A FACTOR STRUCTURE WITH MEANS CONFIRMATORY FACTOR ANALYTIC APPROACH TO MULTITRAIT-MULTIMETHOD MODELS

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A FACTOR STRUCTURE WITH MEANS CONFIRMATORY FACTOR ANALYTIC APPROACH TO MULTITRAIT-MULTIMETHOD MODELS

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ABSTRACT

The traditional correlated trait – correlated method (CT-CM) approach to multitrait – multimethod (MTMM) models, though easy to interpret, suffers from problems of identification. Alternative identified MTMM models are generally less conceptually desirable and more difficult to interpret. Existing MTMM models are covariance-based, and do not provide researchers with important information regarding mean levels of the trait or method factors. A factor structure with means (FSM) approach to the CT-CM model is proposed to remedy the identification problem and maintains the desirable structure and ease of interpretation of the CT-CM model while providing mean level information about trait and method factors. In an example data set, the FSM model converged, suggesting the model was identified. Additional models including scaling factors correcting for inappropriate measurement level assumptions yielded significant improvements in model fit, indicating erroneous measurement level assumptions are detrimental to model fit. Although the proposed FSM model is a useful alternative to traditional MTMM models, it must be evaluated relative to alternative forms of the model that may be suggested by theory or modification indices. In this case, modification indices indicated an unmodeled systematic source of variance within trait-specific method units. Thus, future models should include trait-specific method factors rather than general method factors, as suggested by previous researchers. Models allowing for multidimensional method effects or second-order factors should also be examined.

A Factor Structure with Means Confirmatory Factor Analytic

Approach to Multitrait – Multimethod Models

In all disciplines, researchers wish to make inferences about latent variables that represent constructs of interest. In some fields, observations of the latent variable are more clearly defined than in others. For example, in medicine, a researcher who is concerned with cholesterol levels can run simple blood tests and use cholesterol levels in the sample to infer the overall cholesterol level in the blood. However, in psychology, more abstract constructs such as intrinsic motivation are not necessarily convincingly measured through such direct means. As such, social science researchers are faced with the often daunting task of ensuring that any measures they create or employ adequately represent the construct, and thus the latent variable, of interest.

Construct validity has been defined as the ability of a particular measure to adequately represent a latent construct (Cronbach & Meehl, 1955). That is, the degree of construct validity of a measure represents how much the underlying psychological construct actually accounts for the resulting scores on the measure. Establishing construct validity involves evaluation of both convergent and discriminant validity, as well as the method effects of the measure itself (Campbell & Fiske, 1959). *Convergent validity* refers to the relative agreement between distinct measures or methods as to the existing level of the construct (i.e., high correlations across different measures of the same trait). *Discriminant validity*, on the other hand, is the degree to which the measure of interest, and therefore the construct of interest, is distinct from other constructs that are conceptually different (i.e., low correlations between conceptually distinct trait measures) (Campbell & Fiske, 1959). In essence, the purpose of establishing convergent and discriminant validity is to show that the measure actually represents the construct of interest and not another construct.

The Multitrait – Multimethod Model

Any set of raw scores derived from a given measure reflects not only the overarching trait of interest but also the method effect of the measure itself (Campbell & Fiske, 1959). As such, it is reasonable to want to account for the respective contributions of trait and method factors to the observed variables. Campbell and Fiske (1959) presented the multitrait-multimethod (MTMM) matrix as a means of assessing construct validity. This model requires the measurement of multiple traits, and each trait by multiple methods, which may differ by type of instrument or by perspective, and as such provides a way in which to consider both trait and method effects. The multimethod approach, although potentially time consuming, is both advantageous and necessary because it allows for the partialling out of common method variance from estimates of the relationship between traits. A monomethod approach, though easier to implement, can lead to inflated trait correlation estimates because it does not allow for the decomposition of variance into trait and method components.

Thus, the purpose of MTMM models is to decompose observed variance into distinct method, trait, and error components. There are currently three general approaches to MTMM models: confirmatory factor analysis (CFA), covariance components analysis (CCA), and the direct product (DPA) model (Wothke, 1996). CFA and CCA both assume that raw scores are a result of a linear combination of trait and method effects, whereas the DPA model assumes that raw scores are due to a multiplicative combination of trait and method effects (Dumenci, 2003).

CFA is currently the most commonly taken approach to MTMM analyses, likely because it allows for the linear decomposition of variance into distinct trait, method, and error components while also allowing for testing of model assumptions (Eid, Lischetzke, Nussbeck, & Trierweiler, 2003). The CCA and DPA approaches do have advantages, however they are generally less desirable models. The CCA approach models a general factor that contains both trait and method variance , and thus fails to separate the two components (Wothke, 1996). The DPA model is not appropriate when observed scores are a linear result of trait and method factors, and is a highly restrictive model that some research has suggested may not be falsifiable (Marsh & Grayson, 1991; See Wothke, 1996 for a more detailed review of the CCA and DPA models).

Confirmatory Factor Analytic Approaches to the MTMM Model

As mentioned previously, under the CFA approach, the MTMM matrix is additively decomposed into three distinct parts: common trait and method factors, and disturbance variables that represent any variance not accounted for by the trait and method effects. Generally, the number of common trait factors is equal to the number of traits assessed (t), the number of common method factors is equal to the number of different methods of assessment used (m), and the number of disturbance variables is equal to the number of trait-method combinations (tm) (or the number of manifest variables). However, there are several different forms of the CFA MTMM model, and this overall structure can vary depending upon the form of the particular model used. The structure of the covariance matrix and the interpretation of the model is also determined by the form of the CFA model (e.g., trait-only, correlated trait-correlated method) (Dumenci, 2003). Overall, the CFA models address the issue of how many latent factors are necessary to explain the data and how much variance each latent factor accounts for (Millsap, 1995).

In matrix form, the CFA model is represented as

$$X = \Xi\Lambda' + E \qquad (1)$$

where X is an *n* by *k* matrix of observations, where *k* is the number of manifest variables, $\boldsymbol{\Xi}$ is an *n* by *c* matrix of factor scores, where *c* is the number of factors, $\boldsymbol{\Lambda}$ is a *k* by *c* matrix of factor loadings, and E is an *n* by *k* matrix of uncorrelated error terms. The corresponding covariance structure is then represented as

$$\Sigma_x = \Lambda\Phi\Lambda' + \Theta \qquad (2)$$

where Σ_x is the predicted covariance matrix, Φ is the population factor score covariance matrix, and Θ is the population error covariance matrix (Wothke, 1996).

The Correlated Trait – Correlated Method Model. The correlated trait – correlated method (CT-CM) CFA model (see Figure 1) could be considered the ideal CFA model, and possibly the most representative model for Campbell and Fiske's (1959) discussion of validity. In the traditional CT-CM model, a latent factor is defined for each trait assessed as well as for each method employed. The assumptions of the traditional CT-CM model are that the correlations between trait an method factors are zero and that the disturbance variables are uncorrelated (Eid, 2000). The CT-CM model should allow for the decomposition of observed variance into trait, method, and error variance components, concordant with the purpose of the MTMM model.

The CT-CM model is a beneficial model in several ways. It is straight-forward when considering construct validity and interpretation in that, dependent upon how the model is defined and the underlying assumptions of the model, convergent validity is generally represented as large and significant trait loadings, discriminant validity is represented by low correlations between trait factors, and method effects are quantified by the magnitude of the method factor loadings (Dumenci, 2003). It is necessary to adjust scores for attenuation due to unreliability when assessing convergent and discriminant validity. As such, the CT-CM model is advantageous because it models the relative degree of reliability associated with the manifest variables via estimated factor loadings (Dumenci, 2003).

