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ABSTRACT

The multitrait-multimethod (MTMM) paradigm is used widely to assess construct validity, but D. A. Kenny and D. A. Kashy (1992) lament that even after 30 years we still do not know how to analyze MTMM data. The Composite Direct Product (CDP) model has recently attracted considerable attention. Its strengths and weaknesses are evaluated, and a stronger basis for testing the model is demonstrated. The CDP model is mathematically elegant and extremely parsimonious, but this parsimony is at the expense of very restrictive assumptions that undermine the formative evaluation of MTMM data. Furthermore, the CDP model provides an excellent fit to simulated data in which these assumptions are seriously violated, demonstrating that fit is not a sufficient test of these assumptions. Typically the CDP model is based on single indicators of each trait/method combination, but a stronger multiple-indicator version of the CDP model is demonstrated using new options available in the LISREL 8 computer program. Five tables present data illustrating the CDP model, using data from a study by B. M. Bryne and R. J. Shavelson (1986) on the relations among three academic self-concept traits. An appendix presents a LISREL setup for fitting the multiple indicator CDP model. (SLD)

The Composite Direct Product Model: Strengths, Limitations, and New Approaches

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Running Head: The Composite Direct Product Model

Abstract

The MTMM paradigm is used widely to assess construct validity, but Kenny and Kashy (1992) lamented that even after 30 years we still do not know how to analyze MTMM data. The Composite Direct Product (CDP) model has recently attracted considerable attention. Here we evaluate its strengths and limitations, and demonstrate a stronger basis for testing the model. The CDP model is mathematically elegant and extremely parsimonious, but this parsimony is at the expense of very restrictive assumptions that undermine the formative evaluation of MTMM data. Furthermore, the CDP model provides an excellent fit to simulated data in which these assumptions are seriously violated, demonstrating that fit is not a sufficient test of these assumptions. Typically the CDP model is based on single indicators of each trait/method combination, but we demonstrate a stronger multiple-indicator version of the CDP model using new options available in LISREL 8.

Campbell and Fiske (1959) argued that construct validation requires both convergent and discriminant validity. They proposed the multitrait-multimethod (MTMM) design which is used widely to assess construct validity. In this design measures of two or more traits (e.g., school, reading, and mathematics self-concepts) are each measured with two or more methods (e.g., three different self-concept instruments). Traits are attributes such as abilities, attitudes, behaviors or personality characteristics, whereas methods refer broadly to multiple test forms, methods of assessment, raters, or occasions. Construct validity is supported when convergent validity (e.g., the extent of agreement among math self-concept scales from three instruments) and discriminant validity (e.g., the extent to which mathematics and verbal self-concepts can be distinguished) are high, and method effects (e.g., idiosyncratic variance associated with a method of measurement) are negligible.

Although the original Campbell-Fiske guidelines are still used widely to evaluate MTMM data, important problems with the guidelines are well known (e.g., Althauser & Heberlein, 1970; Alwin, 1974; Campbell & O'Connell, 1967; Marsh & Hocevar, 1983; Marsh, 1988; Schmitt & Stults, 1986; Sullivan & Feldman, 1979). Campbell and Fiske (1959) were aware of most of these limitations, specifically stating that their guidelines should be viewed as "common-sense desideratum" (p. 83). Their intent was to provide a systematic, formative evaluation of MTMM data at the level of the individual trait-method unit, qualified by the recognized limitations of their approach, not to provide summative, global summaries of convergent validity, discriminant validity and method effects. We recommend that these guidelines should be used as an initial formative evaluation of all MTMM data even when more sophisticated latent variable approaches are applied and that this formative orientation in the MTMM paradigm must not be lost in the development of mathematically more sophisticated approaches to MTMM data. More generally, Campbell and Fiske had a heuristic intention to encourage researchers to consider the concepts of convergent validity, discriminant validity, and method effects; in this intention they were remarkably successful. Unfortuately, this formative, heuristic aspect that was the very essence of Campbell-Fiske approach seems to have been lost in the quest to develop ever more mathematically sophisticated approaches to MTMM data. Nevertheless, problems inherent in the application of the original Campbell-Fiske guidelines led to many alternative analytic approaches, including the composite direct product (CDP) model, and the new, multiple indicator CDP (MI-CDP) model that are demonstrated here.

Composite Direct Product Model

Most approaches to MTMM data implicitly assume that trait and method effects are additive, but Campbell and O'Connell (1982) suggested that the relation may be multiplicative. Both the additive and multiplicative models posit that correlations between traits measured with the same method will be higher than correlations between traits measured with different methods -- a method effect. If this method effect is additive, then the increase in correlation due to this method effect is expected to be of a similar size for large and small correlations. In a multiplicative model, however, the method effects are systematically larger for traits that are more highly correlated, systematically smaller for traits that are less correlated, and zero for traits that are uncorrelated (i.e., the method effect multiplied by zero is zero). Campbell and O'Connell (1967, 1982) offered two different interpretations of this multiplicative effect. The differential augmentation perspective is that observed correlations are a multiplicative function of the true correlation and a method bias.

According to this perspective, when true traits are uncorrelated there will be no bias (i.e., the method effect multiplied by zero is zero). In contrast, when traits are substantially correlated the correlation between the traits based on the same method will be biased so long as the method effect is nonzero. This portrayal of method effects differs from a purely additive model that implicitly assumes that the size of method effects does not vary according the size of true trait correlations.[1] The differential attenuation perspective suggests that the use of different methods will attenuate the true correlation between two traits. The extent of this attenuation, however, will vary according to the size of the correlation. If the true trait correlation is already zero, the correlation cannot be attenuated. In contrast, if the true trait correlation is substantial, then the empirical correlation can be attenuated substantially. According to this perspective, the correlation between two traits measured by the same method is a more accurate estimate of the true correlation, and this correlation is attenuated when different methods are used. This perspective is apparently consistent with the typical simplex pattern of relations observed in longitudinal data whereby the size of correlations between traits declines systematically as the time between the collection of the measures becomes longer.

Browne (1984), based in part on earlier work by Swain (1975), described the composite direct product (CDP) model and developed the MUTMUM statistical package (Browne, 1990). The CDP model posits a multiplicative rather than an additive combination of latent trait and method correlations. According to the CDP model there are two component correlation matrices in a MTMM matrix of correlations among latent variable scores (Pc), one containing correlations between latent traits (Pt) and the other containing correlations between latent methods (Pm). The covariance matrix of measured variables with dimension (mt x mt) can be expressed as:

(1) $S = D\ (Pm \times Pt\ + E)\ D$

where Pm is an (m x m) latent variable score correlation matrix of method components, Pt is a (t x t) latent variable score correlation matrix of trait components, D is a (mt x mt) positive definite, diagonal matrix of scale constraints reflecting latent variable score standard deviations, E is a positive definite diagonal matrix of uniquenesses reflecting the ratio of unique score variance to latent variable score variance, and x indicates the right direct (Kronecker) product of Pm and Pt. The values of D are typically of no interest and are designed primarily to absorb scaling changes similar to those involved in going from a covariance matrix to a correlation matrix. The E values, however, represent the ratios of unique score variances to latent variable score variances. Browne (1984, 1989) noted that these values can be interpreted as the correlation between an observed and latent variable score, an "index of communality," when transformed by the formula:

(2) $\text{communality}\ (Ti, Mr) = \ 1 / [1 + (E(Ti, Mr)]$

According to the CDP model, the correlation matrix Pc, appropriately corrected for attenuation, has the direct product structure:

(3) $Pc = Pm \times Pt$

where Pm has typical element r(Mr, Ms) and Pt has typical element being r(Ti, Tj). From this definition it follows that for latent variable scores

(4) $r(TiMr, TjMs) = r(Ti,Tj)\ r(Mr,Ms) = (Tij \times Mrs)$

It is useful to demonstrate the relations among Pm, Pt, and Pc for a MTMM design with 3 traits and 3 methods like that considered here (see Table 1). All elements of Pt are multiplied by each element of Pm. Thus, the correlation between traits 1 and 2 measured with method 1 is T21 multiplied by M11 = 1 so that the product is simply T21. Similarly, the correlation between trait 1 measured with methods 1 and 2 (i.e., a convergent validity) is M21 times T11 = 1 so that the convergent validity is simply M21. Thus, the coefficients in the off-diagonal of Pm reflect convergent validity. Note also, that the correlation between the same traits is assumed to be constant across all methods (i.e., r(T1M1,T2M1) = r(T1M2,T2M2) = r(T1M3,T2M3) = T21). Similarly, the correlation between two methods -- convergent validity -- is assumed to be the same across all traits (i.e., r(T1M1,T1M2) = r(T2M1,T2M2) = r(T3M1,T3M2) = M21). Because the 36 off-diagonal values in Pc are expressed in terms of only 6 estimated parameters (T21, T13, T23, M21, M31, M32), the CDP model is very parsimonious.

