Title
Abstract: Uncrossing the Correlated Trait-Correlated Method Model for Multitrait-Multimethod Data

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Neglect the Structure of Multitrait-Multimethod Data at Your Peril: Implications for Associations With External Variables

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In 1959, Campbell and Fiske introduced the use of multitrait–multimethod (MTMM) matrices in psychology, and for the past 4 decades confirmatory factor analysis (CFA) has commonly been used to analyze MTMM data. However, researchers do not always fit CFA models when MTMM data are available; when CFA modeling is used, multiple models are available that have attendant strengths and weaknesses. In this article, we used a Monte Carlo simulation to investigate the drawbacks of either using CFA models that fail to match the data-generating model or completely ignore the MTMM structure of data when the research goal is to uncover associations between trait constructs and external variables. We then used data from the National Institute of Child Health and Human Development Study of Early Child Care and Youth Development to illustrate the substantive implications of fitting models that partially or completely ignore MTMM data structures. Results from analyses of both simulated and empirical data show noticeable biases when the MTMM data structure is partially or completely neglected.

Keywords: confirmatory factor analysis, construct validity, multitrait–multimethod data, structural equation modeling

In the field of psychology, researchers are interested in estimating relations among trait constructs as accurately as possible. Researchers typically assume that measures of hypothetical constructs have substantial amounts of trait-related variance, but often fail to acknowledge the presence of method-related variance in their measures. Importantly, reliability is often assumed to represent an index of trait-related variance in a measure. However, estimates of reliability are a composite index of trait and method variance, because both are sources of systematic variance. Ignoring the method variance in measures could lead to positive or negative bias in estimates of associations between trait constructs and outside measures. Most investigations focused on multitrait–multimethod (MTMM) data have analyzed just the MTMM structure of data as an end in itself. Extending most prior MTMM work, we are interested in how to exploit

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the MTMM structure of data to estimate optimally unbiased relations with outside variables. We argue that trait latent variables (LVs) purged of method variance will lead to more accurate estimates of relations with external variables than will manifest variables (MVs) or LVs that have not been purged of method variance.

Over 50 years ago, Campbell and Fiske (1959) introduced the idea that a scale score is a "trait–method unit," with some variance attributable to trait content (e.g., personality characteristics, behaviors, or abilities), some variance attributable to the method used to obtain the data (e.g., different measurement procedures or different informants), and remaining variance due to error. In their seminal paper, Campbell and Fiske introduced the MTMM matrix—consisting of intercorrelations among multiple traits measured by multiple methods—and offered several criteria to assess convergent validity, discriminant validity, and method effects from these data. The Campbell and Fiske criteria consisted of rules of thumb that reflected key patterns in correlations in the MTMM matrix, but did not allow precise statistical testing of these patterns.

Since the early 1970s, more sophisticated statistical models have been proposed for analyzing data that have an MTMM structure, and most of these models are implemented in the structural equation modeling (SEM) framework. The most widely known model is the correlated trait-correlated method model (CT–CM; Jöreskog, 1971; Kenny, 1976; Widaman, 1985), and alternatives include the correlated trait-correlated uniqueness model (CT–CU; Marsh, 1989), and the correlated trait-correlated method minus one model (CT–C(M–1); Eid, 2000). Although these models have been discussed extensively in the literature (Bagozzi, 1978; Eid, 2000; Jöreskog, 1971; Kenny, 1976; Kenny & Kashy, 1992; Lance, Noble, & Scullen, 2002; Marsh, 1989; Marsh & Bailey, 1991; Schmitt, 1978; Widaman, 1985), researchers often fail to apply these advanced methods to their MTMM-structured data when attempting to understand external correlates of traits (e.g., Ge et al., 1996). Instead, composite scores are often computed by summing across methods of measurement and these composite scores are used as observed scores in analyses. Researchers might follow this practice because many leading quantitative experts have emphasized certain limitations of MTMM models (Kenny & Kashy, 1992; Lance et al., 2002; Marsh, 1989; Marsh & Bailey, 1991). But, we argue that researchers might inadvertently and unknowingly obtain biased estimates of relations among trait constructs if they neglect the MTMM structure of their data. That is, if composite scores retain substantial method variance, using composite scores could be detrimental for making valid inferences.

In this article, we investigated the possible drawbacks of partially or completely ignoring the MTMM structure of data when the research goal is to uncover associations between trait constructs and external variables. We did this by evaluating the performance of popular MTMM models (some of which do not specify all MVs as trait–method units) for estimating relations of trait constructs with external variables and by fitting models that ignore the structure of the data. Although neglecting the MTMM structure of data should lead to subpar results, it is important to understand the degree of bias that can arise from this technique in relation to alternative approaches that do consider the MTMM data structure. First, we review the nature of MTMM models that can be fit within the SEM framework. We continue by discussing two techniques that are likely to be followed when MTMM data are available, but their structure is disregarded. Then, we use simulated (Study 1) and empirical (Study 2) MTMM data to fit multiple alternative models—some models in which the MTMM structure is accommodated, and others in which it is not. We compare the results from these models and conclude by offering suggestions for dealing with MTMM-structured data.

CORRELATED TRAIT–CORRELATED METHOD MODEL

The criteria introduced by Campbell and Fiske (1959) to assess convergent and discriminant validity are limited because they are based on rules of thumb and the observation of correlations among variables that are not perfectly reliable. For example, evidence of convergent validity is found when high correlations are observed between measures obtained using different methods that purport to assess the same trait. Similarly, if lower correlations are observed between measures purported to assess different traits, then support for discriminant validity is increased. The limitations of the Campbell and Fiske criteria, along with the development of confirmatory factor analysis (Jöreskog, 1969), led researchers to develop and fine-tune the CT–CM model (Jöreskog, 1971; Kenny, 1976; Widaman, 1985).

The CT–CM data model can be expressed in matrix notation as

$$\mathbf{y}_i = \boldsymbol{\Lambda}_t \boldsymbol{\eta}_{ti} + \boldsymbol{\Lambda}_m \boldsymbol{\eta}_{mi} + \boldsymbol{\varepsilon}_i, \tag{1}$$

where $\mathbf{y}_i$ is a $p \times 1$ vector of observed scores for individual i on p MVs, $\boldsymbol{\Lambda}_t$ is a $p \times t$ matrix of trait factor loadings relating p MVs to t trait factors, $\boldsymbol{\eta}_{ti}$ is a $t \times 1$ vector of trait factor scores for individual i, $\boldsymbol{\Lambda}_m$ is a $p \times m$ matrix of method factor loadings relating p MVs to m method factors, $\boldsymbol{\eta}_{mi}$ is an $m \times 1$ matrix of method factor scores for individual i, and $\boldsymbol{\varepsilon}_i$ is a $p \times 1$ vector of unique factor scores for individual i. The t trait factors, the m method factors, and the p unique factors are assumed to be independently distributed, and the p unique factors have the additional assumption of mutual independence. This model gives rise to the covariance structure

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}_t \boldsymbol{\psi}_t \boldsymbol{\Lambda}'_t + \boldsymbol{\Lambda}_m \boldsymbol{\psi}_m \boldsymbol{\Lambda}'_m + \boldsymbol{\theta}^2, \tag{2}$$

where $\boldsymbol{\Sigma}$ is a $p \times p$ covariance matrix of MVs, $\boldsymbol{\psi}_t$ is a $t \times t$ covariance matrix of trait factors, $\boldsymbol{\psi}_m$ is an $m \times m$ covariance matrix of method factors, and $\boldsymbol{\theta}^2$ is a $p \times p$ diagonal matrix of unique factor variances.

The CT–CM model described in Equations 1 and 2 (also see Figure 1a) shows that each MV is a function of a trait factor, a method factor, and a unique factor. MVs measured with the same method load onto one common method factor, and MVs referring to the same trait load onto a common trait factor. Figure 1a is a path diagram of a CT–CM model with three traits and three methods of assessment (or informants, as displayed in the diagram for illustrative purposes) which is the minimum number of trait and method factors for this model to be identified. As seen in Figure 1a, correlations among trait factors are estimated, which gives insight into discriminant validity. Correlations among the multiple method factors can also be estimated. However, trait factors and method factors are specified to be uncorrelated for identification purposes (Widaman, 1985). In the CT–CM model, convergent validity is assessed based on the strength and significance of the trait factor loadings and method effects are evidenced by the strength and significance of method factor loadings.

Researchers have outlined the limitations of the CT–CM model, particularly the fact that solutions might have out-of-range parameter estimates or might not converge (Kenny & Kashy, 1992; Marsh & Bailey, 1991). Alternative models have been proposed as an attempt to deal with these challenges, which are described next.