It must be noted, however, that there are several drawbacks to using the CT-CM approach, including improper parameter estimates, convergence failures, and problems with identification (Eid et al., 2003; Wothke, 1996). Broadly speaking, identification is defined as whether or not the model can be estimated as it is defined. Identifying a model requires: 1) estimating fewer (free) than are known parameters (or number of elements in the covariance matrix) (i.e., *logical identification*), 2) there existing a unique solution to the model (i.e., *mathematical identification*), and 3) that the theoretically sound model can be estimated with the data and/or sample at hand (i.e., *empirical identification*; Kenny, 2004).

A primary problem with the CT-CM model is that the model is either rank deficient or empirically identified (Kenny & Kashy, 1992; Wothke, 1996). Specifically, when the matrix of factor loadings is rank deficient, that is, when there are more factors than manifest variables in the model, the CT-CM model is not identified (Grayson & Marsh, 1994). Furthermore, a model can be empirically unidentified because of redundant or highly collinear factors (Kenny, 2002, 2004), factor loadings that are too close to zero (Rindskopf, 1984a), or because of overfactorization (Rindskopf, 1984a; Eid, 2000). Such problems cause unstable estimates (Rindskopf, 1984a; Kenny, 2002), and thus the solutions that result from such models are potentially untrustworthy. When the CT-CM model is applied, it often fails to converge or yields improper estimates, such as negative variances. It is possible that both problems are a result of the unidentified nature of the CT-CM model (Eid, 2000). It has also been suggested that the CT-CM model does not perform well because it is not well defined conceptually, as there is no real reason to assume that the only appropriate model has orthogonal traits and methods (Wothke, 1996).

Thus, several researchers have suggested that the traditional CT-CM model should be abandoned in favor of alternative CFA models (e.g., Kenny & Kashy, 1992; Eid, 2000). The alternative models are generally modified and/or constrained versions of the CT-CM model that reduce the number of parameters being estimated, or modify the factor structure of the model, in order to prevent identification problems. That is, constraints are placed on the CT-CM model that makes it identified.

The Correlated Trait – Correlated Uniqueness (CT-CU) Model. The prevalent alternate CFA model appears to be the correlated trait – correlated uniqueness (CT-CU) model (see Figure 2). The CT-CU model differs from the CT-CM model in that multiple methods are still used when assessing trait levels, but latent method factors are not defined in the CT-CU model. In place of the latent method factors, disturbance variables are allowed to correlate within methods in the CT-CU model and said to represent the method effects. The advantages of the CT-CU model are that it is always identified when there are at least three methods and two traits, and is identified with specific restrictions when there are only two methods. The CT-CU model also allows for multidimensional method effects in that the model does not force each method to load on one factor (Kenny & Kashy, 1992). As such, the CT-CU model converges and yields proper solutions more often than the CT-CM model (Lance, Noble, & Scullen, 2002).

While the CT-CU model may resolve some of the problems inherent in the CT-CM model, there are disadvantages to the model. As stated previously, in the CT-CU approach models method effects as the correlation among the disturbance variables. Since these disturbance variables represent both measurement error and the method effect, the method and error components are confounded. When using the CT-CU model, one cannot decompose the variance of the observed variables into separate trait, method, and error components, as is desirable and necessary for accurate assessment of convergent and discriminant validity. Thus, in spite of the proper solutions that the CT-CU model yields, it is not as conceptually desirable as the CT-CM model because it fails to serve the general purpose of MTMM analyses: to effectively separate out trait and method effects, free from error.

The CT-CU model also assumes that methods are neither correlated with other methods nor with any of the traits. This assumption may be unreasonable (Kenny & Kashy, 1992). It could be argued that there are times when methods should be expected to correlate, and we usually do not know enough about potential method effects to accurately choose independent methods (Millsap, 1995). Furthermore, violating the assumption that the methods are not correlated would cause inflation or deflation of trait variances, depending upon the direction of the method correlation (i.e., inflation when positive, deflation when negative), which could change conclusions regarding convergent and discriminant validity. When the trait variances are inflated, convergent validity appears better and discriminant validity appears worse, and the opposite holds true for deflated trait variances (Kenny & Kashy, 1992).

Correlated Trait – Correlated Method Minus One [CT-C(M-1)] Model. To resolve the problems inherent in the CT-CM model, Eid (2000) proposed a model wherein one of the method factors is eliminated, and established as a comparison method: the correlated trait – correlated method minus one [CT-C(M-1)] model. Eid et al. (2003) argued that the problems of the traditional CT-CM model were likely due to the model being empirically unidentified because it included too many method factors. They supported this argument by citing previous research (Marsh & Hocevar, 1988) wherein the application of a second-order CT-CM model yielded one non-significant method factor, suggesting the factor was unnecessary. As pointed out earlier, models with factor loadings close to zero are likely to not be empirically identified (Rindskopf, 1984a).

Eid's (2000) single-indicator CT-C(M-1) model is structured much like the standard CT-CM model, but differs in one way: the comparison method is not assigned a method factor (see Figure 3). The single-indicator CT-C(M-1) model is always identified when there are at least three traits and three methods in the MTMM, and still identified under certain circumstances when there are less than three traits or methods (Eid, 2000). Three assumptions underlie the single-indicator CT-C(M-1) model: 1) as the CT-C(M-1) model is a CFA model, it is assumed that the effect of the comparison method relative to the other methods is linear, and thus the model would not be applicable multiplicative relationships exist among methods, 2) method effects are assumed to be homogeneous across traits, and 3) error variances are assumed to be uncorrelated. To control for scaling differences, the comparison loading on each trait factor is set to 1 and thus, the trait factors represent the true-score variables of the respective traits measure by the comparison method. The method factors represent the method-specific effects or the part of the true-score variable that is not explained by the true-score variable representing the same trait measured with the comparison method (Eid, 2000).

There are conceptual problems with the single-indicator CT-C(M-1) model. Specifically, the error variance may represent both measurement error and trait-specific method effects and this might result in low reliability estimates. Furthermore, method effects are not always homogeneous, and thus the assumptions of single-indicator model would impose more restrictions than necessary on the model (Eid et al., 2003). Thus, Eid et al. (2003) expanded the CT-C(M-1) model to include multiple indicators for each trait-method unit (see Figure 4). The multiple-indicator model defines *trait-specific* latent method factors in place of the latent method factor in the single-indicator model. This allows for heterogeneous method effects across traits. It is assumed, however, that each indicator equivalently represents its trait-method unit. The comparison method is still established in the multiple-indicator model, and thus trait-specific method factors that involve the comparison method are not established.

The question of non-homogeneous method effects can be tested under the CT-C(M-1) model by examining the correlations among the trait-specific method factors. Specifically, high correlations among trait-specific method factors for the same method but different traits suggest that the method effects do indeed behave similarly (Eid et al., 2003). Similar to the single-indicator CT-C(M-1) model, the first loading of each trait factor is set to 1, meaning that each trait factor represents the true-score variable of the first indicator of the respective trait measured by the comparison method. The first loading of each trait-specific method factor is also set to 1, and the trait-specific method factors in the CT-C(M-1) model represent how different the other method true-scores are from what is expected based on the true-score variable of the trait measured by the comparison method (Eid et al., 2003).