Insert Table 1 About Here

Relation to Campbell-Fiske Guidelines

Browne (1984, 1989; also see Bagozzi & Yi, 1990; Cudeck, 1988; Goffin & Jackson, 1992) notes that an important advantage of this model is that it provides parameter estimates that can be used to evaluate the original 4 Campbell-Fiske guidelines.

1. Convergent validities are substantial [r(TiMp, TiMs) >> 0]. In the CDP model r(TiMp, TiMq) = r(Ti,Ti) r(Mp,Mq) = r(Mp,Mq) >> 0 so that, each convergent validity is equal to one of the off-diagonal values in Pm. Hence, this criterion is satisfied whenever all the off-diagonal values in Pm are statistically significant, large, and positive.

2. Convergent validities are higher than heterotrait-heteromethod (HTHM) correlations [r(TiMp, TiMq) > r(TjMp, TiMq) and r(TiMp, TiMq) > r(TjMq, TiMp)]. In the CDP model r(TiMp, TiMq) > r(TiMp, TjMq) implies [r(TiMp, TjMq)] / [r(TiMp, TiMq)] = [r(Ti,Tj) r(Mp,Mq)] / [r(Mp, Mq)] = r(Ti, Tj) < 1.0. Hence, the latent variable trait correlations, the off-diagonal values in Pt, are the ratio of HTHM correlations to the convergent validities. Hence, this criterion is met whenever the off-diagonal values of Pt are less than 1.0. This will always be the case so long as the CDP solution is proper (i.e., Pt is positive definite), although stronger support may require the off-diagonals to be significantly or substantively less than 1.0.

3. Convergent validities are higher than heterotrait-monomethod (HTMM) correlations [r(TiMp, TiMq) > r (TiMp, TjMp) and r (TiMp, TiMq) > r (TiMq, TjMq)]. In the CDP model r(TiMp, TiMq) > r(TiMp, TjMp) implies that [r(TiMp, TjMp)] / [r(TiMp, TiMq)] = [r(Ti,Tj)] / [r(Mp, Mq)] < 1.0. According to the CDP model, the ratio of HTMM correlations to the convergent validities is the ratio of trait correlations to method correlations. Hence this criterion is met when all the off-diagonal values in Pt are less than all the off-diagonal values in Pm.

4. The pattern of correlations among different traits is similar for different methods [r (TiMp, TjMq) > r (TkMp, TlMq) implies r (TiMr, TjMs) > r (TkMr, TlMs)]. In the CDP model, this criterion is met whenever the CDP model fits the data because: r(TiMr, TjMs) / r(TkMr, TlMs) = r(Ti, Tj)/ r(Tk, Tl) has the same value for any Mr and Ms.

Method effects -- an typically undesirable source of bias -- are inferred when HTMM correlations substantially exceed HTHM correlations [r(TiMp, TjMp) > r (TiMp, TjMq)]. Campbell and Fiske (1959, p. 85) stated that "the presence of method variance is indicated by the difference in level of correlation between parallel values of the monomethod block and the heteromethod block, assuming comparable reliabilities among the tests" and Marsh (1988) operationalized this test of method effects. In the CDP model, r(TiMr, TjMr) > r(TiMr, TjMs) implies [r(TiMr, TjMs)] / [r(TiMr, TjMr)] = [r(Ti,Tj) r(Mr, Ms)] / [r(Ti,Tj) r(Mr,Mr)] = [r(Ti,Tj) r(Mr, Ms)]/ [r(Ti,Tj)] = r(Mr, Ms) < 1.0. Hence, according to the CDP model, there are method effects whenever the correlations in Pm are less than 1, and so there are always method effects when the CDP results in a proper solution. Also note that r(Mr, Ms) reflects both convergent validity (see guideline 1) and method effects. Whereas this observation appears paradoxical from the traditional "additive" perspective, it follows logically from the "multiplicative" perspective underlying the CDP model.

It is also possible to place further constraints on the CDP model that may be useful in particular situations. Thus, for example, it is possible to further restrict the structure of E, the diagonal matrix of uniquenesses, so that it also has a direct product structure (Browne, 1984, 1989; Wothke & Browne, 1990). This constraint has the effect of creating trait communality indices that have the same rank order for each method (e.g., if math self-concept is most reliable for one instrument it is most reliable for all instruments) and of producing method communality estimates that have the same rank order for each trait. This additional constraint is most reasonable for multiple battery data where, for example, the same instrument is administered to different individuals or the same individual on different occasions. Also, when the general CDP model does not result in proper solution, it is possible that the more restrictive solution with a direct product error structure will be proper. However, the direct product error structure is not central to interpretations of convergent validity, discriminant validity, and method effects that is the focus of the present investigation (for further information see Browne, 1984; 1989). If the covariance matrix rather than the correlation matrix is analyzed, it is possible to further restrict the structure of D, the diagonal matrix of scale constraints reflecting latent variable score standard deviations.

Proper Solutions, Parsimony, and Goodness of Fit.

An important advantage of the CDP model is that, based on the relatively limited number of published applications (e.g., Bagozzi, 1992; in press; Bagozzi & Yi, 1990; 1991; 1992; Bagozzi, Yi, & Phillips, 1991; Browne, 1984; 1989; 1990; Cudeck, 1988; Goffin & Jackson, 1992; Kumar & Dillon, 1992; Lastovicka, Murry & Joachimsthaler, 1990; Wothke & Browne, 1990) it typically results in proper a solutions that is very parsimonious and is able to fit MTMM data at least reasonably well. Marsh and Grayson (in press) further noted that because of its parsimony, it may be appropriate to fit the CDP model in MTMM designs in which the more widely used confirmatory factor analysis (CFA) approach is not typically recommended (e.g., studies with small Ns, only two traits, or only two methods). Also, Fiske and Campbell (1992) have indicated that a number of different researchers are now optimistic about the CDP model.

Whereas a general discussion of goodness of fit and related issues is beyond the scope of this article (see, Bentler, 1990; Cudeck & Henly, 1991; Marsh, Balla & McDonald, 1988; McDonald & Marsh, 1990), there are some specific issues that are particularly important for the evaluation of the CDP model. Because the CDP model is so parsimonious relative to most latent-trait MTMM models, the comparison of goodness of fit with other approaches will vary substantially depending on particular index that is used. Thus, for example, indices that control for model parsimony (e.g., the parsimony indices described by Mulaik, et. al, 1988 or the Tucker-Lewis Index as noted by McDonald & Marsh, 1990) or for capitalizing on chance (e.g., the single-sample cross-validation index described by Browne & Cudeck, 1989) are more likely to favor more parsimonious models like the CDP than indices like the X^2 value or the relative noncentrality index (RNI; McDonald & Marsh, 1990) that do not control for the these characteristics. Apparently, there is also some confusion in the literature as to what constitutes a "proper" CDP solution. We interpret the CDP solution to be proper when Pc, Pt, D, and E are all strictly positive definite. In a recent comparison of the CDP model with other latent-variable approaches to MTMM data, however, Goffin and Jackson (1992) claimed several solutions to be "proper" even though the Pt or E were not positive definite.

Goffin and Jackson (1992) fit the CDP model with Browne's MUTMUM (1990) statistical package that is specifically designed for this purpose. It is much easier to fit the CDP model with MUTMUM than with LISREL 7 (e.g., Wothke & Browne, 1990), and MUTMUM offers considerable advantages (e.g., appropriate standard errors and automatic computation of reliability estimates). Also, MUTMUM automatically imposes inequality constraints on parameter estimates in Pc, Pt, E and D that "result in maximum likelihood estimates in some situations where the likelihood function would otherwise be unbounded" (Browne, 1990, p. 4). However, these inequality constraints are not sufficient to ensure that Pt and Pm are positive definite (Browne, 1990, p. 4), and MUTMUM does not report whether the Pt and Pm are positive definite. Thus, for example, data considered by Goffin and Jackson resulted in a Pt matrix that was not positive definite even though none of the correlations were greater than 1.0, and they mistakenly claimed that this solution was proper. Hence, MUTMUM users need to evaluate the positive definiteness of Pt and Pm.