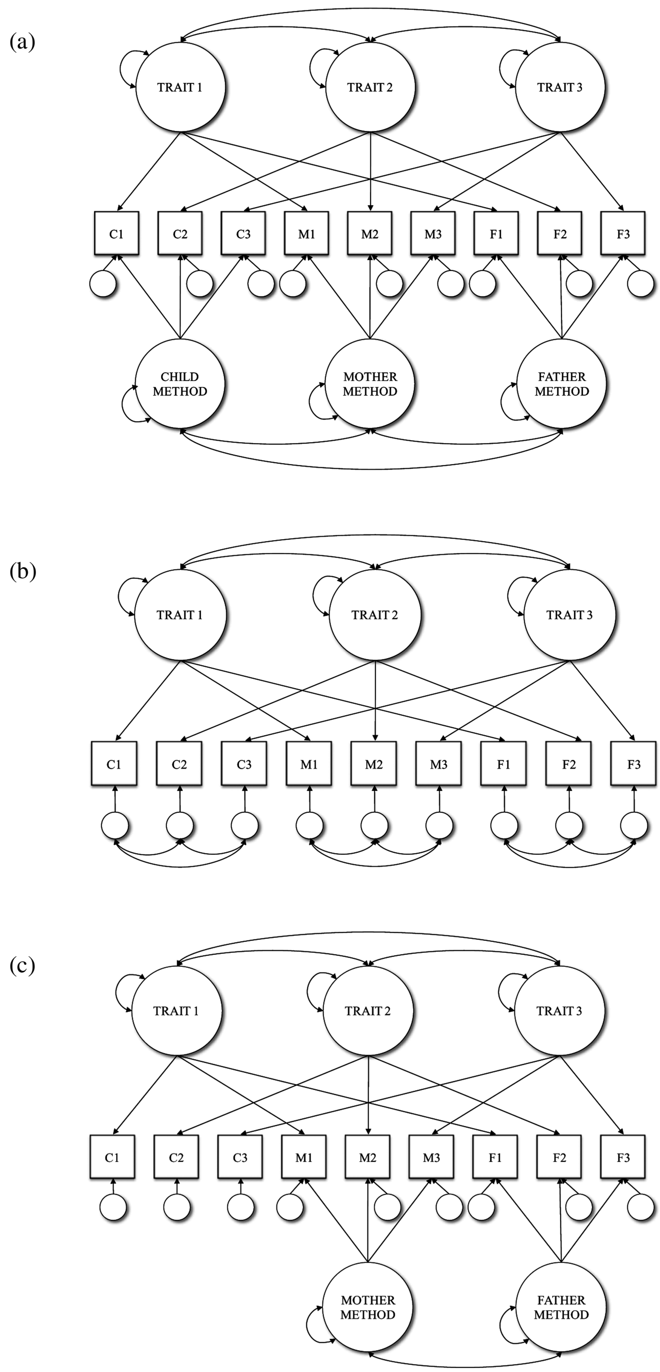

FIGURE 1 Path diagram of (a) correlated trait-correlated method (CT–CM) model, (b) correlated trait-correlated uniqueness (CT–CU) model, and (c) correlated trait-correlated method minus one CT–C(M–1) model in which three traits are measured based on three methods of assessment (in this example, informants: child, mother, and father).

CORRELATED TRAIT–CORRELATED UNIQUENESS MODEL

In an effort to fit an MTMM model with only two traits, Kenny (1976) suggested a model that later fueled the development of the CT–CU model. Rather than specifying method factors as in the CT–CM model, the method structure of the data is modeled by correlating unique factors corresponding to the same method of assessment. This specification permits researchers to model data that were collected with multiple methods of assessment, but including only two trait constructs. Marsh (1989) expanded its application to instances with more than two traits. The CT–CU data model can be expressed in matrix notation as

$$\mathbf{y}_i = \mathbf{\Lambda}_t \boldsymbol{\eta}_{ti} + \boldsymbol{\varepsilon}_i, \tag{3}$$

where all terms are as defined before. In this model, the t trait factors and the p unique factors are assumed to be independently distributed. This model results in a covariance structure model that can be expressed as

$$\mathbf{\Sigma} = \mathbf{\Lambda}_t \mathbf{\Psi}_t \mathbf{\Lambda}_t' + \mathbf{\Theta}^2, \tag{4}$$

where all terms are as defined before, except that $\boldsymbol{\theta}^2$ is a $p \times p$ matrix with unique factor variances on the diagonal and unique factor covariances off the diagonal.

Figure 1b shows the CT–CU model with three traits and three methods of measurement. Here, it can be seen that each observed variable is a function of a trait factor and a unique factor. The latter contains commonly acknowledged specific and error variance, and method-related variance forms part of the specific variance component. Unlike the CT–CM model, the CT–CU model does not assume unidimensionality of the method effects. On the other hand, the CT–CU model assumes uncorrelated method effects across different methods, whereas the CT–CM model does not. Several investigations have reported that the CT–CU model overcomes certain limitations of the CT–CM model, such as problems related to out-of-bounds estimates, poor empirical identification of parameters, and lack of convergence (Becker & Cote, 1994; Conway, 1996; Marsh, 1989; Marsh & Bailey, 1991), whereas others have questioned the theoretical and practical soundness of the CT–CU model (Lance et al., 2002).

CORRELATED TRAIT–CORRELATED METHOD MINUS ONE

Eid (2000) developed the CT–C(M–1) model to overcome the limitations of the CT–CM and CT–CU models. This model is similar to the CT–CM model with one exception—one of the method factors is not specified (see Figure 1c). This model can be written similar to the CT–CM model (see Equation 1) with some additional restrictions in the $\mathbf{\Lambda}_m$ matrix. That is, the method factor loadings of the MVs that correspond to the omitted method are fixed to zero, and the correlations of this method factor with other method factors likewise are fixed at zero. The omitted method factor thus becomes the comparison standard or reference method. For example, the model depicted in Figure 1c has the child's self-report as the comparison standard. The method factors in this model have a different meaning than in the CT–CM model; they represent deviations of their respective indicators from the levels predicted by the reference variables (i.e., the comparison standard). The trait factors also have an altered meaning; they represent the true factor scores on trait constructs under the reference method. Therefore, depending on the chosen comparison standard, the true factor scores will vary and so will associations of the trait and method factors with external variables of interest. With this in mind, researchers must decide which method will act as a reference based on theoretical grounds because changing the reference method will also result in a different fit to the data, different parameter estimates, and different interpretations. Notably, Eid showed that this model is identified under conditions in which the CT–CM model is not.

IGNORING MTMM STRUCTURE OF DATA

Beyond exploring the different aspects of construct validity, a valuable application of MTMM models is to partial out method variance when investigating associations of trait latent variables with external variables (Graham & Collins, 1991). Clearly, when the MTMM structure of data is ignored, method variance is not modeled and is confounded within estimates of trait constructs. Conversely, if the MTMM structure of data is explicitly modeled, trait factors and method factors might be differentially related to external variables. Thus, bias could well be present in the associations of trait constructs with external variables if MTMM data are not modeled as such.

Different approaches can be followed that overlook or ignore the MTMM structure of data; here, we focus on the two commonly followed approaches. The first entails computing composite scores by averaging across variables from multiple methods of measurement that represent the same trait. For example, presuming that child, mother, and father represent the methods of measurement, averaging across child, mother, and father ratings on a given trait allows information from each method (i.e., respondent) to be composited into a score on the trait. The second procedure implies selecting variables from only one of the available methods (e.g., only child report). Both techniques would result in as many variables, or composite variables, as traits present in the original MTMM matrix, but with only a single measurement of each trait construct. Naturally, the second approach suffers from using only a fraction of the available data. However, it is important to note that, if only a single method of measurement (e.g., self-report) is used, as is common in many research areas in psychology, researchers essentially and implicitly adopt this second approach, and method and error variance are inextricably confounded in the measure. Error variance attenuates correlations of measures with external variables, but method variance could positively bias such correlations if an external variable shares the same method of measurement. An additional disadvantage of both preceding methods is that one would no longer be able to model the trait constructs as LVs.

MOTIVATION FOR THIS STUDY

Even when the structure of MTMM data is not disregarded, fitting SEM models that do not consider observed variables as trait–method units can be problematic, particularly when researchers are interested in assessing the relations of traits with external variables. Our reasoning is that traits and methods are not always hypothesized to be related to external variables in the same direction. An example of this is a trait, such as good parenting, that is expected to be positively associated with social competence in children, yet the method factor (or reporter bias, in this case) from a depressed parent might be negatively associated with the outcome. Therefore, the degree of bias in the link between traits and external variables might be conditional on the ratio of trait-to-method variance in the observed variables. The CT–CM model should be safe from this challenge, as it decomposes all MVs into trait, method, and unique factor variance. The CT–CU model does not make an explicit distinction between method and unique factor variance, and the CT–C(M–1) model decomposes the variance into trait, method, and unique variance, but only for the observed variables that have a specified method factor. In sum, we believe it is important to investigate the performance of these alternative MTMM models for capturing the true associations between traits and external constructs.

In the following two studies, we investigate the potential biases that arise from (a) fitting MTMM models that do not explicitly specify all MVs as trait–method units and (b) fitting models that completely ignore the MTMM structure of the data. In the first study, we investigate these biases with simulated data, and in the second study we use empirical data.

STUDY 1: LINKS OF SIMULATED MTMM DATA CONSTRUCTS WITH EXTERNAL VARIABLES

Using simulated MTMM data allows us to control the proportion of trait and method variance in MVs. Fiske and Campbell (1992) were clear when they discussed the state of affairs with regard to MTMM matrices:

> In 1959, we presented all of the matrices we knew about, plus some newly computed ones. The results were very disappointing ... reliable method-specific variance was ordinarily higher than reliable trait-specific variance.... Matrices published today continue to be about as unsatisfactory as those published more than 33 years ago. (p. 393)

We believe it is unrealistic to expect that this important issue of low trait-to-method variance ratio has been solved in the last 20 years. With this in mind, we simulated data that have higher method variance than trait variance in this study.

Method

Data

In this study, we varied the direction of the association of method factors with external variables (positive, no association, and negative), whereas the direction of the association of trait factors with external variables was always positive (except in the no association condition). We also varied the role of the external variables—first they acted as predictors of LVs in the MTMM model, and second, as outcomes of the LVs. For each of the six resulting conditions (effectively there are five conditions because the no association condition requires the same data whether the external variables are predictors or outcomes), we used R (R Development Core Team, 2010) to simulate 100 data sets with 12 variables and 500 observations each. Nine MVs were indicators of three trait factors and three method factors, and the remaining three MVs were external variables. These data were simulated based on Equation 2, but with the addition of **B** matrices to specify external associations to and from the trait and method LVs.