Eid et al. (2003) suggest that the CT-C(M-1) is the most viable alternative CFA MTMM approach to date, as it has several advantages over other MTMM models. Specifically, they claim that it separates true trait, method, and measurement error variability, allowing for proper estimation of convergent and discriminant validity, reliability, method specificity, and consistency. It also allows for trait-specific method effects that are not homogeneous across traits, and finally, the factors and the correlations amongst factors have clear and specific meanings. However, there are several limitations to the CT-C(M-1) approach. The multiple-indicator CT-C(M-1) model assumes homogenous indicators within each trait-method unit, which is not necessarily realistic, and the model is not symmetric because a comparison method is selected (Eid et al., 2003). Additionally, the latent variables are defined relative to the comparison method; thus, method and trait effects for the trait-method units that involve the comparison method cannot be estimated (Lance, Noble, & Scullen, 2002). Finally, interpretation of the model, relative to convergent and discriminant validity, is not as simple as with the traditional CT-CM model.

Furthermore, Eid (2000, 2003) acknowledges that the CT-C(M-1) method is most appropriate for instances when there is a known or obvious standard for comparison. In fact, when there is not an obvious standard of comparison, it may be more appropriate to choose a different MTMM approach. Indeed, in later work, Eid, Lischetzke, and

Nussbeck (2006) acknowledged that the CT-C(M-1) model is only truly appropriate when a researcher wishes to make hypothesized comparisons among methods and when the methods are structurally distinct. That is, when a researcher is interested in modeling a unified factor, and not specifically interested in hypothesizing contrasts, the CT-CM and CT-CU models are more appropriate. Thus, Eid et al. (2003) may have rectified the identification problems of the CT-CM model for those who wish to test hypothesized comparisons among methods, but the CT-C(M-1) model fails to address these problems for those researchers interested in modeling a unified latent factor.

The Current Study

To reiterate, attempts to remedy the identification problems often seen in the CT-CM model have resulted in models that estimate a reduced number of parameters or a reduced number of factors. This may be an effective approach identifying the model, however, it may result in difficult to interpret or computationally intensive models, or models that do not necessarily test the questions of interest. Thus, it is possible that there is a different approach to this problem that does not require the removal of an entire method factor, as in the case of Eid's (2000) work, or a reduced number of estimated parameters to identify the CT-CM model.

In all of the CFA MTMM models discussed, the analyses are based on the variance/covariance matrix. When analyses are based on the covariance matrix, information is lost regarding the means in the data. That is, the covariance-based approaches fail to give the researcher information about the mean level effect of the methods and traits, which is likely to be of substantive interest. One thing that does not appear to have been considered in the attempts to remedy the identification problems of the CT-CM model is the possibility of increasing the size of the matrix used in the analyses rather than decreasing the number of parameters or factors that are estimated. Thus, a possible alternative to the existing approaches to MTMM models is to fit a factor score with means (FSM) model to the data. When fitting an FSM model to the data, the number of elements in matrix underlying the analyses will have increased, as the sums of squares and cross products (SSCP) matrix is used instead of the covariance matrix. It is possible that by adding in the mean information, the model will be more likely to be empirically identified.

It should be noted that the suggested FSM model is not without limitations. When including mean information in the model, additional considerations must be addressed. Covariance-based factor analysis of continuous level variables assumes an interval scale of measurement (Sörbum, 1984). Alternatively, factor analysis which includes the mean makes the additional assumption that variables are measured on a ratio level of measurement (i.e., that variables have a meaningful zero point). However, in practice the choice of the values for a rating scale may follow a consistent, but arbitrary scale of reference. For example, researchers may believe that a five point likert scale may represent an interval scale of measurement, but the choice of whether to assign values of 0 to 4 or 1 to 5 for such items is generally an arbitrary coding convention. As such, for the assessment of ratio scales it may be necessary to shift the values of such measures by some constant value in order for the measures to conform to the assumed ratio level of measurement. Thus, a scaling factor, termed a *shift operator* can be applied to the factors to essentially convert interval level to ratio level data (Wood and Jackson, under review).

Under the FSM model (Sörbom, 1984), assuming that each trait is assessed using the same assessment format, the observed scores are represented (in matrix form) as:

$$X = \nu + \Xi\Lambda + E \qquad (13)$$

where X is an *n* by *k* (number of variables) matrix of manifest variables, ν is an *n* by *k* scalar matrix, Ξ is an *n* by *c* (number of factors) matrix of factor scores, Λ is a *c* by *k* matrix of factor loadings, and E is an *n* by *k* matrix of prediction errors associated with each of the manifest variables. In the standard factor analytic model, means can also be specified at the level of the latent variables. In matrix form, the means of the latent variables can be specified via the following equation:

$$\Xi = \alpha + \eta \quad , \qquad (14)$$

where α is an *n* by *c* column scalar matrix of factor means and η is an *n* by *k* matrix of latent variable scores in deviation form.

If the manifest variables can be thought of as sharing the same scalar, as might occur if the same assessment format is used, or if the variables are repeated in time or taken from a genetically informative sample, it is possible to estimate both ν and α. Substituting equation 14 into equation 13 yields the equation:

$$X = \nu + \alpha\Lambda + \eta\Lambda + E \; . \qquad (15)$$

The scalar matrix ν and the column scalar matrix $\alpha\Lambda$ can be estimated using phantom variables (Rindskopf, 1984b) by specifying latent variables for these terms which have means but no variances. The scalar column matrix $\alpha\Lambda$ can be estimated by means of a latent variable with zero variances, mean α, and factor loadings constrained to be Λ.

More generally, scaling factors uniquely associated with subsets of traits and/or methods can also be specified via appropriate phantom variables in which scalar values are chosen to represent shift operators associated with particular methods and/or traits. In practice, care must be taken to assure that identification considerations are taken into account in the specification of such shift operators. Specifically, the number of estimated shift operators in the model may not exceed the number of manifest variables in the study.

Based on the lack of such research, it seems that there is a need to examine how including mean information in a CT-CM model would affect identification, convergence, and parameter estimation. It is possible that the identification problems of the CT-CM model can be remedied by making the assumption that the data are ratio, and then centering the distribution at the appropriate point. If the FSM CT-CM model is identified, it might allow us to keep the conceptually desirable structure of the CT-CM model in practice rather than using modified, less desirable, models for the sake of identification (e.g., CT-C(M-1), CT-CU models). Indeed, Lance, Noble, and Scullen (2002) argue that the CT-CM model should be preferred over both the covariance-based CT-CU and CT-C(M-1) models, because the advantages of the CT-CM model outweigh the advantages of the alternative models, provided the issues of identification, convergence, and improper parameter estimates can somehow be addressed. The FSM CT-CM model has the conceptual advantage over the covariance-based CT-CM model that it provides the researcher with important information regarding the magnitude and direction of mean trait and method effects, where the covariance-based models do not.

Thus, the purposes of the proposed study are multiple. First is to explore the possibility of rectifying the identification, and other, problems of the CT – CM model by including the mean in the model. The second purpose is to assess the utility of a shift operator (for either traits and methods) in fitting a FSM CT-CM MTMM model to Eid et al.'s (2003) data. Last is to reexamine Eid et al.'s (2003) assertions that the CT-C(M-1) method is a good fit to his the data, given the findings from the first two stated purposes.

Method

Permission was granted by Dr. Michael Eid for use of the data from the Eid et al. (2003) publication in the present study. As such, all analyses in the present study were conducted using the Eid et al. (2003) dataset.