MUTMUM also restricts negative variance estimates to be non-negative. Typically this results in the offending parameter taking on a zero value that is on the boundary of the constrained parameter space and in a slight decrement in goodness of fit reflecting this implicit inequality constraint. Thus, for example, when values of the E matrix are zero, the corresponding communality estimate is 1.0, and this is referred to as a "boundary condition" in the MUTMUM output. Joreskog and Sorbom (1989) emphatically stated that "it should be emphasized that constraining error variances to be non-negative does not really solve the problem. Zero estimates of error variances are as unacceptable as are negative estimates" (p. 215). In the context of MTMM data, Marsh (1989) argued that whereas such reparameterizations may be useful in some situations, solutions with a zero variance estimate are still improper and should be treated with the same caution as if the parameter estimate were negative. Hence, we disagree with the claim by Goffin and Jackson that their solutions are "proper" even though they contain boundary conditions in which variance estimates that would otherwise be negative are constrained to be zero.

Demonstration of the CDP Model For the Byrne Data.

Byrne and Shavelson (1986; also see Marsh, 1988; 1989) examined the relations among three academic self-concept traits (Math, Verbal, and General School) measured by three different instruments (see Table 2). The 9 scores representing all combinations of the 3 traits and 3 methods were based on multi-item scales and the three instruments had strong psychometric properties. Consistent with a priori predictions, they found that the Math and Verbal self-concepts were nearly uncorrelated with each other and were substantially correlated with School self-concept. Marsh (1989) noted that this "is an exemplary MTMM study because of the clear support for the Campbell-Fiske guidelines, the large sample size (817, after deleting persons with missing data), the good psychometric properties of the measures, and the a priori knowledge of the trait factor structure" (p. 348). Also, the predicted lack of correlation between Math and Verbal self-concept satisfies the Campbell and Fiske recommendation to include two traits "which are postulated to be independent of each other" (p. 104). There is good support for the Campbell-Fiske guidelines in that:

Insert Table 2 About Here

1. Convergent validities are substantial, varying between .54 and .87 (mean r=.70);

2. Convergent validities are higher than HTHM correlations (mean r=.31) in all 36 comparisons;

3. Convergent validities are higher than HTMM correlations (mean r=.35) for 33 of 36 comparisons. [All three failures involve M3 where correlations among the traits (mean r = .44) are higher than for M1 (.28) or M2 (.33), suggesting moderate method effects associated with at least M3].

4. The pattern of correlations among different traits is similar for different methods in that correlations between T2 (Reading self-concept) and T3 (Math self-concept) are consistently small (mean r=.06) whereas T1 (General Academic self-concept) is substantially correlated with both T2 (mean r=.42) and T3 (mean r=.45).

Results and Discussion of the CDP Model With the Byrne Data.

The CDP model resulted in what we interpreted to be an improper solution in that parameter estimates from the E diagonal matrix included one estimate of 0 -- a boundary condition (see Table 3). Hence, even though this model provided a good fit to the data (RNI = .966, X^2 (21, N=817)= 201), we chose to interpret this model cautiously. As a pragmatic alternative, we fit the CDP model in which the errors are posited to be structured as direct products (see Browne, 1984; Cudeck 1988). This resulted in a fully proper solution and a somewhat poorer fit to the data (RNI = .956, X^2 (25, N=817)= 262). For both solutions, the Pm correlations (Table 3) are consistently very large and consistently larger than the Pt correlations, whereas the Pt correlations are substantially smaller than 1. This implies clear support for all the Campbell-Fiske guidelines and strong support for the construct validity of these measures. The relative lack of correlation between T2 and T3 observed in the MTMM matrix and predicted a priori is evident in Pt. Similarly, the apparently stronger agreement between measures based on M1 and M2 is evident in Pm.

Insert Table 3 About Here

The CDP model offers a mathematically elegant and parsimonious model of MTMM data. Subject to the continued demonstration of its success, we recommend that the CDP model should be used in MTMM studies. We do, however, have some reservations. In particular, its parsimony is achieved at the expense of implicit assumptions that we find worrisome.

1. In the CDP model, the convergent validities for all the different traits are necessarily equal (i.e., r(TiM1, TiM2) = r(M1, M2) for all values of i). In the Byrne data, however, the convergent validities are consistently larger for T3 (mathematics self-concept) than T1 or T2. In many MTMM studies this restriction would be unreasonable. Furthermore, imposing these constraints may undermine the formative value of the MTMM design, since a major focus of many studies is to compare convergent validities for different traits.

2. In the CDP model, the size of method effects is necessarily the same for different traits (i.e., r(TiMr,TjMs)/r(TiMr,TjMr) = r(Ti,Tj) x r(Mr,Ms)/ r(Ti,Tj) = r (Mr,Ms) for all values of i and j). In the Byrne data, however, there appear to be stronger method effects associated with M3 than with M1 or M2. Again, this restriction would be unreasonable in many MTMM studies and may detract from the formative value of the procedure. The focus of many MTMM studies is to compare the extent of method effects associated with different methods of measurement.

3. In the CDP model, the size of correlations among traits is necessarily the same for all methods (i.e., r(TiMr,TjMr) = r(Ti,Tj) for all values of r). In the Byrne data, however, correlations among traits are systematically lower for M1 and systematically higher for M3. It is also possible that Ti and Tj are the most highly correlated traits for M1, but are the least highly correlated for M2, but the CDP model does not allow for this possibility. Again, this restriction would be unreasonable in many MTMM studies.

In the CDP model, Pt correlations typically reflect the pattern of correlations among traits in the MTMM matrix, but only if this pattern is consistent across methods. Pm correlations typically reflect the extent of agreement between different methods, but only if the agreement is consistent across all traits. Whereas the overall fit of the model provides an indirect test of these assumptions, overall fit indices do not provide information that is particularly useful in evaluating the specific assumptions. Furthermore, there is an implicit assumption that these assumptions are necessarily satisfied when the overall fit is good, but in the next section we question the validity of this assumption. Common sense suggests that these assumptions will typically be false so that a more detailed evaluation of the implications of violating these assumptions is needed in actual applications of the CDP model. Finally, because of these implicit invariance constraints, the CDP model does not provide a very useful formative evaluation of specific trait-method units which is, perhaps, the primary purpose of the MTMM design.

Results and Discussion of the CDP Model With Artificial Data.

In the CDP model, researchers must rely heavily on the overall goodness of the model to evaluate the reasonableness of a host of very restrictive assumptions. It is clear that in at least some -- perhaps most -- MTMM studies these assumptions are not reasonable. Yet, our informal reading of published applications of the CDP model (e.g., Bagozzi, 1992; in press; Bagozzi & Yi, 1990; 1991; 1992; Bagozzi, Yi, & Phillips, 1991; Browne, 1984; 1989; 1990; Cudeck, 1988; Goffin & Jackson, 1992; Kumar & Dillon, 1992; Lastovicka, Murry & Joachimsthaler, 1990; Wothke & Browne, 1990) has not revealed any situations in which the CDP model resulted in a particularly poor fit to the data. This may call into question the falsifiability of the CDP model or, alternatively, may merely reflect biases in the data used to illustrate the CDP model.

In order to illustrate our concerns more clearly, we constructed an artificial MTMM matrix that seriously violates CDP assumptions but is easily evaluated with the Campbell and Fiske (1959) guidelines. We generated the data from a CFA population model (see Table 4) in which there were small method effects [samll method factor loadings], small to moderate trait correlations, substantial trait variance for T1 and T2 [large trait factor loadings], and only weak trait variance for T3. Inspection of the resulting (simulated) MTMM matrix (Table 4), consistent with the design of the data, indicates good support for the convergent and discriminant validity of T1 and T2, but little or no support for either the convergent or discriminant validity of T3. This MTMM matrix should be particularly troublesome for the CDP model, because the CDP model requires that all convergent validities associated with a given method are equal whereas the convergent validity of T3 is weak and much weaker than that of T2 and T3. Based on a hypothetical N=500, however, the CDP model provided a remarkably good fit to this artificial data (RNI = 1.011, X^2 (21) = 11.15). Parameter estimates for the CDP model (Table 4) reflect the pattern of trait correlations with reasonable accuracy but not the large differences in convergent validities for the three traits. Furthermore, the Pm correlations -- the convergent validities -- are all greater than .9. These appear to be grossly inflated in relation to the actual population model used to generate the data -- particularly for T3 that had very weak convergent validity.