Thus, the covariance structure model from Equation 2 with the added **B** matrices takes the form

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}_t(\mathbf{I}_t - \mathbf{B}_t)^{-1}\boldsymbol{\psi}_t(\mathbf{I}_t - \mathbf{B}_t')^{-1}\boldsymbol{\Lambda}_t' + \boldsymbol{\Lambda}_m(\mathbf{I}_m - \mathbf{B}_m)^{-1}\boldsymbol{\psi}_m(\mathbf{I}_m - \mathbf{B}_m')^{-1}\boldsymbol{\Lambda}_m' + \boldsymbol{\theta}^2, \quad (5)$$

where $\mathbf{I}_t$ and $\mathbf{I}_m$ are identity matrices with dimensions that depend on the number of external variables (three in our simulation example), $\mathbf{B}_t$ and $\mathbf{B}_m$ are matrices of regression weights indicating the influence of external variables on trait or method LVs or vice versa. The dimensions of these matrices also depend on the number of external variables predicting or being predicted by the LVs. All other symbols are as defined earlier.

The $\boldsymbol{\Lambda}$ matrix used for the simulation of all data sets is presented in Table 1. We arbitrarily chose all MVs under the first method to have more trait variance ($\lambda = .60$) than under the second and third methods ($\lambda = .40$), and loadings on all three method factors were set at .60. In all instances, the trait and method factors, respectively, were simulated to correlate moderately with each other ($r = .40$) and the external variables were set to correlate .50 among themselves. Our goal was to simulate data that resemble typical empirical MTMM data. Finally, each of the external variables was simulated to predict positively one of the traits ($b = .50$) and to predict both positively and negatively, depending on the condition, one of the method factors ($b = .50$ and $b = -.50$, respectively). For the no association condition, the paths from the external variables to the trait and method factors were set to zero. We also simulated data in which the external variables were predicted by the trait and method factors. The same magnitude of regression coefficients was specified; each trait factor predicted one of the outcomes positively ($b = .50$), and each of the method factors predicted one of the outcomes both positively and negatively, depending on the condition ($b = .50$ and $b = -.50$). Trait and method factors did not predict the external variables in the no association condition.

A conceptual depiction of the different conditions in our simulation study is shown in Figure 2. Figure 2a shows the condition in which external variables are predictors of trait and method factors, and Figure 2b shows the case in which trait and method factors are predictors of the external variables. A single † indicates that the path was set to .50 (except set to zero in the no association condition) and †† indicates that the path was set to .50 in the positive

TABLE 1
Lambda Matrix for Data Simulation

	T1	*T2*	*T3*	*M1*	*M2*	*M3*	*Z1*	*Z2*	*Z3*
X_{T1M1}	0.60	—	—	0.60	—	—	—	—	—
X_{T2M1}	—	0.60	—	0.60	—	—	—	—	—
X_{T3M1}	—	—	0.60	0.60	—	—	—	—	—
X_{T1M2}	0.40	—	—	—	0.60	—	—	—	—
X_{T2M2}	—	0.40	—	—	0.60	—	—	—	—
X_{T3M2}	—	—	0.40	—	0.60	—	—	—	—
X_{T1M3}	0.40	—	—	—	—	0.60	—	—	—
X_{T2M3}	—	0.40	—	—	—	0.60	—	—	—
X_{T3M3}	—	—	0.40	—	—	0.60	—	—	—
$Z1$	—	—	—	—	—	—	1.00	—	—
$Z2$	—	—	—	—	—	—	—	1.00	—
$Z3$	—	—	—	—	—	—	—	—	1.00

Note. T = trait; M = method; Z = external variable; X = manifest variable.

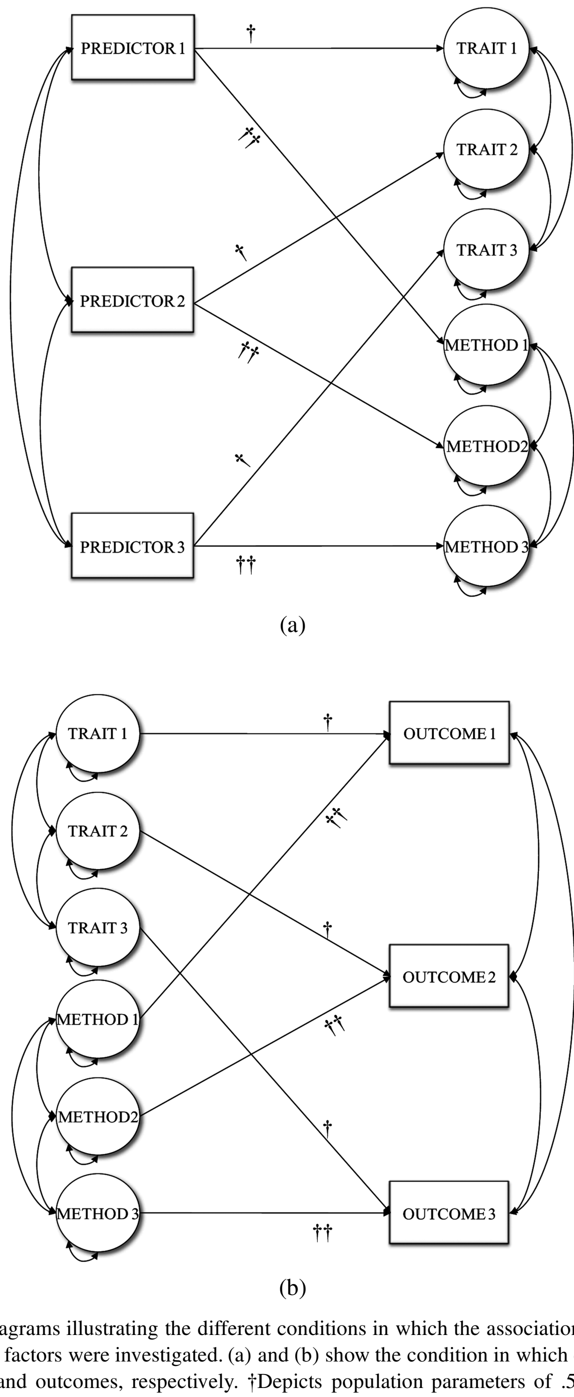

FIGURE 2 Path diagrams illustrating the different conditions in which the associations of external variables with trait and method factors were investigated. (a) and (b) show the condition in which external variables were acting as predictors and outcomes, respectively. †Depicts population parameters of .50 for the positive and differential conditions, and zero in the no association condition. ††Depicts predictive paths that varied in each condition (all †† paths were .50 in positive condition, zero in no association condition, and −.50 in differential condition).

condition, zero in the no association condition, and −.50 in the differential condition (i.e., negative associations of external variables with method factors and positive associations of external variables with trait factors).

Data Analysis

In the first set of analyses, we wanted to investigate if choosing one MTMM confirmatory factor analysis (CFA) model over another would result in biases in the predictions of traits to or from external variables. With this in mind, we first fit the CT–CM, followed by the CT–CU and the CT–C(M–1) models. For all models, we specified each trait and method factor (where method factors existed) as predictors or outcomes of the corresponding external variables. Because the CT–CM model maps exactly onto the simulated data, we expected this model to recover population parameters best, even though convergence problems and out-of-bounds estimates were also foreseen.

Then, to assess the consequences of ignoring the MTMM structure of data on the links of traits with external variables (which we claim is most often done in psychological research), we computed composite (average) scores of the three traits. We proceeded to fit a path model for each data set in which the composites were either predicting, unrelated, or being predicted by the external variables (depending on the condition). Finally, we chose one of the methods of measurement (and ignored the rest) to fit a second path model in which the selected trait–method variables predicted, were unrelated, or were predicted by the external variables. The method of measurement we selected for this latter approach was one with lower trait variance ($\lambda = .40$). Following our illustration of three informants (i.e., child, mother, and father) reporting on the "child," we believed that choosing the mother as the method of measurement would be a realistic choice. The "mother" would have one of the lower trait-related variances as she would have less insight about the child's behavior than the child himself or herself. All analyses were conducted using the M*plus* program (Muthén & Muthén, 2010).

Results

Associations between traits and method factors with the external variables in the no association condition were, as expected, zero. Therefore, we do not discuss the results from those analyses in the remainder of this section. Moreover, for the sake of brevity, summary statistics are provided only for parameters of interest; that is, regression parameters in the **B** matrices (see Equation 5), even though brief mention of all parameters is given (and all summary statistics are available from the first author). For each model in the simulation, the results are structured in the following way: First, we discuss convergence issues and out-of-bounds estimates. Then, we describe the findings with regard to the predictive parameters between the external variables and trait and method factors. Finally, we describe briefly the biases observed in other parameters of the respective model.