Eid at al.'s (2003) Data

Eid at al. (2003) employed an 18-item German questionnaire to assess three traits: attention to feelings, clarity of feelings, and habitual pleasant/unpleasant mood. Each trait was measured by 6 questions. Each trait was measured via three methods; methods varied by rater. Thus, each complete record included a questionnaire completed by the participant, a close-friend, and an acquaintance. Each questionnaire was completed in reference to the participant (e.g., how the friend views the participant in attention to feelings). Rather than calculating a single value for each subscale, and thus having a single-indicator for each report, the researchers divided each subscale into 3 groups of 2 questions, resulting in three indicators for each trait-method unit. There were 203 complete records in the dataset.

The Current Study

First, Eid et al's (2003) analyses were replicated. Following from this, a FSM CT-CM model (see Figure 5) was fit to the data. As mentioned previously, to ensure that a FSM model is identified, and that both ν and Λ are estimated, constraints must be placed on the model. In the case of Eid et al.'s (2003) data, the rating scale for all three methods was the same, so it was assumed that the scaling factor, ν, was the same across the three methods. Additionally, when considering means in an MTMM model, both factor and manifest means cannot be simultaneously estimated because the model will not be mathematically identified.

In addition to the FSM model, 12 FSM-shift models were assessed (see Figure 6): one set with trait shifts and one set with method shifts. Per Wood and Jackson's (under review) work, each shift operator was defined as a latent factor with free mean and variance set to 0. Shift models were specified by constraining shift loadings to 0 (representing an inactive shift operator) or 1 (representing an active shift operator), and shift loadings are not allowed to be free (see Table 1 for specified shift models). A separate scaling factor was specified for each trait and each method, as each trait and method could require distinct adjustments. However, it must be noted that a model with all possible shifts being active simultaneously could not be specified because such a model would not be mathematically identified.

Results

Eid et al.'s (2003) Analyses and Results

Eid et al. (2003) fit covariance-based CT-CM, CT-CU, and CT-C(M-1) models to their dataset. However, the CT-CM and CT-CU models that Eid et al. (2003) fit to the data differed from the models discussed earlier in that they were second-order factor models. The multiple-indicator CT-CM model failed to converge. This is not surprising given the known identification and convergence problems with the CT-CM model. The multiple indicator CT-CU model did converge, $\chi^2_{ML}(303, N = 203) = 367.73$, $p = .01$, $\chi^2_{MLMV}(100, N = 203) = 120.17$, $p = .08$, RMSEA = .08, $p = 1.00$, CFI = .98. The CT-CU model yielded a comparable fit to the multiple-indicator CT-C(M-1) model, $\chi^2_{ML}(276, N = 203) = 339.87$, $p = .01$, $\chi^2_{MLMV}(95, N = 203) = 115.45$, $p = .08$, RMSEA = .03, $p = .99$, CFI = .98. Eid et al. (2003) suggested that in this case, the CT-C(M-1) model was a better fit to the data than the CT-CU model, in spite of the comparable model fits because there were three distinct raters. Eid et al. (2003) also claimed that the CT-C(M-1) model was preferable in this case because there is a clear interpretation of the consistency coefficient under that model, whereas there is no such clarity with the CT-CU model. In other words, in the CT-CU model, the factor loadings are difficult to interpret because the method variance is not entirely partitioned out, and therefore the loadings represent a compounded effect of trait and method, whereas the method effect is partitioned out in the CT-C(M-1) model so the trait factor loadings represent only the trait effects.

Covariance-based models

All analyses were conducted in MPlus, version 4.1 (Muthén & Muthén, 1998-2006). First-order covariance-based CT-CM and CT-CU models were fit for comparison to the first order FSM models. Uniqueness constraints were defined by setting factor variances to 1, rather than setting a factor loading to 1 in the present study. The covariance based first-order CT-CM model converged, $\chi^2(291) = 1049.64$, $p_{\chi^2} < .01$, RMSEA = .11, CFI = .77, TLI = .73, BIC = 9486.85. The first-order CT-CU model yielded a proper solution with good model fit, $\chi^2(291) = 227.39$, $p_{\chi^2} = .24$, RMSEA = .02, CFI = .996, BIC = 9079.02. In spite of the convergence of the covariance-based CT-CM model, the results of the model are questionable because of the unidentified nature of the model, as discussed earlier. Thus, model fit statistics and parameter estimates from the covariance-based CT-CM model are potentially inaccurate.

Model fit statistics from these CT-CM and CT-CU models differed from Eid et al.'s (2003) results. The models specified in the current study were first-order factor models. Eid et al. (2003) fit a second-order models that included trait-specific method factors. The second-order factor CT-CM and CT-CU models were also fit, to confirm the results reported by Eid et al. (2003), and the results were replicated.

Simple FSM models

First, the base FSM CT-CM model, without any active shift operators, was fit to the data, χ^2 (312) = 1186.56, $p_{\chi^2} < .001$, RMSEA = .12, CFI = .74, TLI = .71, BIC = 9512.19. The additional FSM-shift models were then fit to the data (see Table 2 for fit statistics). All 13 of the FSM models (with and without shifts) converged, suggesting the model was identified. Comparisons of fit statistics and information criteria across the converged models indicated that the shifted models generally yielded significantly better model fit than the base FSM CT-CM model, with one exception. One model (TS-12) resulted in higher fit statistics and information criteria than the base model, suggesting a local minimum.

Modified FSM models

In spite of the improved fit of the shifted models over the base model, the fit statistics for the simple FSM and FSM-shift models did not indicate good model fit. As such, modification indices were examined for ways to improve model fit. Modification indices strongly indicated to a need to include correlated errors on the indicators for some trait-method units. This is an indication that some source of variance is not being sufficiently modeled by the existing latent variables. For both the trait-shift and method-shift models, modification indices indicated a need for correlations among the errors within acquaintance-report of habitual mood and clarity of feelings indicators. However, correlated errors for friend-report of clarity of feelings were indicated for the trait-shift models, and correlated errors for self-report of clarity of feelings were suggested for the method-shift models. Thus, modified FSM CT-CM and FSM-shift models were fit (see Table 3 for fit statistics). Since different correlated indicators were suggested between the shift models, a separate base FSM model was fit for the trait-shift and method-shift models, reflecting the appropriate correlated error structure. Although it has been suggested that sequential model modifications in response to modification indices may be problematic in practice (Kaplan, 1988), such model adjustments seem reasonable in the current study, as we will that see the same conclusions were drawn regarding the utility of the shift operator when using the simple and adjusted models, and the suggested correlated error terms have implications of their own.

Modified trait-shift models. Parallel to the simple FSM models, the trait-shift models generally yielded significantly better fit than their corresponding base FSM model (see Table 3 for fit statistics), and the TS-12 model showed an increase in fit statistics over the base model, suggesting a local minimum. The greatest improvement in model fit among the modified trait-shift models over the modified base trait-shift FSM model was in the TS-13 and TS-23 models, that included active shift operators for attention to feelings and habitual moods, and clarity of feelings and habitual mood, respectively.

Modified method-shift models. The modified method-shift model analyses also yielded parallel results to the simple models (see Table 3 for fit statistics). All of the modified method-shift models yielded significantly better model fit over the modified base method-shift FSM model. The greatest improvement in model fit among the method-shift models over the modified base method-shift FSM model was seen in the MS-2, MS-12, MS-13, and MS-23 models, which included active shift operators for friend-report, self-report and friend-report, self-report and acquaintance-report, and friend-report and acquaintance-report, respectively.