Insert Table 4 About Here

These results provide one example in which the CDP model provides an apparently excellent fit to the data even though assumptions underlying the CDP model were seriously violated. A comparison of the parameter estimates with the population model, however, revealed that the CDP model seriously misrepresented the MTMM data even though it provided such a good fit to the data. This example, even more than the results of the Byrne data, demonstrates that it is important to critically evaluate parameter estimates based on the CDP solution. Overall goodness of fit tests apparently do not always provide an adequate basis for evaluating the assumptions underlying the CDP model and can be very misleading. This can be very dangerous.

Multiple Indicator Composite Direct Product Models

The heuristic value of the original Campbell-Fiske guidelines is widely recognized, but their application is criticized in particular for issues related to their reliance on correlations among measured variables instead of latent constructs. Ironically, latent variable models -- including the CDP model emphasized here -- typically begin with single indicators of each trait/method combination even though each trait/method combination is often based on multiple indicators (e.g., the individual items in the self-concept scales used for the Byrne data). However, incorporating multiple indicators of each trait/method combination into the latent variable approaches has important advantages (also see Marsh, in press; Marsh & Hocevar, 1988).

Insert Table 5 About Here

1. Implicit in all latent-variable MTMM models based on relations among scale scores is the assumption that the researcher's a priori structure (i.e., the one implied by how scores are combined) accurately reflects the true factor structure. In particular, it is implicitly assumed that the multiple indicators can be represented by a single common factor. Unless there is empirical support for this a priori factor structure, however, the interpretation of the MTMM results is problematic. If multiple indicators designed to measure the same scale actually reflect different traits, or multiple indicators from different scales actually reflect the same trait, then scale scores cannot be interpreted in terms of trait and method effects. Indeed, it is ironic that latent-variable approaches to MTMM analyses suffer from this problem even when multiple indicators of each scale are collected. With the multiple indicator approach demonstrated here, the evaluation of the typical first-order model (e.g., Table 5) provides an explicit test of this a priori model that is implicit and untestable in latent variable approaches based on scale scores. An evaluation of the fit of the first-order model provides a test of the implicit assumption that the multiple indicators associated with a particular trait/method combination reflect a single, well-defined, common factor. If this first-order model is unable to fit the data reasonably well, then it may be necessary to include additional parameters (e.g., correlated uniqueness -- particularly for multiple battery data) that may alter the pattern of relations among the latent constructs. If no theoretically defensible first-order model is able to fit the data, further inferences about trait and method effects are dubious no matter what approach is used. A major problem in MTMM studies is the use of instruments with weak psychometric properties. Whereas the multiple indicator approach advocated here may not solve this problem, its application will more clearly identify the source of the problem. This initial step contributes substantially to the formative evaluation of MTMM data at the level of each trait/method combination which is a primary purpose the MTMM design.

2. In the first-order model using the multiple indicator approach, the MTMM matrix consists of correlations among latent constructs that are appropriately corrected for measurement error. These latent constructs can be directly evaluated with the traditional Campbell-Fiske guidelines and many criticisms of the guidelines are met by this multiple-indicator procedure. Whereas single-indicator latent variable approaches are designed to provide information more or less relevant to the Campbell-Fiske guidelines, the guidelines themselves are applied directly in the multiple indicator approach advocated here. It is clearly better to apply the Campbell and Fiske (1959) guidelines to a MTMM matrix of correlations among latent variables than to a MTMM matrix of correlations among observed variables.

3. In latent variable models that begin with scale scores, reliability estimates are based on communality estimates. A scale is inferred to lack reliability when it is not substantially correlated with at least some of the other scales in the MTMM design. This approach, however, confounds a lack of correlation due to unreliability in the scale scores and a lack of correlation among the latent constructs. In the multiple indicator approach, however, unreliability in the scales is estimated separately from correlations among the latent constructs. The ability to separate these two sources of information is particularly important in the formative evaluation of the different measures and their construct validity.

4. Particularly in multiple battery studies in which the multiple methods are multiple occasions or multiple raters responding to the same materials, correlated specific variances are likely to positively bias estimates of convergent validities and inferred trait effects. When the multiple methods are different occasions, the problem of autocorrelated specific variances is well known. Joreskog (1979), for example, noted that if the same measurements are used on

multiple occasions, the corresponding error variables will tend to correlate, and in order to get accurate estimates of relations among the constructs, correlations among errors must be included in the model. The problem is also relevant, however, when the same indicators are given to multiple raters (e.g., when employees evaluate their own work performance, are evaluated by peers, and are evaluated by superiors using the same multitrait rating instrument). In the typical latent variable approach that begins with scale scores, however, this potentially serious source of bias cannot be tested and there is no way to control the bias if it does exist. Using the multiple indicator approach, however, researchers are able to test for the existence of such correlated errors and their inclusion in the model controls for this source of bias in inferences about trait and method effects.

5. The multiple indicator approach actually results in a MTMM matrix of correlations among latent constructs and so it can be extended to incorporate any latent variable model that is based on MTMM correlations. Furthermore, all latent variable models based on the multiple indicator approach are nested under the corresponding first-order model so that the first-order model provides the optimal fit for the more parsimonious latent variable models. In this sense, the latent variable model is merely trying to explain covariation among latent constructs in the first-order model with a more parsimonious structure. Thus, using the multiple indicator approach, the first-order model provides an important basis for evaluating latent variables models. If the goodness of fit of the latent MTMM model is substantially poorer than that of the first-order model or if interpretations based on the latent MTMM model differ substantially from those based on the first-order model, then the latent variable model should be rejected in favor of the first-order model. Marsh (in press; Marsh & Hocevar, 1988) applied this multiple indicator approach to CFA models from the taxonomies proposed by Widaman (1985) and Marsh (1989).

Marsh (in press) also noted that the multiple indicator approach could be generalized to other latent variable approaches such as the CDP model described here. Because there are apparently no published demonstrations of this proposal, we illustrate the multiple indicator CDP (MI-CDP) model with the Byrne data considered earlier. Whereas this model can be fit with several different statistical packages, it apparently cannot be fit with the MUTMUM package that is specifically designed for the single-indicator approach to the CDP model. However, the type of constraints required to fit the CDP model (i.e., requiring one parameter to be the product of two other parameter estimates) is greatly facilitated by new options available in LISREL 8 (the LISREL 8 set-up is summarized in Appendix 1). Hence, a secondary purpose of this demonstration is to illustrate this new option in LISREL.

Results of the Multiple Indicator Approach

For purposes of this analysis, three-item parcels were constructed to reflect each of 9 trait/method combinations in the Byrne data -- a total of 27 measured variables. Thus, for example, the items used to infer School self-concept (T1) with the first self-concept instrument (M1) were divided into three item-parcels to form three indicators of this trait/method combination. A critical first step in this analysis is to fit a typical first-order CFA model in which the 27x27 covariance matrix is fit to a first-order factor model. This first-order model is well-defined (Table 5) in that the solution is proper, each of the 27 measured variables loads substantially on its first-order factor, and the goodness-of-fit is good (RNI = .939) even though the X^2 (288, n=817) = 1506 is substantial.

Of particular relevance to the present application is the 9 x 9 matrix of correlations among the first order factors (see Table 5). Whereas this latent MTMM matrix is like a typical manifest MTMM matrix based on scale scores that is used to assess the Campbell-Fiske guidelines, there are important differences. In particular, the correlations in this latent MTMM matrix are correlations among latent constructs that have been appropriately corrected for measurement error.

Hence, the Campbell-Fiske guidelines can be applied directly to this latent MTMM matrix and many of the objections to the application of these guidelines to correlations among scale scores are overcome.