External Variables as Predictors

CT–CM model. As expected, convergence issues were encountered with the CT–CM model. In the positive condition, 27 of 100 models (27%) did not converge; in the differential condition, 69 of 100 models (69%) did not converge. Therefore, results presented in this section are based only on those models for which converged solutions were available. Summary statistics of the predictive parameters from the external variables to the trait and method factors derived from the CT–CM model are presented in the top half of Table 2. The first column shows the mean of the parameters across all data sets with converged estimation in which the external variables positively predicted trait and method factors. The next column lists the standard deviation, followed by the simulated data population values. The column titled % Bias was computed by multiplying 100 by the ratio of the difference (mean of estimated parameters − population values) divided by the population value of the parameter. Thus, a positive value in this column represents positive bias and a negative value reflects negative bias. In line with other simulation studies, positive or negative bias less than 10% is considered small. The last set of columns on the right side of Table 2 show the summary statistics of the parameters when trait factors were positively predicted by the external variables, but method factors were negatively predicted by them (i.e., the differential association condition). As shown in the top half of Table 2, the degree of bias on the predictions from external variables to trait and method factors for the positive and differential association conditions was small (mean percentage bias = 1.57% and 6.43%, respectively). However, the variability around each of the mean parameters was relatively large, with *SD*s ranging from 0.073 to 0.128 in the positive associations condition and from 0.069 to 0.170 in the differential condition. Percentage biases on the factor loadings were also close to zero, ranging from −9.29% to 6.40% in the positive condition and from −13.12% to 3.78% in the differential condition. For the most part, unique variances were also free of noticeable biases (range = −30.86% to 0.20% and −5.19% to 3.60% in the positive and differential condition, respectively). Covariances within trait and method factors on the other hand, displayed some degree of bias due to out-of-bounds estimates (range = −127.82% to 11.87% and −320.03% to 30.47% in the positive and differential condition, respectively). Out-of-bounds estimates occurred often as shown by the negative mean covariance between Trait 1 and Trait 2 in the positive condition (mean covariance = −0.077) and between all the traits in

TABLE 2
Summary Statistics From CT–CM Model

	Positive Associations				*Differential Associations*			
Parameter	*M*	*SD*	β	*% Bias*	*M*	*SD*	β	*% Bias*
External variables as predictors								
Predictor1 → Trait1	0.488	0.111	0.500	−2.40	0.591	0.145	0.500	18.20
Predictor2 → Trait2	0.482	0.095	0.500	−3.60	0.558	0.170	0.500	11.60
Predictor3 → Trait3	0.495	0.095	0.500	−1.00	0.545	0.146	0.500	9.00
Predictor1 → Method1	0.558	0.128	0.500	11.60	−0.511	0.138	−0.500	2.20
Predictor2 → Method2	0.504	0.068	0.500	0.80	−0.498	0.069	−0.500	−0.40
Predictor3 → Method3	0.520	0.073	0.500	4.00	−0.490	0.088	−0.500	−2.00
External variables as outcomes								
Trait1 → Outcome1	0.476	0.138	0.500	−4.80	0.522	0.084	0.500	4.40
Method1 → Outcome1	0.499	0.123	0.500	−0.20	−0.522	0.073	−0.500	4.40
Trait2 → Outcome2	0.501	0.090	0.500	0.20	0.503	0.067	0.500	0.60
Method2 → Outcome2	0.491	0.079	0.500	−1.80	−0.506	0.053	−0.500	1.20
Trait3 → Outcome3	0.533	0.374	0.500	6.60	0.500	0.068	0.500	0.00
Method3 → Outcome3	0.500	0.084	0.500	0.00	−0.506	0.054	−0.500	1.20

TABLE 3
Summary Statistics From CT–CU Model

	Positive Associations				*Differential Associations*			
Parameter	*M*	*SD*	β	*% Bias*	*M*	*SD*	β	*% Bias*
External variables as predictors								
Predictor1 → Trait1	0.557	0.041	0.500	11.40	0.244	0.050	0.500	−51.20
Predictor2 → Trait2	0.539	0.043	0.500	7.80	0.258	0.049	0.500	−48.40
Predictor3 → Trait3	0.546	0.044	0.500	9.20	0.264	0.053	0.500	−47.20
External variables as outcomes								
Trait1 → Outcome1	0.723	0.032	0.500	44.60	0.230	0.109	0.500	−54.00
Trait2 → Outcome2	0.675	0.043	0.500	35.00	0.345	0.065	0.500	−31.00
Trait3 → Outcome3	0.673	0.040	0.500	34.60	0.344	0.063	0.500	−31.20

the differential condition (mean covariance = −0.605, −0.161, and −0.955, among Trait 1 and Trait 2, Trait 1 and Trait 3, and Trait 2 and Trait 3, respectively). These results suggest that, although the CT–CM model tends, on average, to recover parameters with a minimal amount of biases, these parameters can be unstable (as shown by the large variability around the mean predictive parameters), and the model might not converge in many instances.

CT–CU model. All CT–CU models converged and no out-of-bounds estimates were found. Summary statistics of the predictive parameters from the external variables to the trait factors derived from the CT–CU model are presented in the top half of Table 3. As with the CT–CM model, the percentage bias in the positive condition was low (ranging from 7.80% to 11.40%). However, in the differential condition negative biases were quite noticeable (mean percentage bias ranged from −51.20% to −47.20%). Unlike the CT–CM model, the variability in bias estimation was much lower in both conditions, suggesting that the results from the CT–CU model were more stable from sample to sample, even though they were considerably biased in the differential condition. That is, in the differential condition, the CT–CU model consistently led to the wrong answer. As has been noted by others (Lance et al., 2002), the factor loadings in this model tend to be overestimated. In our simulation, this was true of the positive association condition, in which biases in the $\mathbf{\Lambda}$ matrix ranged from a low of 21.96% to a high of 59.65%. In the differential condition, the parameters in the lambda matrix were estimated more accurately with percentage biases ranging from a low of 4.87% to a high of 19.94%. Naturally, because method factors were not explicitly modeled in this approach, the unique factor variances and covariances were all positively biased. In the positive association condition, the biases ranged from 61.16% to 229.09% and in the differential condition they ranged from 27.91% to 44.49%. Moreover, covariances among the trait factors were all severely biased in an upward direction (range of percentage biases = 116.04% to 120.78% and 114.13% to 120.86%, in the positive and differential conditions, respectively). Finally, because the method factors are not modeled explicitly, no information about associations of external variables with method factors was available from this model.

CT–C(M–1) model. All CT–C(M–1) models converged without out-of-bounds estimates. The top half of Table 4 shows the summary statistics for the parameters linking external

TABLE 4
Summary Statistics From CT–C(M–1) Model

	Positive Associations				*Differential Associations*			
Parameter	*M*	*SD*	β	*% Bias*	*M*	*SD*	β	*% Bias*
External variables as predictors								
Predictor1 → Trait1	0.477	0.036	0.500	−4.60	0.238	0.056	0.500	−52.40
Predictor2 → Trait2	0.423	0.039	0.500	−15.40	0.268	0.047	0.500	−46.40
Predictor3 → Trait3	0.428	0.039	0.500	−14.40	0.270	0.048	0.500	−46.00
Predictor2 → Method2	0.487	0.056	0.500	−2.60	−0.396	0.054	−0.500	−20.80
Predictor3 → Method3	0.492	0.052	0.500	−1.60	−0.394	0.051	−0.500	−21.20
External variables as outcomes								
Trait1 → Outcome1	0.722	0.026	0.500	44.40	0.172	0.040	0.500	−65.60
Trait2 → Outcome2	0.501	0.036	0.500	0.20	0.373	0.039	0.500	−25.40
Method2 → Outcome2	0.485	0.034	0.500	−3.00	−0.418	0.036	−0.500	−16.40
Trait3 → Outcome3	0.499	0.035	0.500	−0.20	0.372	0.036	0.500	−25.60
Method3 → Outcome3	0.485	0.038	0.500	−3.00	−0.419	0.036	−0.500	−16.20

variables to trait and method factors of the CT–C(M–1) model, for both positive and differential conditions. Percentage biases in the positive association condition were very small (range = −1.60% to −15.40%) and the variability across the parameters was also very small (range = 0.036 to 0.052). However, when differential associations were present between external variables and trait and method factors, biases in the parameters were large (range = −20.80% to −52.40%), although variability remained small (range = 0.047 to 0.056). Thus, in the positive condition, the CT–C(M–1) model does an excellent and reliable job at recovering population parameters. But, in the differential condition, the model consistently resulted in biased parameter estimates. Estimates in other matrices displayed some biases. Specifically, in the $\mathbf{\Lambda}$ matrix, factor loadings for the MVs that did not have a method factor associated with them were biased upward (range = 54.61% to 65.07% and 29.65% to 37.78%, for the positive and differential condition, respectively). However, the remaining elements of the lambda matrix had small biases (range = −6.64% to 4.14%). Also, the $\mathbf{\Psi}$ matrix for the trait factors exhibited large positive biases (range = 24.88% to 133.66% and 19.50% to 132.47%). The remaining parameters had negligible biases.

Composite scores. As would be expected, all path models converged without out-of-bounds estimate issues. A summary of results for the path model with composite scores is presented in the top half of Table 5. In the positive condition, the biases were minimal (range = −13.60% to −12.40%), but in the differential condition downward biases were very large (range = −66.20% to −65.20%). In both instances, the variability of the estimates was small (all < 0.040), suggesting that these biases (or lack of thereof) were consistently found. Because this approach does not allow the specification of method factors, no information about associations of external variables with method factors is estimable. Finally, bias was evident in the variance–covariance matrix of the traits (or composites); in the positive condition, positive bias in trait covariances was present (range = 7.56% to 94.80%) and in the differential condition, positive bias resulted in all trait variances and covariances (range = 29.12% to 69.59%).

