.2	.00	0.1	.00	0.2	.00	0.1	.00
PV x PS	1	9.0	.04	8.0	.03	9.1	.04	8.4	.04

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C8

Analysis of Variance for ρ_{42} = -.348 Continued

Source	*df*	M x Z x P *F*	M x Z x P η^2	M x Z x L *F*	M x Z x L η^2	M x R x P *F*	M x R x P η^2	M x R x L *F*	M x R x L η^2
Type of Missing (T)	1	63.3*	.29	72.5*	.31	63.6*	.29	73.5*	.31
Number of Studies (S)	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
Percent Studies (PS)	1	7.8	.04	8.8	.04	7.8	.04	8.6	.04
Percent Variables (PV)	1	66.6*	.30	67.9*	.29	67.0*	.30	69.1*	.29
T x S	1	0.3	.00	0.5	.00	0.3	.00	0.5	.00
T x PS	1	10.1	.05	11.7	.05	10.0	.05	11.3	.05
T x PV	1	62.6*	.29	64.0*	.27	63.0*	.29	65.5*	.28
S x PS	1	0.5	.00	0.2	.00	0.4	.00	0.3	.00
S x PV	1	0.1	.00	0.1	.00	0.1	.00	0.1	.00
PV x PS	1	8.4	.04	8.1	.03	8.3	.04	8.0	.03

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C9

Analysis of Variance for ρ_{51} = -.121

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	1156.7*	.75	1217.6*	.75	1199.2*	.75	1265.8*	.75
Number of Studies (S)	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
Percent Studies (PS)	1	171.5*	.11	177.8*	.11	179.7*	.11	186.0*	.11
Percent Variables (PV)	1	27.0*	.02	30.6*	.02	27.5*	.02	30.8*	.02
T x S	1	0.3	.00	0.2	.00	0.4	.00	0.3	.00
T x PS	1	149.1*	.10	159.9*	.10	156.7*	.10	168.6*	.10
T x PV	1	27.2*	.02	26.7*	.02	27.3*	.02	27.0*	.02
S x PS	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
S x PV	1	0.8	.00	0.8	.00	0.9	.00	0.9	.00
PV x PS	1	1.6	.00	2.0	.00	1.5	.00	1.8	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C10

Analysis of Variance for ρ_{51} = -.121 *Continued*

Source	*df*	M x Z x P *F*	M x Z x P η^2	M x Z x L *F*	M x Z x L η^2	M x R x P *F*	M x R x P η^2	M x R x L *F*	M x R x L η^2
Type of Missing (T)	1	1039.5*	.75	1217.0*	.75	1046.0*	.75	1265.8*	.75
Number of Studies (S)	1	0.1	.00	0.0	.00	0.1	.00	0.0	.00
Percent Studies (PS)	1	150.3*	.11	177.3*	.11	150.4*	.11	186.0*	.11
Percent Variables (PV)	1	25.7*	.02	30.4*	.02	26.5*	.02	30.8*	.02
T x S	1	0.3	.00	0.2	.00	0.3	.00	0.3	.00
T x PS	1	133.2*	.10	159.8*	.10	133.8*	.10	168.6*	.10
T x PV	1	25.2*	.02	26.4*	.02	25.8*	.02	27.0*	.02
S x PS	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
S x PV	1	0.8	.00	0.8	.00	0.8	.00	0.9	.00
PV x PS	1	1.3	.00	2.0	.00	1.4	.00	1.8	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C11

Analysis of Variance for Path Estimates for Parameter $V1 \rightarrow V5$ = -.07

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	159.8*	.69	152.4*	.69	157.9*	.67	155.3*	.69
Number of Studies (S)	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
Percent Studies (PS)	1	25.2*	.11	20.6*	.09	25.8*	.11	21.4*	.10
Percent Variables (PV)	1	13.1	.06	12.6	.06	12.6	.05	12.0	.05
T x S	1	0.7	.00	0.6	.00	0.9	.00	0.9	.00
T x PS	1	11.0	.05	11.7	.05	11.1	.05	12.1	.05
T x PV	1	16.8*	.07	13.2	.06	16.4*	.07	13.5	.06
S x PS	1	1.0	.00	0.8	.00	1.0	.00	0.8	.00
S x PV	1	1.7	.00	1.4	.00	1.9	.01	1.6	.01
PV x PS	1	2.1	.01	1.5	.00	2.0	.01	1.4	.01