The shifted models are directly related to recent work by Maydeau – Olivares and Coffman (2006) regarding random intercept factor models that suggests what is essentially the same as allowing for freely estimated variances on the shift operator, although Maydeau – Olivares and Coffman (2006) work with a covariance-based factor model. This possibility was explored briefly as a potential improvement over the defined shifted models. There was some improvement in model fit when estimating a free shift variance in the non-correlated errors models, however the improvement in fit was not as much as the improvement cause by correlating the error variables. Furthermore, there was no improvement in model fit in the modified (correlated errors) models, and in some cases the inclusion of the freely estimated shift variance caused improper parameter estimates (i.e., negative variances on a latent variable).

Of all of the FSM models considered (simple and modified, trait-shift and method-shift), the best model fit as evidenced by the lowest relative chi-squared fit statistics, BICs, RMSEAs, and the highest TLIs, was seen in the method-shift models, with emphasis on those mentioned specifically above. If we can believe that the FSM models are empirically identified, then the fit statistics and parameter estimates would be more trustworthy than those from the covariance-based CT-CM model.

Factor scores. Factor scores were also computed in each of the models and the distributions of the factor scores were examined for indications of participants with extreme values that might exert undue influence on the estimation of the method and trait factors. The dataset used in the current study was relatively small, and as such, the effect of extreme values is a concern. Scatterplots of the factor scores from correlated latent variables suggested no bivariate distribution violations. Indeed, visually the plots appeared to be co-plots of two uniformly distributed variables, with no obvious overly influential observations.

Discussion

When working within a CT-CM framework, FSM models are easier to identify than the traditional covariance-based CT-CM model because it is based on the SSCP matrix. However, when employing an FSM model, scaling considerations such as measurement level assumptions are crucial. In many situations it would be reasonable to include scaling factors to ensure that the assumptions of the FSM model are met. This is indeed the case with the example dataset used in the current research.

As mentioned before, Eid et al. (2003; 2006) pointed out that the CT-C(M-1) model would fit best to data that have structurally distinct methods, and when the researcher is specifically interested in hypothesizing contrasts among methods. Results of the current study support the notion that the CT-C(M-1) model is appropriate for Eid et al.'s (2003) purposes and data: the RMSEA from the CT-C(M-1) model is lower than the RMSEAs for the FSM and FSM-Shift models in the present study.

In spite of the model fit of the CT-C(M-1) model, there are substantive advantages of the FSM model over the CT-C(M-1) model, and other proposed alternative MTMM models, in both the contrast and unified factor hypothesis cases. In the contrast hypothesis case, the CT-C(M-1) model poses questions of differences among methods, and thus a researcher employing the CT-C(M-1) method may conclude that one rater reports significantly different ratings from another. This statement may be important, but is not necessarily terribly informative as many researchers wish to know the direction of that difference. For example, in the case of three methods such as parent-report, child-report, and teacher-report, a substantive researcher would likely be concerned with whether teacher ratings are consistently lower than parent ratings, or if parent ratings are consistently lower than teacher ratings. The FSM models allow researchers to answer such questions, whereas the covariance-based CT-C(M-1) model does not.

Similarly, Eid et al. (2003) claims that the CT-C(M-1) model is identified and decomposes method and trait effects, and as such is preferable over alternative models. However, as psychologists, when evaluating different modeling approaches we must not only consider what is logically, mathematically, and empirically identified, but also what has applied substantive use and importance. The CT-C(M-1) model might be preferable over a CT-CU model in the contrast hypothesis case because it models distinct method effects when the CT-CU model does not. However, when the direction of the difference is important, as it often is in substantive work, the FSM models would likely be preferable over both the CT-C(M-1) and CT-CU models.

As Eid, Lischetzke, and Nussbeck (2006) noted, the CT-C(M-1) model is not appropriate when a researcher wishes to model a unified factor instead of making method contrast hypotheses; the CT-CM and CT-CU models would be appropriate in that case. Yet we know that the CT-CM model is often unidentified and as such, if the FSM models are identified, then they would obviously be preferred over the CT-CM model. The CT-CU model, on the other hand, is an identified model, but it confounds method and error variance. Indeed, fit statistics for the CT-CU model in the present study suggested good model fit, in that it yielded a non-significant χ^2 goodness of fit statistic, a very small RMSEA, and showed better model fit than the FSM CT-CM models. However, despite these fit statistics, the CT-CU model is not conceptually desirable as it fails to separate method and error variance, and as such, estimated trait correlation estimates from the CT-CU model may be biased. Thus, we would argue that the CT-CM model is more conceptually desirable and advantageous over the CT-CU model, concordant with the claims made by Lance, Noble, & Scullen (2002), and that using an FSM CT-CM model may be one way to address the identification problems of the covariance-based CT-CM model. Finally, the advantage of the FSM models outlined previously, regarding the ability to consider the direction of halo effects also applies when considering unified factor hypotheses, and thus the FSM models would be preferred in this respect over both the CT-CU and covariance-based CT-CM models.

Recall the third assumption of the traditional CT-CM model: error variables are assumed to be independent. Modification indices from the present study indicated a need for correlations among the errors associated indicators of some trait-method units. Thus, either the defined factor model is not true, and there is, for example, a multiplicative relationship among the trait and method factors, or the factor model is true but there is a source of systematic variance that is not being adequately modeled in the CT-CM model. Some researchers (e.g., Eid et al., 2003; Marsh & Hocevar, 1988) have argued for trait-specific method factors in place of general method factors, so as to allow for non-homogeneous method effects across traits. As such, additional studies should examine the behavior of FSM CT-CM models that include trait-specific method effects, for it may be that these trait-specific method factors are what is not being adequately modeled. As Marsh and Hocevar (1988) and Eid et al. (2003) defined these models in the context of a second-order factor model, such future research should also look at FSM CT-CM models as second-order factor models.

We have established that FSM CT-CM models allow for examination of the direction of method bias. However, one possible limitation of this is that the FSM CT-CM models that have been specified do not consider the possibility of the bias being an individual difference. Following from the previous example, if the FSM CT-CM model shows that teachers show significantly different ratings than parents, and examination of the means shows a positive bias such that teachers rate children consistently higher on IQ than parents; there is no reason to assume that this is not due to individual differences. The FSM CT-CM models specified herein are structural equation models, and as such they can be easily adapted to accommodate a latent mixture approach, such as a latent growth mixture model or latent class model, in order to take into account such individual variation.

Similarly, it is worth noting that the MTMM models considered in the present study do not exhaust the universe of possible multitrait-multimethod matrices which might be considered under the proposed FSM models. Consider Cattell's (1988) data box: there are ten dimensions along which experiments can be designed (e.g., the person/organism, the state of the organism, the variant of the stimulus, the style of the response; see Cattell, 1988 for more information), and corresponding slices of the data box are used as the score matrix for analyses of covariation. Indeed, the dimensions of the data box form analysis facets that can be unfolded to allow specification of models which compare successive facets of the BDRM dimensions as traits or methods of interest. For example, it would be possible, using these techniques, to investigate the possibility of trait-level change in individuals who are assessed on multiple occasions (modeled as a method factor) as a function of the lifespan period of the individual (modeled as an inter-individual difference). This would not only be an elegant extension of the mathematical MTMM models to novel research contexts, but would also address some of the conceptual limitations of traditional MTMM studies that use single measurement occasions, and as such, confound intra- and inter-individual variation sources.