TABLE 5
Summary Statistics From Path Model With Composite Scores

	Positive Associations				*Differential Associations*			
Parameter	*M*	*SD*	β	*% Bias*	*M*	*SD*	β	*% Bias*
External variables as predictors								
Predictor1 → Trait1	0.438	0.035	0.500	−12.40	0.174	0.037	0.500	−65.20
Predictor2 → Trait2	0.432	0.034	0.500	−13.60	0.169	0.037	0.500	−66.20
Predictor3 → Trait3	0.437	0.036	0.500	−12.60	0.170	0.040	0.500	−66.00
External variables as outcomes								
Trait1 → Outcome1	0.501	0.031	0.500	0.20	0.240	0.034	0.500	−52.00
Trait2 → Outcome2	0.508	0.033	0.500	1.60	0.238	0.039	0.500	−52.40
Trait3 → Outcome3	0.504	0.032	0.500	0.80	0.238	0.037	0.500	−52.40

Single method of assessment. All path models converged and no out-of-bounds estimates were found. The results from fitting the path model with only one method of assessment to the simulated data sets are shown in the upper half of Table 6. The predictions of external variables to traits showed large biases in both positive and differential conditions. In the former condition, negative bias in the predictive parameters was found, ranging from −24.60% to −40.20%; in the latter condition, negative bias ranged from −95.80% to −81.00%. As with the previous path models, the variability of the estimates was very small (range = 0.036 to 0.037, and 0.041 to 0.046, in the positive and differential condition, respectively). Thus, when using a single method of assessment (in this case one that loaded 0.40 and 0.60 to trait and method factors, respectively), estimates of predictive parameters showed considerable negative bias, regardless of whether the true associations of external variables with trait and method factors were positive or differential. The small variability of these biased estimates suggests that this approach consistently leads to wrong answers.

External Variables as Outcomes

CT–CM model. Only seven (or 7%) CT–CM models did not converge in the positive condition, and all models converged in the differential condition. However, a few parameters were

TABLE 6
Summary Statistics From Path Model With Single Method of Assessment

	Positive Associations				*Differential Associations*			
Parameter	*M*	*SD*	β	*% Bias*	*M*	*SD*	β	*% Bias*
External variables as predictors								
Predictor1 → Trait1	0.299	0.037	0.500	−40.20	0.095	0.043	0.500	−81.00
Predictor2 → Trait2	0.377	0.036	0.500	−24.60	0.021	0.046	0.500	−95.80
Predictor3 → Trait3	0.305	0.037	0.500	−39.00	0.092	0.041	0.500	−81.60
External variables as outcomes								
Trait1 → Outcome1	0.222	0.035	0.500	−55.60	0.191	0.031	0.500	−61.80
Trait2 → Outcome2	0.451	0.034	0.500	−9.80	−0.019	0.038	0.500	−103.80
Trait3 → Outcome3	0.226	0.041	0.500	−54.80	0.192	0.036	0.500	−61.60

estimated out of bounds, as indicated by some large standard deviations of the parameters in the $\mathbf{\Psi}$ matrix. Summary statistics of the parameters derived from the CT–CM model for the positive association and differential association conditions are presented in the lower half of Table 2.

The **B** matrices, containing the predictions of trait and method factors to the external variables, exhibited very small biases. On average, these parameters were, at a maximum, only 0.03 and 0.02 (respectively, for the positive and differential condition) units away from their population values. The percentage bias on these parameters ranged from a low of −4.80% to a high of 6.60% in the positive condition and 0% to 4.40% in the differential condition. However, in the positive condition, the variability of some parameters was large. Specifically, in models in which trait factors predicted the external variables, parameter estimates exhibited considerable variability (range of *SD*s = 0.123 to 0.374). The predictive parameters in the differential condition, on the other hand, exhibited small variability (*SD* range = 0.053 to 0.084), suggesting that the CT–CM model did an excellent job at recovering the parameters of the predictions of trait and method factors to external variables under the differential association condition.

On average, biases on the factor loadings under both conditions were negligible (percentage bias range = −4.34% to 16.15% and −2.00% to 1.57%). However, in the positive condition, the standard deviations for certain parameters were larger than desirable (range = 0.062 to 0.397). The lack of bias was also true of the unique factor variances in the differential association condition (range = −2.23% to 1.14%), but in the positive condition one of these parameters was negative and had large variability (mean percentage bias = −44.17%, *SD* = 1.367), suggesting out-of-bounds estimate problems across the CT–CM models with this particular parameter. Covariances among trait factors exhibited, on average, minimal biases (range = −16.76% to −7.97% and −2.97% to 1.46%, in the positive and differential condition, respectively); yet in the positive association condition, the variability of these parameters was large (range = 0.241 to 0.312), suggesting these parameters were unstable in the model. The same pattern of results was found with regard to covariances among method factors. Small biases were present in both conditions, with percentages ranging from −12.00% to −5.10% in the positive condition and −0.26% to 0.93% in the differential condition, even though parameters in the positive condition, but not the differential condition, had large variability (range = 0.129 to 0.192).

The covariances among the outcome variables were, on average, overestimated (median percentage bias range = 104.00% to 104.00% and 102.33% to 106.00% in the positive and differential condition, respectively; note that mean bias is not reported here, as the presence of out-of-bounds estimates makes the median a better estimator of the middle point in the distribution). Out-of-bounds estimates across the model runs were observed and corroborated by the large variability in these parameter estimates (range = 0.051 to 103.528 and 99.840 to 171.169 in the positive and differential conditions, respectively). In the positive condition, the residual variance of one outcome was considerably underestimated (percentage bias = −35.83%) and appeared unstable (*SD* = 1.629), but the rest were estimated without biases and reliably. In the differential condition, the residual variances of the outcomes were also recovered without substantial bias (range = −11.38% to −2.83%), but the variability of these parameters was slightly larger than ideal (range = 0.105 to 0.164).

CT–CU model. All models in the positive condition converged, but two (2%) out of the 100 models did not converge in the differential condition. Thus, the results presented in this section are based on the 98 models that did converge. Results from this model are listed in the lower half of Table 3. Numerous parameter estimates in this model exhibited large bias. Parameter estimates of primary interest (i.e., those in the **B** matrix) all showed large positive bias in the positive condition (ranging from a low of 34.60% to a high of 44.60%) and large negative bias in the differential condition (ranging from a low percentage bias of −54.00% to a high of −31.00%). As seen in Table 3, the variability of the parameters was small in the positive condition and also fairly small in the differential condition (with the exception of the regression of the first trait on the first outcome variable). These results suggest that, under the current circumstances, the CT–CU model results in consistently biased estimates of the relations between traits and external variables.

Due to space limitations, the mean parameters in the remaining matrices are not displayed, but the biases in other parts of the CT–CU abounded. The $\mathbf{\Lambda}$ matrix showed positive bias in all the loadings, ranging from 12.70% to 49.23%, for the positive condition. In the differential condition, about half of the loadings were estimated appropriately, but others were positively biased up to 64.17%. In the positive condition, all unique factor variances were overestimated, with percentage biases ranging from 33.68% to 93.28%. Similar results were true of the differential condition (percentage biases ranged from 26.54% to 74.43%), with the exception of two unique factor variances for which the bias was quite large but in the negative direction (percentage bias = −121.06% and −132.89%). The percentage biases of the unique factor covariances ranged from a low of 29.40% to a high of 43.50% in the positive condition (note that these covariances are zero in the population). However, when the associations of method factors with the external variables were set to a negative value in the population, the mean estimates for three out of the nine unique factor covariances were largely overestimated, clearly due to out-of-bounds parameter estimates (mean estimates ranged from 204.367, *SD* = 404.447 to 275.089, *SD* = 448.712, and median percentage bias ranged from 36.10% to 57.00%), and the remaining mean percentage biases of the unique factor covariances in the differential condition ranged from 35.40% to 39.50%. Moreover, covariances among the trait factors were overestimated in both conditions (percentage biases ranged from 55.68% to 56.43% and 28.51% to 43.18% in the positive and differential condition, respectively), and the variances and covariances of the outcomes were severely overestimated in the differential condition (percentage biases ranged from −75.34% to 102.06%), but not greatly in the positive condition (percentage biases ranged from −4.64% to 32.46%).

CT–C(M–1) model. This model converged in all instances and no out-of-bounds estimates were found. The lower half of Table 4 shows the summary statistics for the results of the CT–C(M–1) model, for both positive and differential conditions. This model showed only one positively biased parameter in the positive condition (percentage bias = 44.40%), which corresponded to the prediction of Trait 1 to the first outcome. The variability for this parameter was small (*SD* = 0.026). The results in the differential condition were not as favorable, as considerable negative bias was shown in three of the five estimated parameters (ranging from −65.60% to −16.20%), although the variability was small for all these parameters (*SD* range = 0.036–0.040). These findings suggest that the CT–C(M–1) model led to consistent biases in the link of trait and method factors to external variables that cannot be ignored.

With regard to the remaining parameters in the model, upward biases ranging from −11.51% to 48.26% and −12.35% to 54.70% in the positive and differential condition, respectively, were observed in the factor loadings of those MVs that did not have a method factor influencing them.

The $\boldsymbol{\Theta}$ matrix, which contains the unique factor variances, had, for the most part, appropriate estimates in the positive condition (percentage bias range = −25.80% to 4.36%), but in the differential condition the comparison standard MVs had biases in the negative direction ranging from −51.39% to 15.06%. The $\boldsymbol{\Psi}$ matrix exhibited the most problems in this model. In both conditions, all covariances among trait factors were, on average, overestimated (percentage biases ranging from 55.73% to 64.01% and 43.02% to 45.01% in the positive and differential conditions, respectively). The latter was also true of covariances among external outcome variables (biases ranging from 88.69% to 93.79% and 126.79% to 129.02% in the positive and differential conditions, respectively). In the differential condition—but not the positive—the residual variances of the external variables were also overestimated (biases ranging from −4.45% to 2.76% and 36.65% to 93.78%).