In the present application, because of the psychometric strength of the scales used in the Byrne data, the interpretation of the guidelines to the latent MTMM matrix of correlations among latent variables is reasonably similar to that described earlier for the manifest MTMM matrix based on scale scores. Support for the Campbell-Fiske guidelines applied to the latent MTMM matrix (Table 5) is, however, somewhat stronger. The mean convergent validity is higher for the latent MTMM matrix than the manifest MTMM matrix (.80 vs. .70), even though the mean HTHM correlation (.31 vs. .31) and the mean HTMM correlation (.37 vs. .35) differ only slightly. Consistent with these results, Campbell and Fiske's second and third guidelines were satisfied in 69 of 72 comparisons for the manifest MTMM matrix but are satisfied for all 72 comparisons for the latent MTMM matrix. Inspection of the parameter estimates for the latent MTMM matrix reveals trends similar to those observed earlier in the manifest MTMM matrix: (a) convergent validities tend to be higher for T3 (mean r = .90) than for T1 (mean r = .74) or T2 (mean r = .75), (b) convergent valdities relating M1 and M2 tend to be higher than those associated with M3, (c) within each method, T1 is substantially correlated with T2 (mean r = .50) and T3 (mean r = .56), but T2 and T3 are nearly uncorrelated (mean r = .07); and (d) correlations among traits are systematically higher for M3 (mean r = .48) than for M1 (mean r = .30) or M2 (mean r = .31), suggesting that there is more method effect associated with M3. We suspect, that differences in interpretations in the latent and manifest MTMM matrices will be larger in other studies in which the psychometric properties of the responses are not so strong as in the Byrne data.

Using the multiple indicator approach, the CDP model merely posits a more restrictive pattern of correlations among the first-order latent constructs such that Pc = Pm x Pt (see earlier discussion of Table 2). Thus, the 36 correlations in the 9 x 9 correlation matrix can be represented by only 6 parameter estimates -- the 3 correlations in Pm and the 3 correlations in Pt. All correlations in the MTMM matrix are either equal to one of these 6 parameter estimates or are the product of two of these parameter estimates. With new options available in LISREL 8, this pattern can be represented directly as constraints on the estimated correlations (see Appendix 1). In the multiple indicator approach in which the MTMM matrix represents correlations among latent constructs, there is no need to posit additional parameters associated with the E and D diagonal matrices in the typical CDP model. This is a very important advantage because it separates issues associated with the hypothesized structure of trait and method effects from those associated with measurement issues.

The MI-CDP model is well-defined (Table 5) in that the solution is proper, each of the 27 measured variables loads substantially on its first-order factor, and the goodness-of-fit is reasonably good (RNI = .911) even though the X^2 (318, n=817) = 2100 is substantial. Because the MI-CDP model is nested under the first-order model, the comparison of the two models is facilitated. The change in X^2 (2100 - 1506 = 594) seems large relative to the change in df (318 - 288 = 30), as does the change in RNIs (.939 vs .911). Whereas the fit of the MI-CDP model appears to be reasonable, the overall fit statistics should be interpreted cautiously. Much of the good fit due to the MI-CDP model is due to the fact that much of the covariation among the measured variables can be explained in terms of the first-order factors. Thus, for example, a first-order model in which all 9 latent constructs are posited to be uncorrelated (i.e., the factor correlation matrix is an identity matrix) is able to explain a substantial amount of variation ((RNI = .644, X^2 (324, n=817) = 6886). Whereas the MI-CDP model is obviously able to fit the data much better than this model, the comparison of these three models demonstrates the much of the ability of the MI-CDP model to fit the data has nothing to do with the posited pattern of correlations among the latent MTMM variables (see further discussion of the "target coefficient" proposed by Marsh, in press; and Marsh & Hocevar, 1988).

A comparison of the parameter estimates (Table 5) based on the first-order model and the MI-CDP model is, perhaps, even more critical than the comparison of the ability of each model to fit the data. Whereas the first-order factor loadings and measured variable uniquenesses are reasonably similar for the two solutions, the factor correlations that are of critical concern differ substantially. In comparing the two models, it is important to recall that the MI-CDP is nested under the first-order model. In this sense, the MI-CDP is merely trying to approximate the parameter estimates in the first-order model with a more parsimonious model. Hence, if the factor correlations in the first-order model do not reflect a direct product structure, then the MI-CDP model is inappropriate. An inspection of the factor correlations in the MI-CDP solution suggests that the imposition of the direct product structure seriously distorts the pattern of correlations. The mean convergent validity is approximately .80 across all traits in both solutions. By definition, however, the mean convergent validity is the same for T1, T2, and T3 (.80) in the MI-CDP solution, even though the convergent validities are much higher for T3 (mean r = .90) than for T1 (mean r = .75) or T2 (mean r = .74). Also by definition, the average correlation of the three traits within each method is the same for each method in the MI-CDP model, even though correlations among traits are larger for M3 (mean r = .48) than for M1 (mean r = .30) or M2 (mean r = .31). Finally, the relative size of correlations among the three traits differs in the two models. Whereas T2 (reading self-concept) and T3 (math self-concept) were posited to be nearly uncorrelated and found to be nearly uncorrelated in the first-order model (mean r = .07), the correlation between T2 and T3 is substantially larger (r = .23 within each method) for the MI-CDP model. Also, whereas T1 (general school self-concept) was posited to be substantially correlated with T2 and T3 and found to be substantially correlated in the first-order model (mean rs of .50 and .56), these correlations were substantially smaller in the MI-CDP model (r = .37 for both correlations within all three methods). This inspection of parameter estimates, even more than the evaluation of goodness-of-fit, suggests that the MI-CDP model is not able to explain adequately the Byrne data. These results led us to reject the CDP model as an appropriate representation of the Byrne data.

A Comparison of the Single and Multiple Indicator Approaches

A basic supposition of this article is that the multiple indicator approach to MTMM data is always superior to approaches that begin with a single indicator of each trait/method combination. There are important advantages to the multiple indicator approach that are particularly important for the CDP model. The a ability to explicitly test the underlying factor structure and to apply the Campbell-Fiske guidelines directly to correlations among latent variables are sufficiently important advantages of the multiple indicator approach to justify its consideration. Particularly in the CDP single-indicator approach, measurement error is determined so as to optimize support for the assumptions underlying the CDP model. Hence, measurement issues may be confounded with tests of the structure of trait and method effects in the single-indicator CDP model. In the MI-CDP model, however, these aspects of the model are separated. Furthermore, in multiple battery data that may be most appropriate for the CDP model, there are likely to be correlated errors that cannot be easily tested or controlled with the single-indicator approach. We suspect that the advantages of the MI-CDP approach will be even greater than observed with the Byrne data in studies where the psychometric properties of the scales are not so strong or multiple battery data is considered.

For present purposes the single-indicator and multiple-indicator approaches have been treated as different approaches to MTMM data, but this is overly simplistic. Ultimately, the single-indicator approach must be viewed as a special case of the more general multiple-indicator approach in which many implicit, usually untested, and perhaps arbitrary restrictions about the structure of the multiple indicators are imposed (e.g., that the multiple indicators of each trait/method combination reflect a single, well-defined, common factor). The implications of these implicit assumptions cannot be easily tested with the single indicator approach but can be tested with the multiple indicator approach. Hence, the critical issue in the comparison of the multiple-indicator and single-indicator approaches is the usefulness of the restrictions imposed in the single indicator approach. Support for the single indicator approach must be based on logical arguments and empirical demonstrations that such restrictions are justified, and these tests require the application of the multiple indicator approach recommended here.

Summary and Implications

Although the CDP model has not been applied as widely as other approaches to MTMM data, particularly the CFA approach, results (e.g., Bagozzi, 1992; in press; Bagozzi & Yi, 1990; 1991; 1992; Bagozzi, Yi, & Phillips, 1991; Browne, 1984; 1989; 1990; Cudeck, 1988; Goffin & Jackson, 1992; Kumar & Dillon, 1992; Lastovicka, Murry & Joachimsthaler, 1990; Wothke & Browne, 1990) have suggested that it typically results in proper solutions and provides an apparently good fit to MTMM data. Consistent with Browne's claim, the CDP model provides evidence about the Campbell-Fiske guidelines and about convergent and discriminant validity as embodied in these guidelines. It it also claimed that the CDP model provides parameter estimates that are typically consistent with those observed in the MTMM matrices. However, the results of the present investigation demonstrate some limitations in the usefulness of particularly the single-indicator CDP model.