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C12

Analysis of Variance for Path Estimates for Parameter $V1 \rightarrow V5$ = -.07 *Continued*

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	210.7*	.74	154.4*	.69	221.3*	.74	155.3*	.69
Number of Studies (S)	1	0.1	.00	0.1	.00	0.1	.00	0.1	.00
Percent Studies (PS)	1	29.6*	.10	20.6*	.09	30.1*	.10	21.4*	.10
Percent Variables (PV)	1	9.1	.03	12.7	.06	9.9	.03	12.0	.05
T x S	1	1.1	.00	0.6	.00	1.1	.00	0.9	.00
T x PS	1	15.7	.06	11.8	.05	16.3*	.05	12.1	.05
T x PV	1	11.3	.04	13.2	.06	11.9	.04	13.5	.06
S x PS	1	1.0	.00	0.8	.00	1.1	.00	0.8	.00
S x PV	1	2.1	.01	1.5	.01	2.1	.01	1.6	.01
PV x PS	1	1.2	.00	1.5	.01	1.3	.00	1.4	.01

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C13

Analysis of Variance for Path Estimates for Parameter V1 $\rightarrow$ V2 = .11

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	3309.1*	.77	3225.0*	.77	3406.8*	.77	3169.0*	.77
Number of Studies (S)	1	0.2	.00	0.1	.00	0.2	.00	0.1	.00
Percent Studies (PS)	1	366.0*	.08	353.1*	.08	385.4*	.09	351.7*	.09
Percent Variables (PV)	1	104.5*	.02	99.0*	.02	107.0*	.02	96.6*	.02
T x S	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
T x PS	1	438.5*	.10	423.6*	.10	456.6*	.10	423.2*	.10
T x PV	1	80.3*	.02	79.1*	.02	82.3*	.02	77.2*	.02
S x PS	1	2.0	.00	3.6	.00	2.0	.00	3.7	.00
S x PV	1	0.1	.00	0.3	.00	0.1	.00	0.3	.00
PV x PS	1	2.4	.00	2.0	.00	1.9	.00	1.5	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C14

Analysis of Variance for Path Estimates for Parameter V1 $\rightarrow$ V2 = .11 *Continued*

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	2652.7*	.77	3178.3*	.77	2514.4*	.77	3169.0*	.77
Number of Studies (S)	1	0.0	.00	0.1	.00	0.0	.00	0.1	.00
Percent Studies (PS)	1	294.3*	.08	347.4*	.08	277.5*	.08	351.7*	.08
Percent Variables (PV)	1	92.6*	.03	97.5*	.02	89.4*	.03	96.6*	.02
T x S	1	0.1	.00	0.1	.00	0.0	.00	0.1	.00
T x PS	1	343.5*	.10	417.6*	.10	325.4*	.10	423.2*	.10
T x PV	1	70.9*	.02	77.2*	.02	69.5*	.02	77.2*	.02
S x PS	1	2.4	.00	3.6	.00	2.2	.00	3.7	.00
S x PV	1	0.1	.00	0.3	.00	0.1	.00	0.3	.00
PV x PS	1	1.9	.00	2.1	.00	1.8	.00	1.5	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C15

Analysis of Variance for Standard Error Estimates for Path V1 → V5

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	6.4	.12	0.0	.00	6.7	.13	0.0	.00
Number of Studies (S)	1	1.3	.03	0.7	.05	1.2	.02	0.6	.04
Percent Studies (PS)	1	31.1*	.57	3.8	.26	29.2*	.56	3.9	.26
Percent Variables (PV)	1	3.6	.07	0.4	.03	3.4	.07	0.3	.02
T x S	1	0.0	.00	0.0	.00	0.1	.00	0.1	.00
T x PS	1	1.7	.03	0.0	.00	1.4	.03	0.0	.00
T x PV	1	2.4	.04	1.0	.06	2.1	.04	1.0	.07
S x PS	1	0.2	.00	0.1	.01	0.2	.00	0.2	.01
S x PV	1	0.1	.00	0.1	.01	0.1	.00	0.1	.00
PV x PS	1	2.9	.05	3.4	.23	2.7	.05	3.5	.24

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C16

Analysis of Variance for Standard Error Estimates for Path V1 $\rightarrow$ V5 Continued