The present research could not, and did not attempt to, address all criticisms of the traditional CT-CM model. As such, some of the criticisms should be considered in future work. For example, the current study does not address the issue raised by Eid et al. (2003) that the traditionally defined CT-CM model assumes zero correlations between trait and method factors, and it is not entirely clear when that is a reasonable constraint. This is another avenue of possible future research; to consider the behavior of FSM models when correlations are allowed across trait and method factors. It should also be noted that the proposed FSM models suffer the same limitation that all CFA models do, in that they would not be appropriate when observed scores are the result of a multiplicative combination of trait and method factors. In such a case, multiplicative models such as the DPA model should be considered instead.

The comparisons made in the present study across the covariance-based CT-CM, CT-CU, CT-C(M-1), and FSM CT-CM models are in some cases informal or substantive in nature, and are based on a flawed dataset that is not necessarily appropriate for all models. As such, a simulation study comparing the performance of all models with a known dataset would be prudent. Only after such controlled comparison could we say with certainty which models yield accurate parameter estimates and are most frequently identified.

Finally, the implications of the performance of the so-called "shift operators" must also be addressed. It has been demonstrated that including factor means in MTMM models is advantageous, however it has also been demonstrated that measurement level adjustments are necessary for optimal model performance. The shifted models also have conceptual implications. Specifically, the superior performance of the method-shifted models suggests that the scales assigned to the methods are indeed arbitrary. The application of the trait shifts implies an assumption that there is a common shift value across all individuals, and that the existing scale was interval level. Indeed, since allowing a free variance on the shift operator, essentially allowing for a random intercept, did not yield significantly better model fit over the models with a shift operator with a zero variance, there did not appear to be a need for differential shift values among individuals.

The increase in model fit seen with the inclusion of scaling factors in these models have implications beyond MTMM models. Indeed, this suggests that it may be necessary to examine the behavior of such scaling factors in other analyses that assume ratio level data. Researchers in psychology frequently assume a level of measurement (i.e., interval, ratio) out of convenience without true consideration for the actual measurement level of the data. Furthermore, it can be argued that many variables examined in the psychological sciences are not ratio level data, and yet researchers continue to employ analysis techniques that assume such. The results of the current study suggest that such blind assumptions may cause problems for the researcher, as it may be detrimental to model fit. As such, researchers should be aware of the measurement level assumptions of their analyses, and make the appropriate adjustments.

Finally, the present research is limited in that, for the sake of parsimony, only models with up to two active shift operators were explored. Additionally, the active shifts were always within the same set of factors; that is, if two shift operators were active, they referenced either trait or method indicators exclusively. There are many additional FSM-Shift models that could potentially be explored, including models with a higher number of active shift operators (i.e., more than 2 simultaneously active shift operators) or models with active shift operators over a combination of method and trait factors (e.g., an active shift on trait 1 and an active shift on method 2). As such, future research will examine the performance of shift operators in, and consider conditions for identification under, such models.

In conclusion, the proposed FSM CT-CM models are potentially a viable alternative approach to MTMM analyses, but require further study. Such models may be restrictive in the sense that they require measurements be made on, or adapted to fit, a ratio-level of measurement. However, FSM CT-CM models have the conceptual advantages of providing the researcher with information concerning the directionality of method effects, and retaining the desirable structure of the traditional CT-CM model for single assessment MTMM models. Finally, FSM CT-CM models have the further advantage that they can be extended to accommodate research situations such as behavior genetic models or longitudinal assessments where differential growth and change are of central importance.

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Table 1. *Shift loading constraints for specified models*

Model	*Trait Shift 1 Loading*	*Trait Shift 2 Loading*	*Trait Shift 3 Loading*	*Method Shift 1 Loading*	*Method Shift 2 Loading*	*Method Shift 3 Loading*
Base FSM	0	0	0	0	0	0
TS-1	1	0	0	0	0	0
TS-2	0	1	0	0	0	0
TS-3	0	0	1	0	0	0
TS-12	1	1	0	0	0	0
TS-13	1	0	1	0	0	0
TS-23	0	1	1	0	0	0
MS-1	0	0	0	1	0	0
MS-2	0	0	0	0	1	0
MS-3	0	0	0	0	0	1
MS-12	0	0	0	1	1	0
MS-13	0	0	0	1	0	1
MS-23	0	0	0	0	1	1

Table 2. *Fit Statistics for simple models.*

Model	χ^2	RMSEA (90% CI)	CFI	TLI	BIC
CT-CM (CFA)	1049.64	.04 (.03, .05)	.77	.73	9486.85
CT-CM (FSM)	1186.56	.12 (.11, .13)	.74	.71	9512.19
Trait Shift Models					
TS-1	1118.09	.11 (.11, .12)	.76	.73	9449.03
TS-2	1159.91	.12 (.11, .12)	.75	.71	9490.85
TS-3	1129.63	.11 (.11, .12)	.76	.72	9460.58
TS-12	1309.29	.13 (.12, .13)	.70	.66	9645.55
TS-13	1091.47	.11 (.11, .12)	.77	.74	9427.72
TS-23	1100.68	.11 (.11, .12)	.76	.73	9436.93
Method Shift Models					
MS-1	1173.25	.117 (.11, .124)	.74	.71	9504.47
MS-2	1104.76	.112 (.105, .119)	.76	.73	9435.70
MS-3	1122.85	.113 (.106, .121)	.76	.73	9453.79
MS-12	1104.17	.112 (.105, .12)	.76	.73	9440.43
MS-13	1115.26	.113 (.106, .12)	.76	.73	9451.52
MS-23	1104.65	.112 (.105, .12)	.76	.73	9440.91

Note. All Chi-Square statistics were significant.

Table 3. *Model Fit Statistics*

Model	χ^2	RMSEA	CFA	TLI	BIC
CT-CM (CFA) *Simple*	1049.64***	.04 (.03, .05)	.77	.73	9486.85
CT-CM (CFA) *Modified*	366.75*	.04 (.03, .05)	.98	.97	8851.77
CT-CU (CFA)	227.39	.02 (.00, .04)	1.00	.99	9079.00
CT-CU (FSM)	272.31	.03 (.00, .04)	.99	.98	8996.43
Trait Shift Models					
FSM	542.13*	.06 (.05, .07)	.93	.92	8915.58
TS-1	436.61*	.05 (.04, .06)	.96	.95	8815.37
TS-2	492.77*	.06 (.05, .07)	.94	.93	8871.54
TS-3	460.76*	.05 (.04, .06)	.95	.95	8839.53
TS-12	452.24*	.05 (.04, .06)	.96	.95	8836.31
TS-13	418.65*	.04 (.03, .05)	.97	.96	8802.72
TS-23	428.55*	.05 (.04, .06)	.96	.96	8812.62
Method Shift Models					
FSM	539.58*	.06 (.05, .07)	.93	.92	8913.03
MS-1	493.86*	.06 (.05, .07)	.94	.93	8872.62
MS-2	415.56*	.04 (.03, .05)	.97	.96	8794.32
MS-3	461.38*	.05 (.04, .06)	.95	.95	8840.14
MS-12	400.28*	.04 (.03, .05)	.97	.97	8784.35
MS-13	418.53*	.04 (.03, .05)	.97	.96	8802.61
MS-23	400.48*	.04 (.03, .05)	.97	.97	8784.56

Figure 1. Single-indicator CT-CM model.