Composite scores. All path models with composite scores converged without out-of-bounds estimates. A summary of results for the path model with composite scores is presented in the bottom half of Table 5. In the condition of positive associations with external variables, the bias in the **B** matrix was minimal (range = 0.20% to 1.60%) and so was the variability of the estimates across the models (range = 0.031 to 0.033). However, the variances of the external variables in this condition were considerably overestimated (biases ranged from 48.27% to 49.57%). As expected, the biases in the differential condition were quite severe. All of the predictive parameters in the **B** matrix were negatively biased by about half their population value (percentage bias ranged from −51.97% to −52.50%) and had very small *SD*s (all < 0.039), pointing to the fact that these substantial negative biases occur reliably. All the remaining parameters were, on average, overestimated by anywhere from 31.63% to 91.16%.

Single method of assessment. The results from fitting this model to the simulated data sets are in the lower half of Table 6. As before, all the models converged, and no out-of-bounds estimates were produced. The predictions of the traits to the external variables were substantially negatively biased in both the positive (range: −55.60% to −9.80%) and differential (range: −103.80% to 61.60%) conditions. In the positive condition, two of the three predictive parameters were estimated, on average, at less than half their population value (percentage bias = −55.60% and −54.80%, for Trait 1 to Outcome 1 and Trait 3 to Outcome 3, respectively). In the differential condition, the equivalent parameters were even more biased; the prediction of Trait 2 to the second outcome had, on average, a percentage bias of −103.80%, more than twice its population value. For both conditions, the variances and covariances of the traits were estimated properly (all absolute value biases $< 7.02\%$), but the variances and covariances of the external variables were overestimated in all instances (biases ranged from 49.25% to 89.91% and 75.38% to 99.65% in the positive and differential condition, respectively). The variability of all the parameters from this model was very small (*SD* range = 0.031–0.036).

Discussion

Results from this study show the advantages and disadvantages of certain models that can be fit with MTMM data. Overall, the CT–CM model had the least bias in parameter estimates. However, this model resulted in many convergence issues, many out-of-bounds estimates, and large variability in the estimates across data sets in the condition where external variables were predictors of trait and method factors. In contrast, when trait and method factors were predictors of the external variables, the results were more promising. Few models failed to converge in the positive condition, and all models converged in the differential condition. Furthermore, although the positive condition resulted in somewhat unstable predictive parameters, the variability in parameter estimates was quite small in the differential condition.

Results for the CT–CU model were encouraging for the positive condition in which external variables were predictors of the traits. However, under all other circumstances, the biases for this model were noticeable, with relations being underestimated in the differential condition and overestimated in the positive condition where external variables were specified as outcomes. With the exception of two instances, the CT–CU model showed little in the way of convergence problems, but some out-of-bounds estimates were also produced.

The CT–C(M–1) model exhibited mostly negative biases in the differential condition, regardless of the direction of the associations between external variables and traits. These biases were present in the predictions of most interest, that is, the links of traits with external variables. In the positive condition, this model performed well when the external variables were predictors. But, when external variables were outcomes, one of the trait-to-outcome paths was consistently and substantially overestimated.

The path models using MVs produced very interesting results. When composite scores were formed by averaging across methods, biases were minimal in the positive condition (regardless of whether external variables were predictors or outcomes). However, large levels of bias arose in the differential condition, where all associations of traits with external variables (as predictors or outcomes) were underestimated by more than half their population values.

More concerning were the results from the path model with a single method of assessment, where large biases were found under all conditions. More pronounced negative biases appeared in the differential condition, where some associations were estimated as almost zero when in fact their population value was set at .50. The small variability of the estimates suggests that using a single method of assessment consistently leads to the wrong answer. These results are alarming because, if MTMM data are not collected, one is essentially pursuing this last approach for investigating relations of traits with external variables.

STUDY 2: EMPIRICAL EXAMPLE FROM THE NICHD STUDY OF EARLY CHILD CARE AND YOUTH DEVELOPMENT

Several empirical data sets have MTMM data that, if the MTMM structure were modeled explicitly, would allow researchers to get better estimates of the relations among constructs of interest. The National Institute of Child Health and Human Development's (NICHD) Study of Early Child Care and Youth Development (SECCYD) is one such example. Here, we used data from the SECCYD to compare the relations of trait and method factors with external variables that result from employing different MTMM models. We also intend to illustrate the substantive implications of fitting models that ignore the MTMM data structure. For brevity, we focused on the case where external variables are predictors of the trait and method factors.

Method

Data

The SECCYD recruited a diverse sample of children ($N = 1{,}364$) from 10 sites across the country and followed them from 1 month of age. Data were collected in four phases from 1991 to 2007 to answer questions related to child care characteristics and experiences as well as the developmental outcomes of children. More information about these data is available online (http://secc.rti.org). For this study, we selected a sample of first-grade children ($N = 775$) for which MTMM data (methods of assessment were mother, father, and teacher reports on the child's behavior) and external variables of interest were available. The traits consisted of child social problems, internalizing behavior problems, and externalizing behavior problems. The external variables were mother and father depression, child ethnicity, and child gender. The sample was constrained to 775 children because any cases with missing data on the external variables were deleted. Full information maximum likelihood could have been used to deal with the incomplete data (by specifying distributions for the input variables). However, we decided against this to illustrate sample size issues that can result when ignoring the structure of MTMM data. Furthermore, publications utilizing these data often restrict their analyses to participants with complete data (e.g., NICHD Early Child Care Research Network, 2004).

The final sample of 775 children was well balanced with regard to gender, with 389 boys and 386 girls. The sample consisted mostly of Whites (88.26%), followed by African Americans (6.45%), and the remainder were classified as other (5.29%).

Measures

Child Behavior Checklist. Children's social problems, internalizing behavior problems, and externalizing behavior problems at first grade were assessed by mothers, fathers, and teachers using the appropriate form of the Child Behavior Checklist (CBCL/4–18; Achenbach, 1991a) or Teacher Report Form (TRF; Achenbach, 1991b). Both parent and teacher forms have 118 items, 93 of which are identical and 25 in the TRF are school-specific. A 3-point Likert scale (0 = *never,* 1 = *sometimes,* 2 = *very often*) is used for all items in both forms. Subscales for our three constructs of interest are part of the CBCL/4–18 and were used in this study. Higher scores on each of the three subscales point to a child with more social, internalizing, or externalizing behavior problems.

Parental depression. Paternal and maternal depression were measured when the children were 54 months old using the Center for Epidemiological Studies Depression Scale (CES–D; Radloff, 1977). The CES–D is a 20-item self-report questionnaire on which responses are given in a 4-point Likert scale (0 = *rarely or none of the time,* 1 = *some or little of the time,* 2 = *occasionally or a moderate amount of time,* 3 = *most or all of the time*). This measure is designed to measure depressive symptomatology in the general population. Scores can range from 0, indicating no depressive symptoms, to 60, suggesting depressive symptoms are experienced most of the time.

Gender and ethnicity. Children's gender and ethnicity were documented at the beginning of the study in a home interview, at which time the children were 1 month old.

Analytic Procedures

The first step in our data analysis consisted of fitting the CT–CM model to the MTMM data from the CBCL, excluding all external variables in the model. This was done as a first attempt to understand the structure of the data. Next, we fit all the MTMM CFA models (including the external variables) with the goal of comparing the substantive implications garnered from each model that does consider MTMM data, even if some do so with certain challenges. Then, we fit the two path models that ignore the MTMM structure of the data completely. Again, we compared the results of these models to each other and to those of the MTMM CFA models.

The first MTMM CFA model that we fit was the CT–CM model with the external variables as predictors of the trait and method factors. Specifically, paternal and maternal depression were specified to predict all three traits (i.e., children's social problems, internalizing behaviors, and externalizing behavior problems) and the father and mother method factors, but not the teacher method factor, as no association with this LV was expected. To test the effect of gender on all the traits and the teacher method factor (gender and ethnicity were only specified to predict the teacher method factor because they are the only ones that have exposure to children from either gender and several ethnic backgrounds), a dummy variable of male was created (female = 0, male = 1). Also, two dummy variables of African American (African American = 1, all others = 0) and other (other = 1, all others = 0) were created, with the White group as the reference ethnic group, to test the effect of ethnicity on all the traits and the teacher method factor. We continued by fitting the CT–CU model with all external variables as predictors of all trait factors. This model did not allow us to test the influence of predictors on method factors, because no method factors were specified in this model. The CT–C(M–1) model with predictive parameters to the trait and method factors was then fit to the data. We chose to omit the teacher method factor, making it the gold standard. We selected the teacher method factor because we believe this is a choice that is likely to be made in empirical investigations that have similar informants. The external variables in the CT–C(M–1) model were specified to predict the trait and method factors in the same fashion as in the CT–CM model, although no predictions could be made to the omitted teacher method factor.

In the next step, we computed composite scores by averaging the ratings for a given trait from the multiple reporters. This resulted in three composite variables—each representing a trait of interest—which can no longer be modeled by parsing out trait and method variance. A path model was fit in which these composites were specified as a function of all external variables. Finally, we fit another path model; but in this one, we used variables only from one informant (i.e., one method of assessment) as the traits. Mother was the chosen informant because mother ratings are most common in social science research. As before, all external variables were modeled as predictors of the traits (in this case, mother ratings on the child outcome variable).