		M x Z x P		M x Z x L		M x R x P		M x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	27.5*	.41	0.0	.00	26.9*	.40	0.0	.00
Number of Studies (S)	1	1.1	.00	0.7	.05	1.0	.01	0.6	.03
Percent Studies (PS)	1	20.9*	.31	4.5	.28	20.4*	.31	3.9	.27
Percent Variables (PV)	1	3.7	.05	0.5	.03	4.0	.06	0.3	.02
T x S	1	0.0	.00	0.0	.00	0.0	.00	0.1	.00
T x PS	1	5.7	.08	0.0	.00	5.9	.09	0.0	.00
T x PV	1	1.0	.00	1.0	.07	0.9	.00	1.0	.07
S x PS	1	0.2	.00	0.1	.01	0.2	.00	0.2	.01
S x PV	1	0.0	.00	0.1	.00	0.0	.00	0.1	.01
PV x PS	1	2.5	.04	4.0	.25	2.4	.04	3.5	.24

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C17

Analysis of Variance for Standard Error Estimates for Path V2 → V5

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	14.4	.13	0.0	.00	13.0	.13	0.2	.02
Number of Studies (S)	1	0.4	.00	0.1	.00	0.2	.00	0.1	.00
Percent Studies (PS)	1	7.3	.07	0.1	.00	7.1	.07	1.1	.09
Percent Variables (PV)	1	31.5*	.29	0.4	.03	28.0*	.30	0.3	.03
T x S	1	0.0	.00	0.1	.00	0.2	.00	0.4	.03
T x PS	1	1.0	.01	0.6	.04	0.6	.01	0.8	.07
T x PV	1	32.4*	.30	2.9	.18	27.0*	.29	1.2	.11
S x PS	1	1.5	.01	2.4	.20	0.7	.01	0.5	.05
S x PV	1	0.0	.00	0.1	.00	0.0	.00	0.0	.00
PV x PS	1	13.7	.13	4.4	.28	11.8	.13	1.8	.16

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C18

Analysis of Variance for Standard Error Estimates for Path V2 → V5 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	5.4	.08	0.0	.00	6.0	.09	0.2	.02
Number of Studies (S)	1	0.6	.01	0.1	.01	0.6	.01	0.1	.00
Percent Studies (PS)	1	2.5	.04	0.1	.00	2.6	.04	1.1	.09
Percent Variables (PV)	1	22.9*	.34	0.4	.02	22.6*	.33	0.3	.03
T x S	1	0.0	.00	0.1	.00	0.1	.00	0.4	.03
T x PS	1	0.5	.00	0.7	.04	0.4	.00	0.8	.07
T x PV	1	18.7*	.28	2.9	.18	19.3*	.28	1.2	.11
S x PS	1	1.1	.02	2.2	.14	1.4	.02	0.5	.05
S x PV	1	0.0	.00	0.1	.00	0.0	.00	0.0	.00
PV x PS	1	10.0	.15	4.1	.26	9.9	.15	1.8	.16

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C19

Analysis of Variance for Standard Error Estimates for Path V3 → V5

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	83.0*	.72	0.0	.00	67.8*	.73	0.1	.01
Number of Studies (S)	1	4.1	.04	5.6	.28	4.0	.04	4.9	.27
Percent Studies (PS)	1	2.8	.02	1.7	.09	1.2	.01	2.4	.13
Percent Variables (PV)	1	1.5	.01	0.0	.00	0.7	.01	0.1	.01
T x S	1	0.2	.00	0.0	.00	0.1	.00	0.1	.01
T x PS	1	16.6*	.14	1.0	.05	12.6	.13	0.8	.05
T x PV	1	0.4	.00	5.8	.29	0.8	.01	4.2	.23
S x PS	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
S x PV	1	0.1	.00	0.4	.02	0.1	.00	0.2	.01
PV x PS	1	1.3	.01	0.2	.01	1.0	.01	0.1	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C20

Analysis of Variance for Standard Error Estimates for Path V3 → V5 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	41.5*	.66	0.0	.00	38.9*	.66	0.1	.01
Number of Studies (S)	1	2.7	.04	6.0	.28	1.9	.03	4.9	.27
Percent Studies (PS)	1	0.1	.00	1.9	.09	0.1	.00	2.4	.14
Percent Variables (PV)	1	0.0	.00	0.0	.00	0.0	.00	0.1	.01
T x S	1	0.3	.00	0.0	.00	0.6	.01	0.1	.01
T x PS	1	11.0	.18	1.1	.05	10.6	.18	0.8	.05
T x PV	1	1.8	.03	6.5	.30	1.7	.03	4.2	.23
S x PS	1	0.0	.00	0.0	.00	0.0	.00	0.0	.00
S x PV	1	0.2	.00	0.6	.03	0.1	.00	0.2	.01
PV x PS	1	0.1	.00	0.4	.02	0.0	.00	0.1	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C21