The CDP model does not always results in proper solutions and there appears to be some confusion among researchers as to what constitutes a proper solution. The CDP model is extremely parsimonious, but this is only at the expense of very restrictive assumptions. Even when the CDP model provides an apparently good fit to a manifest MTMM matrix, much of the richness of detail in the MTMM data is lost. This parsimony undermines the formative evaluation of MTMM data that was the reason why Campbell and Fiske (1959) first proposed the MTMM design. Whereas this inevitable compromise between parsimony and detail is both a strength and a weakness of the CDP approach, researchers need to be aware of this consideration when interpreting the results of the CDP model. Also, tests of these restrictions rely heavily on the evaluation of the overall fit of the model. Thus, we find it worrisome that we were able to find no published applications of the CDP model that resulted in particularly poor fits. This concern was reinforced by the finding that the CDP model provided an excellent fit to simulated data generated from a population model in which assumptions underlying the CDP model were seriously violated. Whereas the fit of the CDP model was excellent, the CDP parameter estimates led to seriously distorted interpretations of convergent validity, discriminant validity, and method effects. These results may call into question the falsifiability of the model and suggest that goodness of fit may be a necessary but not sufficient basis of support for the CDP model. This problem was easily identified for the artificial data in which the underlying population model was known, but is more difficult to identify in analyses of real data in which researchers only have manifest MTMM matrices as a basis for evaluating CDP estimates.

The multiple indicator approach to the CDP model apparently provides a much stronger basis for evaluating assumptions underlying the CDP model than the single indicator approach that is typically used. The simple first-order model that is the starting point in the multiple indicator approach provides a critical basis of comparison for the MI-CDP model. Because the MI-CDP model is nested under the corresponding first-order model, the intent of the MI-CDP is merely to provide a much more parsimonious representation of the first-order model that tests the hypothesized direct product structure. Hence, the MI-CDP model can be rejected if its fit is substantially poorer than the first-order model or parameter estimates differ substantially from those in the first-order model. This provides a potential solution to two potential problems identified in the single-indicator CDP model. First, single-indicator CDP seems to always provide at least a reasonably good fit to the data -- even when the CDP model is inappropriate, whereas the falsifiability of the MI-CDP model is easier to evaluate. Second, parameter estimates in the single-indicator model must be evaluated in relation to a manifest MTMM matrix, whereas the latent MTMM matrix in the multiple indicator approach provides a much stronger basis of comparison.

We also have some broader, philosophical concerns about the CDP model (also see Kumar & Dillon, 1992). The model, at least as applied to MTMM data, is apparently based on an uncritical acceptance of the original Campbell-Fiske guidelines. Thus, for example, Browne (1989) noted that "Campbell & Fiske (1959) listed four requirements for multitrait-multimethod correlation matrices that have become generally accepted. We shall be concerned with the investigation of these requirements" (p. 507). Whereas we agree that the heuristic value and intent of the Campbell-Fiske guidelines is widely endorsed, we do not concur that their literal translation as "requirements" as embodied in the CDP model is widely accepted. Indeed, it is the many problems and potential ambiguities in the guidelines that has spawned so many alternative approaches. Whereas the application of the CDP approach certainly provides an objectivity to evaluating the Campbell-Fiske guidelines, it is not clear that the CDP model eliminates widely recognized ambiguities in the interpretation of the Campbell-Fiske guidelines. Furthermore, it is difficult to conceive of how multiplicative correlations could arise other than through a multiplicative relation of the scores which, if taken literally, would undermine the logic of the Campbell-Fiske guidelines and even the logic of the classical approach to test theory. Whereas Browne (1984) has not claimed that support for the CDP model necessarily leads to such dire consequences, we nevertheless find paradoxical the assumption that support for the CDP implies multiplicative relations <u>and</u> provides a basis for evaluating the Campbell-Fiske guidelines that appear to be based on an assumption of additivity that is invalidated by these multiplicative relation. More generally, we are loath to relinquish the many conceptual and theoretical advantages in the additive assumption of variance components explicit in classical test theory and conventional factor analysis that would have to be abandoned if such a multiplicative model were taken literally (for further discussion see Campbell & O'Connell, 1967, 1982; Kumar & Dillon, 1992).

An unresolved problem is why the single-indicator CDP model is apparently able to fit data so well even when assumptions underlying the model are violated. Whereas we have no definitive answer to this dilemma, we suspect that the problem has to do with the confounding between measurement issues (communality estimates and scaling constraints in the E and D diagonal matrices) and the support for the direct product structure of relations among trait and method effects. This problem appears to be similar to that described by Marsh (1993) for single-indicator and multiple-indicator simplex models of longitudinal data. Rogossa and Willet (1985) claimed that satisfying the quasi-simplex structure was simpler than it should be, calling into question the falsifiability of the model. They demonstrated that the typical quasi-simplex provided a very good fit to simulated data generated from a population model that violated assumptions underlying the simplex model. Based on much of the same logic used to support the MI-CDP model here, Marsh (1993) argued for the superiority of a multiple indicator approach to simplex models. He demonstrated that the single-indicator simplex model produced apparently biased estimates that exaggerated support for a simplex structure, but that the problem was apparently resolved by the application of the multiple-indicator simplex model. In the single-indicator simplex model, as in the single-indicator CDP model, structural parameter estimates are confounded with measurement issues. In the multiple-indicator approach, however, the measurement and structural issues are more clearly separated so that it was easier to reject the simplex model when support for a simplex structure is weak.

Here we have advocated the MI-CDP model. It is, however, important to emphasize that we further recommend the multiple indicator approach as a basis for all MTMM studies. The usefulness of the multiple-indicator approach has been demonstrated with the CFA approach to MTMM data and can be generalized to any approach that begins with a MTMM matrix. Many of the advantages for beginning with a latent MTMM matrix instead of a manifest MTMM matrix in the CDP approach generalize to other approaches as well (e.g., Marsh & Hocevar, 1988; Marsh, in press). The major limitation of this approach is the requirement that researchers collect multiple indicators of each measured variable. Whereas this may not be possible in the continued reanalyses of existing MTMM matrices that seem to pervade the MTMM literature, multiple indicators of each trait/method combination are typically collected in original studies. Indeed, undue attention should not, perhaps, be given to studies that make inferences on the basis of single-item scales -- as opposed to those that use a single score to summarize appropriately constructed multi-item scales. Particularly for MTMM studies that focus on the formative evaluation and improvement of measurement instruments as originally advocated by Campbell and Fiske (1959), the requirement of multiple indicators should not be a problem.

In conclusion, this investigation has an important message for applied researchers who wish to use the MTMM paradigm. MTMM data has an inherently complicated structure that will not be fully described in all cases by any of the models or approaches typically considered. There is, apparently, no "right" way to analyze MTMM data that works in all situations. Instead, we recommend that researchers consider several alternative approaches to evaluating MTMM data -- an initial inspection of the MTMM matrix using the Campbell-Fiske guidelines followed by fitting at least the subset of CFA models recommended by Marsh and Grayson (in press) and the CDP model. Particularly, when researchers have access to raw data and there are multiple indicators of each scale/method combination, the multiple indicator approach described here should be used in conjunction with the Campbell-Fiske guidelines, the CFA models, and the CDP model. The Campbell-Fiske guidelines should be used primarily for formative purposes, the CDP model seems most appropriate for summative evaluations, and the CFA models apparently serve both summative and formative purposes. It is, however, important that researchers understand the strengths and weaknesses of the different approaches. For each of the different latent-variable approaches, researchers should evaluate results in relation to technical considerations such as convergence to proper solutions and goodness of fit, but should also place more emphasis on substantive interpretations and theoretical considerations. Despite the inherent complexity of MTMM data, we feel confident that the combination of common sense, a stronger theoretical emphasis on the design of MTMM studies, a better quality of measurement at the level of trait-method units, an appropriate arsenal of analytical tools such as recommended here, and a growing understanding of these analytic tools will allow researchers to use the MTMM paradigm effectively. Finally, researchers should be aware of the dangers inherent in using the CDP model to "buy" a proper solution by "selling" the ability to make formative evaluations of MTMM data. This problem may be compounded by the ease which the CDP model appears to be able to fit single-indicator data the violates assuptions underlying the model.