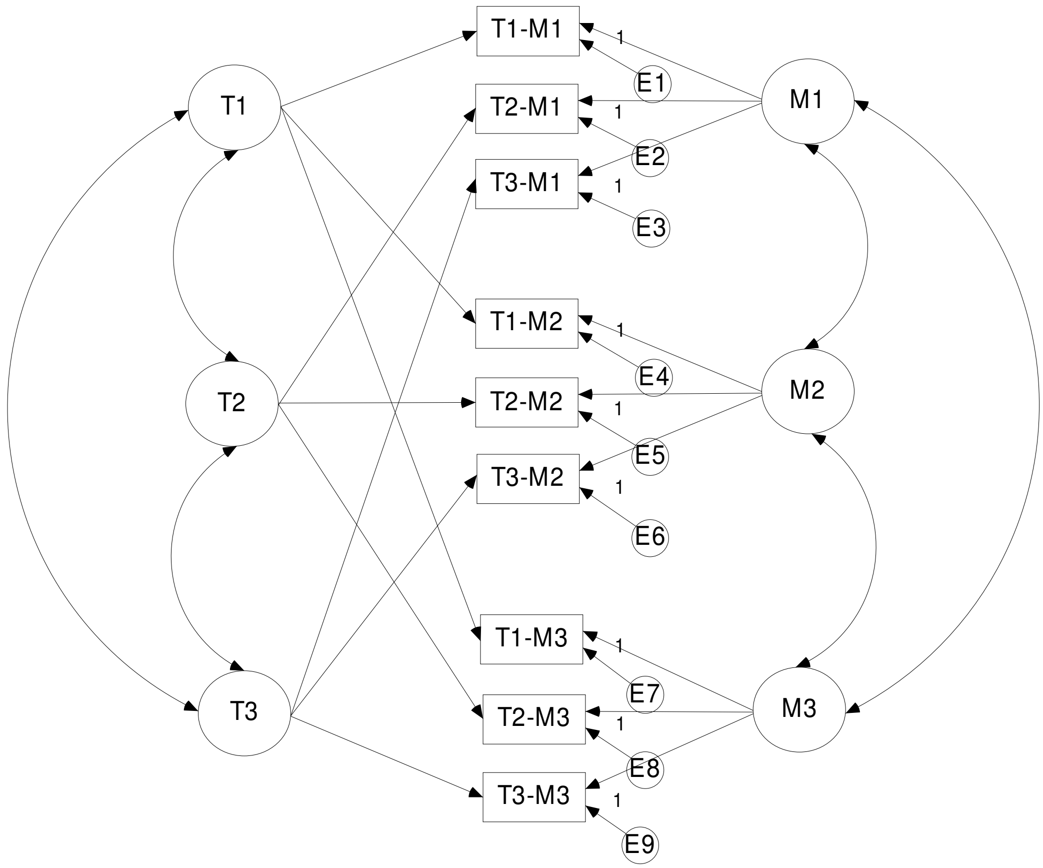

Figure 2. Single-indicator CT-CU model.

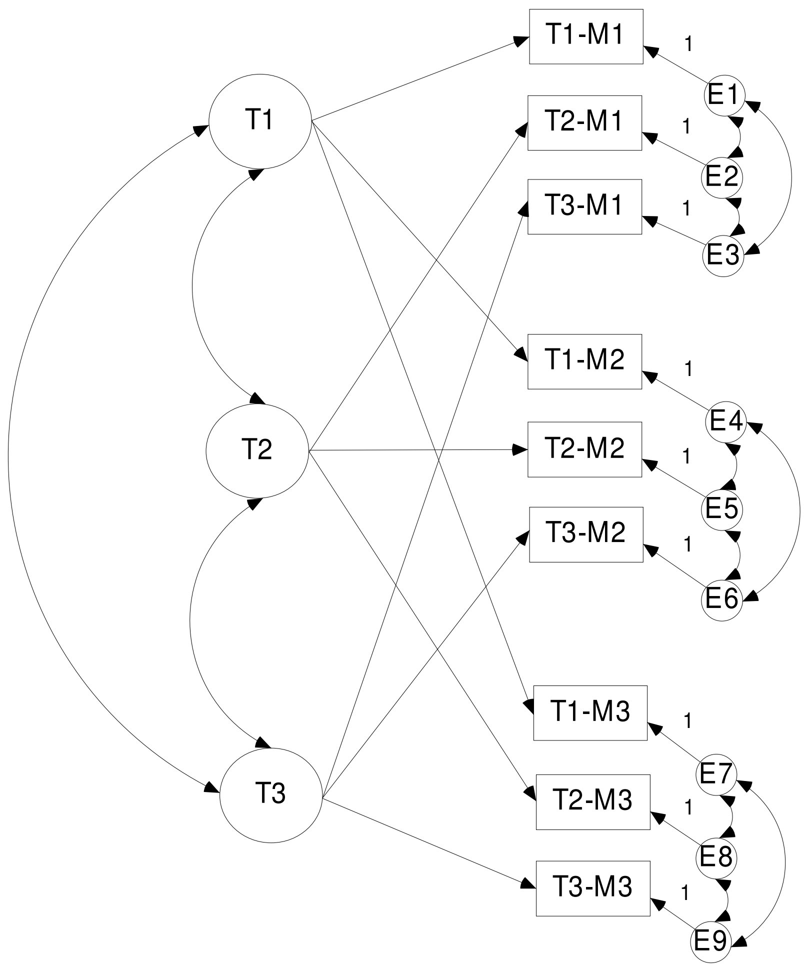

Figure 3. Single-indicator CT-C(M-1) model.

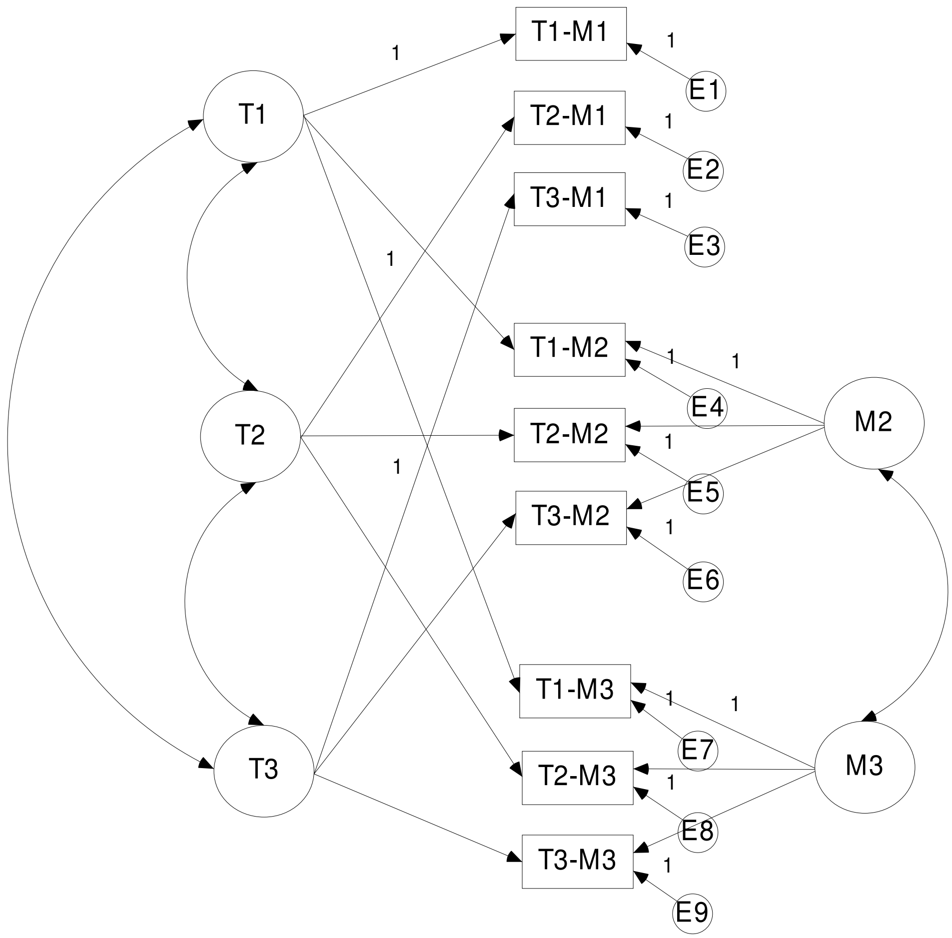

Figure 4. Multiple indicator CT-C(M-1) model.