Analysis of Variance for Standard Error Estimates for Path V4 $\rightarrow$ V5

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	320.4*	.71	0.1	.00	229.5*	.68	0.8	.03
Number of Studies (S)	1	26.0*	.06	54.4*	.47	29.0*	.09	15.4	.60
Percent Studies (PS)	1	0.0	.00	32.7*	.29	2.7	.01	1.6	.06
Percent Variables (PV)	1	17.0*	.04	1.8	.02	10.4	.03	0.0	.00
T x S	1	0.3	.00	7.0	.06	0.2	.00	0.3	.01
T x PS	1	41.1*	.09	1.6	.01	27.9*	.08	0.2	.01
T x PV	1	20.3*	.04	5.2	.04	16.5*	.05	0.8	.03
S x PS	1	8.1	.02	5.9	.05	7.3	.02	0.3	.01
S x PV	1	0.1	.00	0.0	.00	0.4	.00	0.1	.00
PV x PS	1	10.1	.02	3.1	.03	10.3	.03	0.9	.04

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C22

Analysis of Variance for Standard Error Estimates for Path V4 → V5 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	173.7*	.67	0.1	.00	176.6*	.68	0.8	.03
Number of Studies (S)	1	15.7	.06	47.0*	.45	14.0	.05	15.4	.60
Percent Studies (PS)	1	0.5	.00	29.5*	.29	0.4	.00	1.6	.06
Percent Variables (PV)	1	12.1	.05	1.5	.01	12.6	.05	0.0	.00
T x S	1	0.2	.00	6.1	.06	0.1	.00	0.3	.01
T x PS	1	23.6*	.09	0.8	.01	22.8*	.09	0.2	.01
T x PV	1	16.5*	.06	3.7	.04	16.3	.06	0.8	.03
S x PS	1	5.6	.02	6.9	.07	5.4	.02	0.3	.01
S x PV	1	0.1	.00	0.0	.00	0.1	.00	0.1	.00
PV x PS	1	7.8	.03	2.8	.03	6.8	.03	0.9	.04

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C23

Analysis of Variance for Standard Error Estimates for Path V3 → V4

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	128.1*	.68	2.6	.11	87.0*	.67	0.7	.04
Number of Studies (S)	1	10.5	.06	6.5	.27	6.4	.05	3.4	.17
Percent Studies (PS)	1	4.4	.02	3.4	.14	2.4	.02	4.0	.18
Percent Variables (PV)	1	3.4	.02	0.5	.02	2.6	.02	0.8	.05
T x S	1	0.3	.00	0.5	.02	0.4	.00	0.6	.04
T x PS	1	18.0*	.09	0.1	.00	9.7	.07	0.8	.05
T x PV	1	11.0	.06	1.7	.07	10.5	.07	1.6	.08
S x PS	1	0.9	.00	0.5	.02	1.2	.01	0.2	.01
S x PV	1	1.7	.01	0.9	.03	1.4	.01	1.0	.05
PV x PS	1	6.6	.03	2.3	.10	3.6	.02	1.1	.06

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C24

Analysis of Variance for Standard Error Estimates for Path V3 $\rightarrow$ V4 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	76.6*	.61	2.7	.11	84.9*	.62	0.7	.04
Number of Studies (S)	1	8.0	.06	6.9	.28	8.3	.06	3.4	.17
Percent Studies (PS)	1	5.3	.04	3.7	.15	6.3	.05	4.0	.21
Percent Variables (PV)	1	3.4	.03	0.5	.02	3.1	.02	0.8	.04
T x S	1	0.1	.00	0.5	.02	0.1	.00	0.6	.03
T x PS	1	12.5	.10	0.1	.00	15.0	.11	0.8	.04
T x PV	1	8.5	.07	1.7	.07	7.8	.06	1.6	.08
S x PS	1	1.0	.01	0.4	.02	0.9	.01	0.2	.00
S x PV	1	1.1	.01	0.9	.03	1.1	.01	1.0	.05
PV x PS	1	4.5	.04	2.3	.09	4.8	.04	1.1	.05