Results and Discussion

The CT–CM model, without including external variables, was fit to the data. Because one unique factor variance was estimated negatively, with a value close to zero, and a small standard error comparable to that of other parameters, we ran the model a second time with this parameter fixed to zero, which is a common approach (see van Driel, 1978). The resulting model converged without further issues and fit the data quite well (comparative fit index = 0.990; root mean square error of approximation = 0.047). Standardized factor loadings for this

TABLE 7
Standardized Factor Loadings From CT–CM Model

Trait Factors	λ	*SE*	*p*	*Method Factors*	λ	*SE*	*p*
(1) Social problems				(4) Mother method			
Soc_Mother	0.572	0.085	< .001	Soc_Mother	0.554	0.067	< .001
Soc_Father	0.395	0.069	< .001	Int_Mother	0.787	0.065	< .001
Soc_Teacher	0.334	0.070	< .001	Ext_Mother	0.671	0.040	< .001
(2) Internalizing behaviors				(5) Father method			
Int_Mother	0.314	0.132	< .05	Soc_Father	0.651	0.044	< .001
Int_Father	−0.046	0.125	0.714	Int_Father	0.890	0.048	< .001
Int_Teacher	0.258	0.072	< .001	Ext_Father	0.660	0.037	< .001
(3) Externalizing behaviors				(6) Teacher method			
Ext_Mother	0.635	0.048	< .001	Soc_Teacher	0.943	0.025	< .001
Ext_Father	0.532	0.047	< .001	Int_Teacher	0.560	0.032	< .001
Ext_Teacher	0.434	0.048	< .001	Ext_Teacher	0.564	0.031	< .001

model are presented in Table 7. These loadings show a pattern of results that is common in psychological MTMM data. That is, the loadings for the trait factors were weak in comparison to the loadings of the method factors. Overall, mothers had higher trait factor loadings than other reporters. Fathers and teachers had weak loadings on traits, particularly the internalizing behavior problems trait. This is not surprising, as research in the personality field has found that one aspect in accurate judgment of traits is whether these traits are available to observation (Funder, 1995). In line with this notion, the loadings for externalizing behavior problems were the strongest, because indicators of this trait are more easily seen than observations of other traits. The loadings for the method factors were alarmingly strong. Given that this method variance was extracted from the MVs, researchers should be skeptical of any statistical analysis that fails to consider such method variance, particularly given its magnitude. The Social Problems factor was positively correlated with the Internalizing and Externalizing factors, $r(773) = .615$ and $.538$, ps $< .001$, respectively. Internalizing and externalizing behaviors, however, were not significantly correlated, $r(773) = .073$, $p = .738$. The method factors showed weaker correlations; the Mother method factor was positively related with the Father factor, $r(773) = .325$, $p < .001$, and the Teacher factor, $r(773) = .138$, $p < .05$. Father and teacher method factors also showed a positive association, $r(773) = .150$, $p < .01$. Moreover, standardized unique factor variances ranged from .147 to .620 and were all statistically significant, ps $< .05$ (note that one unique factor variance was fixed to zero).

For brevity, in the remaining models, we focus our discussion of results on the associations of the external variables with the trait and method factors. All remaining models converged successfully and did not result in any out-of-bounds estimates.

Table 8 shows the results for all the models we fit with the external variables as predictors of the trait and method factors (where available). In the top section of Table 8, sample sizes used for each of the models and fit indexes are presented. Importantly, fitting either one of the path models resulted in a smaller sample size. In the case of the path model with composite variables, the sample was reduced by 27.5% because of listwise deletion in the computation of the averages. Similarly, when choosing one of the methods of measurement (or informants in this case), any missing data for that individual reduces the effective sample size. As mentioned before, we did not use modern missing data techniques to maintain our full sample size to

TABLE 8
Standardized Coefficients (*SE*s) of Predictive Parameters From the External Variables to the Trait and Method Factors in All Models

	CT–CM	*CT–CU*	*CT–C(M–1)*	*Composites*	*1 Method Only*
N	775	775	775	562	750
CFI	0.979	0.962	0.947	1.000	1.000
RMSEA	0.043	0.051	0.062	0.000	0.000
RMSEA (CI)	0.032, 0.055	0.042, 0.061	0.053, 0.072	0.000, 0.000	0.000, 0.000
Mother depression → Social problems	0.071 (0.063)	**0.229 (0.048)**	0.070 (0.039)	**0.108 (0.040)**	**0.193 (0.036)**
Father depression → Social problems	**0.203 (0.062)**	**0.268 (0.051)**	**0.124 (0.038)**	**0.207 (0.040)**	**0.118 (0.036)**
African American → Social problems	0.070 (0.063)	0.065 (0.050)	0.057 (0.040)	**0.200 (0.039)**	0.044 (0.036)
Other → Social problems	0.025 (0.059)	0.019 (0.048)	0.002 (0.039)	0.000 (0.040)	−0.010 (0.035)
Male → Social problems	0.025 (0.056)	0.050 (0.048)	**0.107 (0.038)**	0.062 (0.040)	−0.006 (0.035)
Mother depression → Internalizing behaviors	0.057 (0.102)	**0.333 (0.059)**	0.053 (0.050)	**0.131 (0.041)**	**0.230 (0.035)**
Father depression → Internalizing behaviors	0.179 (0.098)	**0.297 (0.067)**	0.091 (0.049)	**0.214 (0.041)**	**0.088 (0.036)**
African American → Internalizing behaviors	−0.060 (0.088)	−0.050 (0.062)	−0.036 (0.051)	0.040 (0.041)	−0.037 (0.036)
Other → Internalizing behaviors	0.019 (0.088)	0.020 (0.058)	−0.051 (0.049)	−0.035 (0.041)	0.029 (0.035)
Male → Internalizing behaviors	−0.080 (0.086)	−0.027 (0.057)	−0.013 (0.048)	−0.018 (0.040)	−0.027 (0.035)
Mother depression → Externalizing behaviors	**0.132 (0.052)**	**0.275 (0.042)**	**0.122 (0.041)**	**0.169 (0.040)**	**0.251 (0.035)**
Father depression → Externalizing behaviors	**0.163 (0.056)**	**0.226 (0.044)**	**0.118 (0.040)**	**0.195 (0.040)**	**0.119 (0.035)**
African American → Externalizing behaviors	0.032 (0.051)	0.013 (0.045)	**0.134 (0.042)**	**0.100 (0.040)**	−0.031 (0.035)
Other → Externalizing behaviors	0.023 (0.048)	0.020 (0.042)	−0.008 (0.040)	0.020 (0.040)	0.007 (0.035)
Male → Externalizing behaviors	**0.191 (0.046)**	**0.163 (0.042)**	**0.212 (0.040)**	**0.161 (0.039)**	**0.077 (0.035)**
Mother depression → Mother method	**0.278 (0.049)**	—	**0.284 (0.039)**	—	—
Father depression → Mother method	0.021 (0.058)	—	**0.091 (0.041)**	—	—
Mother depression → Father method	0.025 (0.046)	—	0.038 (0.047)	—	—
Father depression → Father method	**0.290 (0.046)**	—	**0.321 (0.044)**	—	—
African American → Teacher method	0.046 (0.042)	—	—	—	—
Other → Teacher method	—0.012 (0.041)	—	—	—	—
Male → Teacher method	**0.107 (0.039)**	—	—	—	—

Note. Significant coefficients at the .05 alpha level are shown in bold font. CFI = comparative fit index; RMSEA = root mean square error of approximation; CI = confidence interval.

illustrate potential additional issues of ignoring the structure of MTMM data. All models resulted in generally adequate fit indexes. However, the CT–CM model exhibited the best fit to the data, followed by the CT–CU model and then the CT–C(M–1) model. Noticeably, the path models resulted in "perfect fit" because these models are just identified and their fit cannot be tested. Thus, the 1.000s and 0.000s should not be interpreted as excellent fit, but rather as untestable fit. Although the CT–CM model fit the data best, in the following paragraphs we interpret the results from all models to compare differences in the substantive implications of results from each model.

In the CT–CM model, fathers' depression was a significant predictor of children's social problems and externalizing behaviors. Mothers' depression was predictive of externalizing behaviors in this model. Finally, boys appeared to have higher levels of externalizing behaviors. No other associations between external variables and trait factors were significant. With regard to method factors, mothers' depression was directly related to the Mother method factor. The directionality of this coefficient suggests that higher levels of depressive symptomatology result in harsher reports on all traits. The same pattern was true of fathers' depression, which predicted the Father method factor; thus, father reports were harsher if fathers had more depressive symptoms. Finally, teachers' reports were affected by the gender of the child. Teachers reported more negative behaviors for boys than they did for girls.

Results from the CT–CU model vary from the CT–CM in several ways. Most noticeably, no method factors were present to be predicted by the external variables. In this model, mothers' and fathers' depression influenced significantly all of the traits. Thus, mothers and fathers with more depressive symptoms had children who would be reported to have higher levels of social problems, internalizing behaviors, and externalizing behaviors. As with the CT–CM model, boys exhibited more externalizing behaviors than girls.

Different results were obtained from the CT–C(M–1) model. As with the CT–CM model, mother depression influenced only externalizing behaviors, and fathers' depression positively influenced social problems and externalizing behaviors. Another similarity with the CT–CM model was the fact that boys exhibited more externalizing behaviors. On the other hand, the CT–C(M–1) model was the only one to suggest that boys had more social problems. This model also indicated that African Americans showed more externalizing behaviors than Whites. Because teachers were the reference method in the CT–C(M–1) model, the significant relation between the African American dummy variable and the Externalizing trait factor appears because the Externalizing factor aligns more with teacher ratings. Thus, the significant difference between African American children and White children in externalizing might be more in the eye of the beholder (i.e., the teacher) than in the children being rated.