Footnotes

[1] Kumar and Dillon (1992) noted that whereas the CDP structure is strictly multiplicative, CFA models that posit trait and method factors can accommodate both additive and apparently multiplicative effects. That is, the effect of a given method can vary for different measured variables associated with the same method. Whereas the CFA structure may be more flexible than the CDP structure, this greater flexibility is typically at the expense of a less of parsimony and, perhaps, problems associated with improper solutions (see Marsh, 1989; Marsh & Bailey, 1991).

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Table 1

The Pm, Pt, and PC Matrices for a CDP Model with 3 Traits and 3 Methods

Pm =

1		
M21	1	
M31	M32	1

Pt =

1		
T21	1	
T31	T32	1

Pc = Pm x Pt =

1xPt		
M21xPt	1	
M31xPt	M32xPt	1xPt

=

1								
T21	1							
T31	T32	1						
M21	M21xT21	M21xT31	1					
M21xT21	M21	M21xT32	T21	1				
M21xT31	M21xT32	M21	T21	T32	1			
M31	M31xT21	M31xT31	M32	M32xT21	M32xT31	1		
M31xT21	M31	M31xT32	M32xT21	M32	M32xT32	T21	1	
M31xT31	M31xT32	M31	M32xT31	M32xT32	M32	T21	T32	

Note. Pm is the correlation matrix among method factors with a typical element being r (Mr, Ms). Pt is the correlation matrix of relations among latent trait factors with a typical element being r (Ti, Tj) = Tij, and Pc is the MTMM matrix appropriately corrected for unreliability that is defined to have the direct (kronecker) product structure Pm x Pt. Thus, for example, T21 is the correlation between traits 1 and 2, M12 is the correlation between methods 1 and 2, and T21xM31 is the product of the correlation between traits 1 and 2 and the correlation between methods 3 and 1. Hence, the 36 off-diagonal elements in Pc are defined in terms of only 6 estimated parameters (M21, M31, M32, T21, T31, and T32); all elements are either equal to one of these six parameters or are the product of two of these six parameters..

Table 2

The MTMM Correlation Matrix for the Byrne Data

t1m1	(.89)								
t2m1	.384	(.79)							
t3m1	.441	.002	(.92)						
t1m2	.622	.368	.353	(.84)					
t2m2	.438	.703	.008	.441	(.89)				
t3m2	.465	.069	.871	.424	.136	(.95)			
t1m3	.678	.331	.478	.550	.380	.513	(.87)		
t2m3	.458	.541	.057	.381	.658	.096	.584	(.90)	
t3m3	.414	.027	.825	.372	.029	.810	.592	.135	(.94)

Note. t1=general school self-concept, t2=verbal self-concept, t3=math self-concept; m1, m2, and m3 are three different self-report instruments This MTMM matrix is derived from data presented by Byrne and Shavelson (1986). Values in parentheses, coefficient alpha estimates of reliability, were not actually used in the analysis.

Table 3

Parameter Estimates For the CDP Model and the CDP Model With a Kronecker Error Structure

CDP Model

Trait Correlations (Pt)				Method Correlations (Pm)			
T1	1			M1	1		
T2	.636	1		M2	.959	1	
T3	.592	.151	1	M3	.834	.837	1

Communality Indices

T1M1	T2M1	T3M1	T1M2	T2M2	T3M3	T1M3	T2M2	T3M3[a]
.766	.901	.963	.879	.817	.953	.939	.900	1.00

CDP Model With a Kronecker Error Structure

Trait Correlations (Pt)				Method Correlations (Pm)			
T1	1			M1	1		
T2	.694	1		M2	.960	1	
T3	.596	.138	1	M3	.848	.831	1

Communality Indices

T1M1	T2M1	T3M1	T1M2	T2M2	T3M3	T1M3	T2M2	T3M3
.810	.827	.953	.842	.857	.962	.927	.935	.985

[a] This error variance corresponding to this communality was constrained to be nonnegative. Because the E matrix in the the CDP model was not positive definite, the solution is improper.

Table 4

Simulated MTMM matrix Used to Evaluate the CDP Model

MTMM Matrix

t1m1	1.000								
t2m1	.442	1.000							
t3m1	.057	.054	1.000						
t1m2	.720	.384	.024	1.000					
t2m2	.432	.640	.024	.424	1.000				
t3m2	.027	.024	.090	.084	.084	1.000			
t1m3	.630	.336	.021	.560	.336	.021	1.000		
t2m3	.378	.560	.021	.336	.560	.021	.314	1.000	
t3m3	.045	.040	.150	.040	.040	.150	.065	.095	1.000

CDP Parameter Estimates

Trait Correlations (Pt)

T1	1.000		
T2	.597	1.000	
T3	.160	.179	1.000

Method Correlations (Pm)

M1	1.000		
M2	.934	1.000	
M3	.943	.904	1.000

Communality Indices

T1M1	T2M1	T3M1	T1M2	T2M2	T3M3	T1M3	T2M2	T3M3
.912	.810	.313	.845	.845	.342	.732	.733	.496

Note: The MTMM matrix was simulated from a confirmatory factor model with 3 correlated trait factors, 3 uncorrelated method factors, and 9 uncorrelated uniquenesses. For each measured variable the trait-factor loading, method-factor loading, and uniqueness was: .9, .1, .18 (T1M1); .8, .1, .35 (T2M1); .3, .3, .82 (T3M1); .8, .2, .32 (T1M2); .8, .2, .32 (T2M2); .3, .3, .82 (T3M2); .7, .1, .50 (T1M3); .7, .2, .47 (T2M3); .5, .3, .66 (T3M3). The three trait correlations were .6 (T1T2), .1 (T1T3), and .1 (T2T3). The MTMM matrix that was then evaluated with the CDP model. Even though the true trait variances for T1 and T2 differed substantially from T3, apparently violating an assumption of the CDP model, the CDP model fit the data very well (X^2 (21) = 11.15 for a hypothetical N=500).

Table 5

Completely Standardized Solutions For the First-Order Model and Multiple-Indicator CDP Model

First-Order Model — Factor Loadings

Measured Variables	T1M1	T2M1	T3M1	T1M2	T2M2	T3M2	T1M3	T2M3	T3M3	Uniq
t1m1-1	.83	.00	.00	.00	.00	.00	.00	.00	.00	.32
t1m1-2	.88	.00	.00	.00	.00	.00	.00	.00	.00	.22
t1m1-3	.88	.00	.00	.00	.00	.00	.00	.00	.00	.23
t2m1-1	.00	.81	.00	.00	.00	.00	.00	.00	.00	.35
t2m1-2	.00	.73	.00	.00	.00	.00	.00	.00	.00	.47
t2m1-3	.00	.66	.00	.00	.00	.00	.00	.00	.00	.56
t3m1-1	.00	.00	.93	.00	.00	.00	.00	.00	.00	.13
t3m1-2	.00	.00	.92	.00	.00	.00	.00	.00	.00	.16
t3m1-3	.00	.00	.87	.00	.00	.00	.00	.00	.00	.24
t1m2-1	.00	.00	.00	.89	.00	.00	.00	.00	.00	.20
t1m2-2	.00	.00	.00	.73	.00	.00	.00	.00	.00	.46
t1m2-3	.00	.00	.00	.80	.00	.00	.00	.00	.00	.36
t2m2-1	.00	.00	.00	.00	.54	.00	.00	.00	.00	.71
t2m2-2	.00	.00	.00	.00	.85	.00	.00	.00	.00	.27
t2m2-3	.00	.00	.00	.00	.91	.00	.00	.00	.00	.18
t3m2-1	.00	.00	.00	.00	.00	.93	.00	.00	.00	.14
t3m2-2	.00	.00	.00	.00	.00	.90	.00	.00	.00	.19
t3m2-3	.00	.00	.00	.00	.00	.88	.00	.00	.00	.22
t1m3-1	.00	.00	.00	.00	.00	.00	.80	.00	.00	.36
t1m3-2	.00	.00	.00	.00	.00	.00	.90	.00	.00	.20
t1m3-3	.00	.00	.00	.00	.00	.00	.78	.00	.00	.39
t2m3-1	.00	.00	.00	.00	.00	.00	.00	.80	.00	.36
t2m3-2	.00	.00	.00	.00	.00	.00	.00	.93	.00	.14
t2m3-3	.00	.00	.00	.00	.00	.00	.00	.83	.00	.32
t3m3-1	.00	.00	.00	.00	.00	.00	.00	.00	.95	.10
t3m3-2	.00	.00	.00	.00	.00	.00	.00	.00	.96	.08
t3m3-3	.00	.00	.00	.00	.00	.00	.00	.00	.87	.25