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C25

Analysis of Variance for Standard Error Estimates for Path V2 → V3

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	0.4	.01	1.1	.10	0.2	.00	4.7	.29
Number of Studies (S)	1	0.3	.01	0.0	.00	0.0	.00	0.0	.00
Percent Studies (PS)	1	0.1	.00	0.3	.03	0.2	.00	0.6	.04
Percent Variables (PV)	1	20.6*	.47	0.9	.09	24.5*	.51	0.3	.02
T x S	1	0.5	.01	0.2	.02	1.4	.03	3.5	.22
T x PS	1	0.9	.02	0.1	.01	0.4	.01	0.2	.02
T x PV	1	9.9	.23	1.9	.19	12.0	.25	0.9	.06
S x PS	1	0.0	.00	0.6	.06	0.0	.00	1.1	.06
S x PV	1	0.4	.01	0.1	.01	0.3	.00	0.0	.00
PV x PS	1	5.6	.13	0.0	.00	3.9	.08	0.0	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C26

Analysis of Variance for Standard Error Estimates for Path V2 → V3 Continued

		M x Z x P		M x Z x L		M x R x P		M x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	0.0	.00	1.0	.11	0.1	.00	4.7	.29
Number of Studies (S)	1	0.3	.01	0.0	.00	0.4	.00	0.0	.00
Percent Studies (PS)	1	0.1	.00	0.3	.02	0.1	.00	0.6	.04
Percent Variables (PV)	1	16.5*	.45	0.8	.08	13.8	.41	0.3	.02
T x S	1	0.5	.01	0.3	.02	0.3	.00	3.5	.22
T x PS	1	0.7	.01	0.1	.01	0.8	.00	0.2	.01
T x PV	1	8.5	.23	1.9	.18	7.5	.23	0.9	.06
S x PS	1	0.0	.00	0.5	.05	0.0	.00	1.1	.06
S x PV	1	0.5	.02	0.1	.01	0.6	.00	0.0	.00
PV x PS	1	4.2	.12	0.1	.01	4.9	.15	0.0	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C27

Analysis of Variance for Standard Error Estimates for Path V1 → V2

		Method							
		U x Z x P		U x Z x L		U x R x P		U x R x L	
Source	*df*	*F*	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	375.4*	.50	0.3	.02	365.1*	.50	0.0	.00
Number of Studies (S)	1	15.3	.02	0.2	.01	12.8	.02	0.1	.01
Percent Studies (PS)	1	99.8*	.13	0.0	.00	97.9*	.13	0.0	.00
Percent Variables (PV)	1	31.2*	.04	0.0	.00	30.6*	.04	0.0	.00
T x S	1	1.2	.00	0.8	.06	0.9	.00	0.7	.05
T x PS	1	102.2*	.13	0.0	.00	94.2*	.13	0.0	.00
T x PV	1	108.6*	.14	2.0	.15	102.1*	.14	2.5	.18
S x PS	1	15.9	.02	5.7	.41	14.3	.02	5.8	.41
S x PV	1	0.2	.00	0.0	.00	0.5	.00	0.1	.01
PV x PS	1	3.0	.00	0.1	.01	2.6	.00	0.0	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

Table C28

Analysis of Variance for Standard Error Estimates for Path V1 → V2 Continued

Source	*df*	M x Z x P		M x Z x L		M x R x P		M x R x L	
		F	η^2	*F*	η^2	*F*	η^2	*F*	η^2
Type of Missing (T)	1	329.6*	.58	0.3	.02	292.2*	.58	0.0	.00
Number of Studies (S)	1	6.6	.01	0.2	.01	6.1	.01	0.1	.01
Percent Studies (PS)	1	46.5*	.08	0.0	.00	40.9*	.08	0.0	.00
Percent Variables (PV)	1	23.9*	.04	0.0	.00	18.8*	.04	0.0	.00
T x S	1	1.8	.00	0.7	.05	1.6	.00	0.7	.05
T x PS	1	84.6*	.15	0.0	.00	73.2*	.15	0.0	.00
T x PV	1	57.7*	.10	2.1	.15	52.5*	.10	2.5	.18
S x PS	1	8.2	.01	5.4	.39	6.9	.01	5.8	.40
S x PV	1	0.3	.00	0.0	.00	0.2	.00	0.1	.01
PV x PS	1	2.8	.01	0.0	.00	2.6	.00	0.0	.00

Note. U = Univariate Weighting. M = Multivariate Weighting. Z = Transformed Correlations. R = Untransformed Correlations. P = Pairwise Deletion. L = Listwise Deletion.
* $p < .01$.

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