With regard to method factors in the CT–C(M–1) model, mothers' and fathers' depression led to higher levels of the mothers' method factor, and only fathers' depression led to higher levels of the fathers' method factor. However, one must keep in mind that the meaning of these method factors is different from that of the method factors in the CT–CM model. Thus, the differences in associations with method factors should not be compared. However, although the trait factors in the CT–C(M–1) model are not identical in meaning to the CT–CM trait factors, we believe the differences in associations with external variables should be compared. This is due to the practical implications of the models. That is, if one were to fit the CT–C(M–1) model only, one might advocate for intervention programs for boys to reduce their social problems (regardless of the actual meaning of the social problems factor in this model), but this suggestion would not have derived from fitting the CT–CM model (again, regardless of the interpretation of the social problems trait factor).

According to the path model with composite variables, mothers' and fathers' depression predicted positively all the traits. Also, this model suggested that African Americans had more social problems and externalizing behaviors than Whites. Furthermore, as in the previous models, boys had more externalizing problems compared to girls.

The final path model in which only the mothers' reports were used suggests that mothers' and fathers' depression positively influenced all the traits. In line with all other models, boys showed more externalizing behaviors than girls.

GENERAL DISCUSSION

This article focused on investigating biases that might arise from ignoring, either partially or fully, the MTMM structure of data in investigations in which the focus is to uncover the associations of external variables with trait and method factors. MTMM structural models that do not specify all MVs explicitly as decomposable trait–method units partially ignore the true structure of the data. Furthermore, path models that rely on composite scores or a single method of assessment completely disregard the MTMM structure of the data.

In the first study, we generated MTMM data with characteristics that are likely to exist in empirical data sets (and results from Study 2 support this conjecture). That is, we specified three trait factors and three method factors with method variance higher than trait variance for two out of three indicators of each trait factor. We included three external variables in the simulated data to assess their associations with the trait and method factors across multiple MTMM CFA models and across path models that ignore the true structure of the data. In the second study, we set out to investigate the substantive differences that might arise from selecting different approaches for handling MTMM data.

Results from both studies highlight several important points. The first and most important conclusion is that alternative MTMM structural models lead to substantively different patterns of results. Thus, researchers should consider carefully how to model their MTMM data, as their results could depend in important ways on the MTMM model selected. The simulation study suggests that the CT–CM model does the best job at recapturing the population parameters of the associations of external variables with trait and method factors. This is not surprising, as the data were generated based on the CT–CM model. However, to the degree that researchers adhere to Campbell and Fiske's (1959) conceptualization of variables as trait–method units, knowing the degree of bias that the CT–CU and CT–C(M–1) models produce is of vital importance. Importantly, the CT–CM model has well-known challenges, including convergence and out-of-bounds estimate problems, that might obstruct its use in empirical research, and these challenges were obvious in our simulation study. The two alternative SEM MTMM models, the CT–CU and CT–C(M–1) models that have been developed to deal with the shortcomings of the CT–CM model have clear advantages over the CT–CM model in certain regards, yet our simulation study also pointed to some important disadvantages of these alternative models. To the degree that psychological data are indeed structured as trait–method units, the simulation study shows that the CT–CU model fails to represent accurately the relations of external variables with trait factors when the former are outcomes to be predicted by the latter. If trait and method factors are positively related to the outcomes of interest in the population, then the relations recovered by the CT–CU model are likely to be substantially positively biased. On the other hand, if the trait and method factors are differentially related to the outcomes (such that the method factors negatively influence the outcomes) in the population, the associations uncovered by the CT–CU model of trait factors with external variables are often significantly and importantly negatively biased. Even greater underestimation of parameters might result if the external variables are predictors, instead of outcomes, of the trait factors. Furthermore, information regarding the links of external variables with method factors is lost in the CT–CU model, which might represent a serious limitation of this model (Lance et al., 2002).

The CT–C(M–1) model also showed some biases, and these were more pronounced when trait and method factors were differentially related to the external variables. Under the differential relation condition, the associations of traits with external variables were noticeably negatively biased. The CT–C(M–1) model, however, performed well when the associations of trait and method factors with external variables were positive, with the exception of one parameter that was consistently overestimated when the external variables were outcomes.

Importantly, we interpret method factors in the empirical study as representing systematic variance unrelated to traits; that is, method factors represent systematic construct-irrelevant variance, where the trait factors are the constructs of interest. This view is consistent with the notion that discrepancies in reports among informants are due to rater biases (as proposed by Campbell & Fiske, 1959). However, others have suggested that informant discrepancies are not only due to rater biases but also to contextual differences in behavior (Dumenci, Achenbach, & Windle, 2011). With this in mind, results from the second, empirical study clearly showed that the substantive implications of fitting alternative MTMM CFA models are different. Which, then, is the "best" MTMM model to fit when dealing with empirical MTMM data? This question cannot be answered easily or definitively. We believe that more work must be done to address the limitations of the CT–CM model, including poor rates of convergence and high levels of out-of-bounds estimates. Fitting MTMM CFA models that are not true to the structure of the data, however, does not seem to be an optimal approach.

Importantly, the results from the path models that completely ignored the structure of MTMM data were alarming. If differential associations between trait and method factors were present in the population, substantive results were highly misleading, with much weaker associations than truly existed. However, with positive associations between trait and method factors in the population, if composite scores are computed across methods of measurement and modeled as MVs, then the results from our simulation study exhibited consistent, but only moderate levels of negative bias. In our simulation study we specified the predictive parameters of trait and method factors with external variables to be of the same magnitude. This is the basis for the relatively optimistic results for path models with composite scores in conditions in which both traits and methods were positively related to external variables. However, if we had specified different magnitudes for those predictive parameters, biases might well have become noticeable, too. The key lies in the fact that MVs in psychology often are loaded with greater amounts of method variance than trait variance, as Campbell and Fiske (1959; Fiske & Campbell, 1992) argued and documented. Most alarming are the results from the path model that utilized the information from only one method of assessment. In all conditions, the predictive parameters of external variables to and from trait and method factors were severely biased downward. Importantly, when MTMM data are not collected, one is basically fitting a path model of this sort. Our results suggest that interesting effects in psychology might be lost due to the neglect of MTMM data collection and MTMM model fitting.

One potential limitation of this simulation study is that data were generated assuming that trait factors were uncorrelated with method factors, which might not be realistic in empirical data. To the extent that trait and method factors do covary in real data, the results from this investigation might vary. We note, however, that trait factors are always specified to be uncorrelated with method factors in MTMM CFA models to avoid model identification problems, so our data generation does conform to the manner in which these models are specified in theoretical and empirical applications. Furthermore, in our second path model, we selected for inclusion the one method that had one of the lowest relative levels of trait variance; if we had chosen a method of measurement with more relative trait-related variance, the results might paint a more positive picture for that particular model, although we still expect results for the second path model to be very discouraging. Also important is that, although the CT–CM model unsurprisingly resulted in the lowest mean bias because the simulated data were generated according to that very model, the CT–CM model maps directly onto the conceptualization of MTMM data put forth by Campbell and Fiske (1959), which is why it is so attractive theoretically.

The accuracy of results from the CT–CM model should be interpreted with caution, as the variability of all the parameters was large. This suggests that, on average, the CT–CM model performs well, but in any one instance, the estimated parameters might fall far from the population parameters. This finding is in line with research comparing the accuracy versus precision of MVs and LVs in mediation models (Ledgerwood & Shrout, 2011). In their study, Ledgerwood and Shrout reported that the accuracy of estimates from mediation models was higher when LVs were employed, but this was at the expense of precision (i.e., higher *SE*s of parameter estimates); using MVs led to higher precision, but at the expense of accuracy (i.e., greater bias). In our results, the large variability (i.e., low precision) of the predictive parameters for the CT–CM model was likely due to the smaller factor loadings of the trait factors, when compared to the method factors. In other words, the trait factors were relatively unstable. Future work should consider alternatives for dealing with MTMM data in a way that identifies trait factors to make them more stable. An obvious approach for achieving this goal is to bolster focus on the research design stages of all investigations. In this way, the construct validity of our measures will be high, and working with MTMM data will be less challenging. Finally, readers should note that results from all CT–CM models that converged in the simulation study were included in our descriptive statistics, regardless of the fact that some had inappropriate solutions. We chose to include such results to highlight the crude reality of problems encountered with the CT–CM model and to encourage future work on MTMM CFA models.

In sum, results from both studies suggest that the collection of MTMM data is crucial to capture accurately the associations of trait constructs with external variables. Researchers should be discouraged from creating averages of observed variables when MTMM data are available. Instead, alternative MTMM CFA models can be fit, and, when substantive implications differ from model to model, these should be reported. Furthermore, we encourage researchers to think about the validity and structure of their data. Our results can aide in the understanding of empirical findings depending on whether researchers foresee positive or differential associations between trait and method factors and external variables. The advancement of psychological science lies in researchers considering the nature of the variables they utilize, as many contradictory findings in the literature could be due to the neglect of method-related variance.

Campbell and Fiske (1959) started a revolution in the realm of construct validity. However, the low levels of importance placed on collecting MTMM data and the lack of application of MTMM models in the literature suggest that Campbell and Fiske's revolution has stalled. The SEM framework has become increasingly popular because of its capacity to model "error-free" latent variables. We hope fitting MTMM models becomes just as attractive, as these models allow us to estimate effects of error and method-free latent trait variables when investigating relations among trait constructs, the core of construct validity.

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