Multiple Indicator CDP Model — Factor Loadings

Measured Variables	T1M1	T2M1	T3M1	T1M2	T2M2	T3M2	T1M3	T2M3	T3M3	Uniq
t1m1-1	.84	.00	.00	.00	.00	.00	.00	.00	.00	.30
t1m1-2	.88	.00	.00	.00	.00	.00	.00	.00	.00	.22
t1m1-3	.87	.00	.00	.00	.00	.00	.00	.00	.00	.24
t2m1-1	.00	.80	.00	.00	.00	.00	.00	.00	.00	.37
t2m1-2	.00	.73	.00	.00	.00	.00	.00	.00	.00	.46
t2m1-3	.00	.66	.00	.00	.00	.00	.00	.00	.00	.57
t3m1-1	.00	.00	.92	.00	.00	.00	.00	.00	.00	.16
t3m1-2	.00	.00	.90	.00	.00	.00	.00	.00	.00	.19
t3m1-3	.00	.00	.85	.00	.00	.00	.00	.00	.00	.28
t1m2-1	.00	.00	.00	.87	.00	.00	.00	.00	.00	.24
t1m2-2	.00	.00	.00	.73	.00	.00	.00	.00	.00	.47
t1m2-3	.00	.00	.00	.79	.00	.00	.00	.00	.00	.37
t2m2-1	.00	.00	.00	.00	.55	.00	.00	.00	.00	.69
t2m2-2	.00	.00	.00	.00	.86	.00	.00	.00	.00	.26
t2m2-3	.00	.00	.00	.00	.91	.00	.00	.00	.00	.16
t3m2-1	.00	.00	.00	.00	.00	.92	.00	.00	.00	.16
t3m2-2	.00	.00	.00	.00	.00	.88	.00	.00	.00	.23
t3m2-3	.00	.00	.00	.00	.00	.87	.00	.00	.00	.25
t1m3-1	.00	.00	.00	.00	.00	.00	.77	.00	.00	.40
t1m3-2	.00	.00	.00	.00	.00	.00	.90	.00	.00	.19
t1m3-3	.00	.00	.00	.00	.00	.00	.78	.00	.00	.39
t2m3-1	.00	.00	.00	.00	.00	.00	.00	.81	.00	.35
t2m3-2	.00	.00	.00	.00	.00	.00	.00	.93	.00	.13
t2m3-3	.00	.00	.00	.00	.00	.00	.00	.83	.00	.31
t3m3-1	.00	.00	.00	.00	.00	.00	.00	.00	.94	.12
t3m3-2	.00	.00	.00	.00	.00	.00	.00	.00	.95	.10
t3m3-3	.00	.00	.00	.00	.00	.00	.00	.00	.83	.31

Factor Correlations — First-Order Model

	T1M1	T1M2	T1M3	T2M1	T2M2	T2M3	T3M1	T3M2	T3M3
T1M1	---								
T1M2	.46	---							
T1M3	.48	-.02	---						
T2M1	.77	.33	.39	---					
T2M2	.43	.81	-.01	.40	---				
T2M3	.49	.03	.95	.46	.08	---			
T3M1	.78	.39	.53	.71	.39	.55	---		
T3M2	.52	.65	.05	.43	.75	.07	.64	---	
T3M3	.46	.02	.87	.43	.01	.87	.65	.14	---

Factor Correlations — Multiple Indicator CDP Model

	T1M1	T1M2	T1M3	T2M1	T2M2	T2M3	T3M1	T3M2	T3M3
T1M1	---								
T1M2	.37	---							
T1M3	.37	.23	---						
T2M1	86	.32	.32	---					
T2M2	[illegible]	.86	.20	.37	---				
T2M3	.32	.20	.86	.37	.23	---			
T3M1	.77	.29	.28	.78	.29	.29	---		
T3M2	.29	.77	.18	.29	.78	.18	.37	---	
T3M3	.28	.18	.77	.29	.18	.78	.37	.23	---

Note. The goodness of fit indices are better for the first-order model than for the multiple-indicator CDP model: X^2 (288) = 1506 vs. X^2 (318) = 2100; RNI = .939 vs. .911. The factor correlation matrix for the CDP model is the direct product of a Pm matrix of correlations among the methods [convergent validities; having off-diagonal elements of .86, .77 and .78] and a Pt matrix of correlations among traits [having off-diagonal values of .37, .37, and .23].

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Appendix 1

LISREL 8 Set-Up For Fitting the Multiple Indicator CDP Model

```
MO NY=27 NE=9 LY=FU,FI PS=SY,FI TE=DI,FR
 PA LY
  1 0 0 0 0 0 0 0 0
  1 0 0 0 0 0 0 0 0
  1 0 0 0 0 0 0 0 0
  0 1 0 0 0 0 0 0 0
  0 1 0 0 0 0 0 0 0
  0 1 0 0 0 0 0 0 0
  0 0 1 0 0 0 0 0 0
  0 0 1 0 0 0 0 0 0
  0 0 1 0 0 0 0 0 0
  0 0 0 1 0 0 0 0 0
  0 0 0 1 0 0 0 0 0
  0 0 0 1 0 0 0 0 0
  0 0 0 0 1 0 0 0 0
  0 0 0 0 1 0 0 0 0
  0 0 0 0 1 0 0 0 0
  0 0 0 0 0 1 0 0 0
  0 0 0 0 0 1 0 0 0
  0 0 0 0 0 1 0 0 0
  0 0 0 0 0 0 1 0 0
  0 0 0 0 0 0 1 0 0
  0 0 0 0 0 0 1 0 0
  0 0 0 0 0 0 0 1 0
  0 0 0 0 0 0 0 1 0
  0 0 0 0 0 0 0 1 0
  0 0 0 0 0 0 0 0 1
  0 0 0 0 0 0 0 0 1
  0 0 0 0 0 0 0 0 1

 PA PS[1]
 0
 2 0
 3 4 0
 5 0 0 0
 0 5 0 2 0
 0 0 5 3 4 0
 6 0 0 7 0 0 0
 0 6 0 0 7 0 2 0
 0 0 6 0 0 7 3 4 0
ST 1 PS(1,1) PS(2,2) PS(3,3) PS(4,4) PS(5,5) PS(6,6) PS(7,7) PS(8,8) PS(9,9)

 CO PS(5,1) = PS(2,1) * PS(4,1)[1]
 CO PS(6,1) = PS(3,1) * PS(4,1)
 CO PS(6,2) = PS(3,2) * PS(4,1)
 CO PS(8,1) = PS(2,1) * PS(7,1)
 CO PS(9,1) = PS(3,1) * PS(7,1)
 CO PS(9,2) = PS(3,2) * PS(7,1)
 CO PS(8,4) = PS(2,1) * PS(7,4)
 CO PS(9,4) = PS(3,1) * PS(7,4)
 CO PS(9,5) = PS(3,2) * PS(7,4)
 CO PS(4,2) = PS(2,1) * PS(4,1)
 CO PS(4,3) = PS(3,1) * PS(4,1)
 CO PS(5,3) = PS(3,2) * PS(4,1)
 CO PS(7,2) = PS(2,1) * PS(7,1)
 CO PS(7,3) = PS(3,1) * PS(7,1)
 CO PS(8,3) = PS(3,2) * PS(7,1)
 CO PS(7,5) = PS(2,1) * PS(7,4)
 CO PS(7,6) = PS(3,1) * PS(7,4)
 CO PS(8,6) = PS(3,2) * PS(7,4)
OU NS TM=6000 EF SE TV SC SO AD=50
```

Note. The model was fit to a 27x27 covariance matrix. Plausible starting values were also provided that are not shown to conserve space.

[1] In PA PS (the pattern matrix psi of factor correlations), all pattern elements greater 1 are used to impose equality constraints (i.e., all parameter estimates with pattern elements of 2 are constrained to be equal). [2] Additional constraints are imposed to fit the CDP model by requiring some fixed parameters to be equal to the product of two parameter estimates (see Table 1).