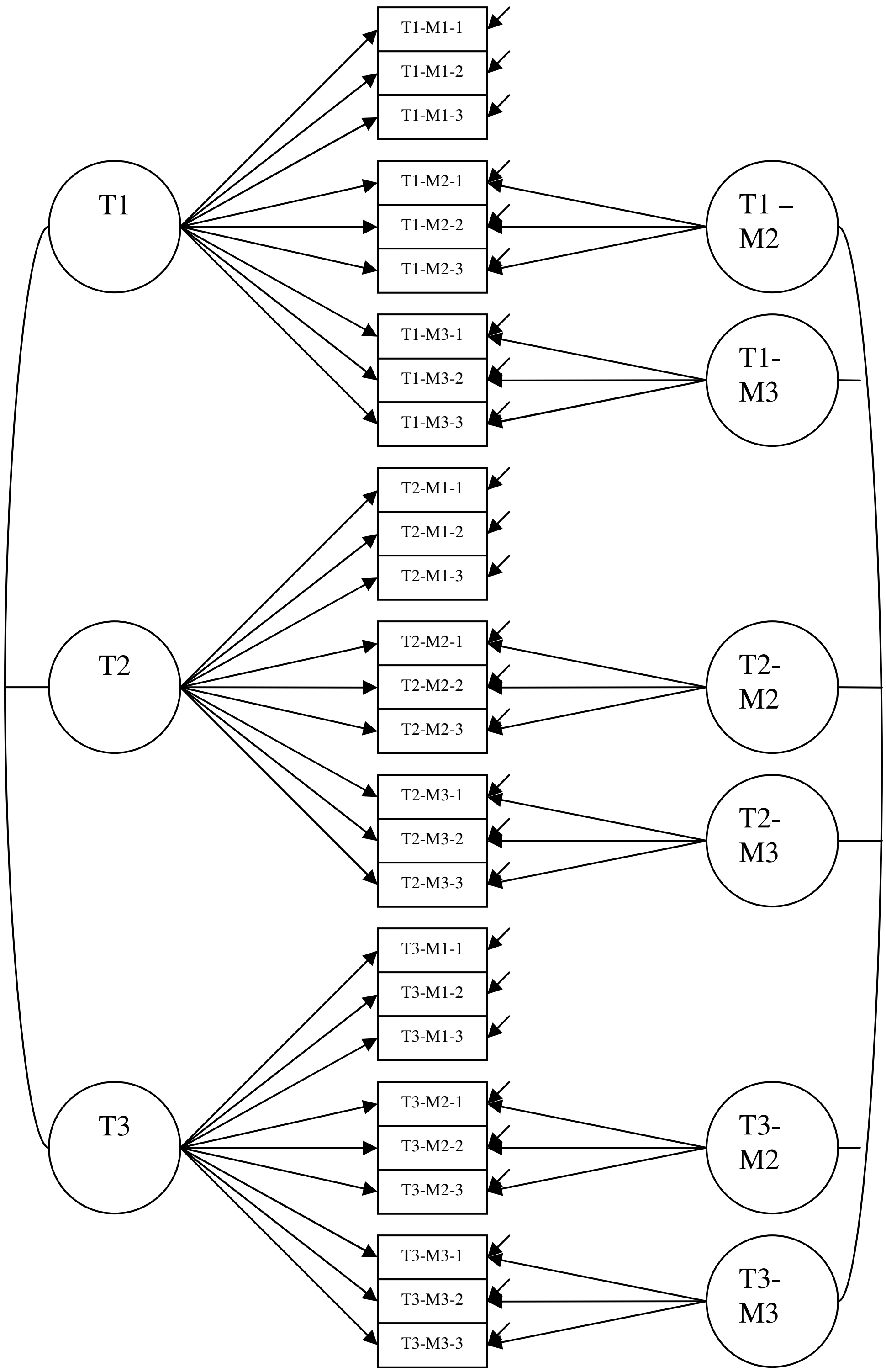

Figure 5. Single-indicator FSM CT-CM model.

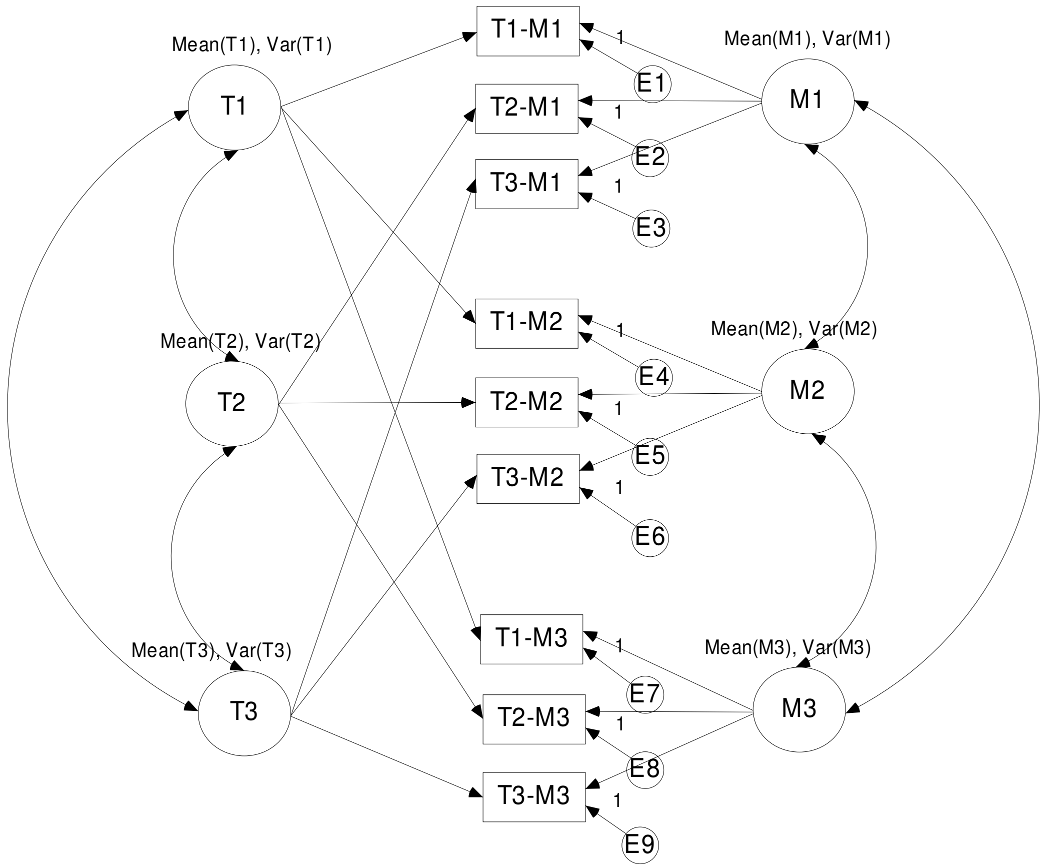

Figure 6. Single-indicator FSM CT-CM with shift models