An Equal-Level Approach to the Investigation of Multitrait-Multimethod Matrices

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An equal-level approach that yields new information for the evaluation of multitrait-multimethod (MTMM) matrices is described. The procedure is based on the analysis of item-composite relations, composite-composite relations, composites, and facets. A main characteristic of the equal-level approach is the induction of equality in data-level prior to carrying out comparisons between coefficients, because in many cases such inequalities may lead to inaccurate conclusions. Methods are proposed for ensuring comparability of coefficients even if an MTMM design includes different numbers of items for traits and methods. The concept of disaggregation is assigned a key position in the investigation of convergent and discriminant validity. In addition, measures are proposed for avoiding other distortions resulting from partial self-correlations. *Index terms: disaggregated correlations, equal-level approach, multitrait-multimethod analysis, partial self-correlations, Spearman-Brown formula.*

The strategy originally proposed by Campbell and Fiske (1959) for the investigation of multitrait-multimethod (MTMM) matrices pertained to correlations between items. Despite the importance of this strategy, which includes four different types of comparisons, it is not regarded as sufficient for a comprehensive evaluation of an MTMM matrix (e.g., Althauser & Heberlein, 1970; Cudeck, 1988; Jackson, 1969). Consequently, various quantitative approaches have been developed for investigating MTMM matrices (Schmitt, Coyle, & Saari, 1977; Schmitt & Stults, 1986), such as analysis of variance (e.g., Boruch & Wolins, 1970), non-parametric analysis (e.g., Hubert & Baker, 1978, 1979), partial correlations (e.g., Schriesheim, 1981), smallest-space analysis (e.g., Levin, Montag, & Comrey, 1983), exploratory factor analysis (e.g., Jackson, 1969), and confirmatory factor analysis (e.g., Werts & Linn, 1970).

By employing these approaches, the evaluation of an MTMM matrix is extended from investigating the relations between individual items to investigating models including the relations between all the items. However, there are also other organizational units that contain additional information concerning the validity of an MTMM matrix. These organizational units and connected relations include item-composite relations, composite-composite relations, composites, and facets of traits and of methods.

An equal-level approach is proposed here for investigating MTMM matrices with respect to other organizational units. This approach requires equality in "data-level" before coefficients are submitted for evaluation. The term *data-level* is used to denote the number of items included in a composite measure. Data-level contributes to the magnitudes of correlation-based coefficients. The effect of test length (e.g., Gulliksen, 1950; Schweizer, 1987) is a prominent example of the influence of data-level.

Differences between the magnitudes of coefficients resulting from differences in data-level are regarded as distortions that may lead to inaccurate conclusions in evaluating an MTMM matrix. For example, it may be concluded from the magnitudes of squared correlations that an item contains more

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method variance than trait variance, although the surplus in variance is attributable to differences between data-levels. Appropriate adjustments of the data-levels using disaggregated correlations are proposed here for obtaining equal data-levels.

The comparability of coefficients may still be impaired by another source of distortion—partial self-correlation. If composites that have an item in common are correlated, the correlation is enhanced as a result of partial self-correlation. This type of distortion can be avoided by appropriate adjustments, such as the application of a correction scheme or disaggregation.

A method for arriving at disaggregated correlations is described below. Then the investigation of MTMM matrices using the equal-level approach is demonstrated at several levels of organization. This includes the induction of equality in data-level before decisions are made, as well as preventing partial self-correlations. An example illustrates the application of the equal-level approach.

The Concept of Disaggregation

Disaggregation denotes the elimination of the effect of aggregating data from correlations. It establishes the basic data-level as well as the basic coefficients necessary for adjusting data-levels. For an appropriate presentation of the concept, it is necessary to provide a mathematical description of the effect of aggregating data that results from increasing the number of items included in a composite.

Assume that there are two sets of variables, $X_1, \ldots, X_{n_x}$ and $Y_1, \ldots, Y_{n_y}$, that are standardized to a variance of 1 and a mean of 0. Summation yields the composites $\dot{X}$ and $\dot{Y}$. The correlation between the two composites $\dot{X}$ and $\dot{Y}$, is,

$$r_{\dot{X}\dot{Y}} = \frac{\sigma_{\dot{X}\dot{Y}}}{\sigma_{\dot{X}}\sigma_{\dot{Y}}} \quad . \tag{1}$$

The three parts of the ratio in Equation 1 will now be modified to obtain a formula for the prediction of the aggregating data effect. The covariance is transformed into the product of n_X and n_Y, and the mean, $\bar{r}_{XY}$, of the correlations between every pair of variables from different sets:

$$\sigma_{\dot{X}\dot{Y}} = \sum_{i=1}^{n_X} \sum_{j=1}^{n_Y} \sum_{k=1}^{n} X_{i_k} Y_{j_k}/n = \sum_{i=1}^{n_X} \sum_{j=1}^{n_Y} r_{XY_{ij}} = n_x n_y \bar{r}_{XY} \quad . \tag{2}$$

The standard deviations of the composites can be modified on the assumption that variances and standard deviations of individual variables are all 1 due to standardization. The respective variances can be transformed into an expression that includes the number of variables and the mean correlation, $\bar{r}_X$, of all the correlations between the variables of one set. This is demonstrated for a set of variables $X_1, \ldots, X_n$ as follows:

$$\sigma^2_{\dot{X}} = \sum_{i=1}^{n} \sigma^2_X + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} 2\, r_{X_{ij}} \sigma_{X_i} \sigma_{X_j} = n + \frac{n\,(n-1)}{2} 2\, \bar{r}_X = n[1 + (n-1)\bar{r}_X] \quad . \tag{3}$$

Finally, the results of Equation 2 and Equation 3 can be substituted in Equation 1:

$$r_{\dot{X}\dot{Y}} = \frac{n_X n_Y \bar{r}_{XY}}{n_X[1 + (n_x - 1)\bar{r}_x]^{1/2} n_Y[1 + (n_Y - 1)\bar{r}_Y]^{1/2}} = \left[\frac{n_x}{1 + (n_X - 1)\bar{r}_X}\right]^{1/2} \left[\frac{n_Y}{1 + (n_y - 1)\bar{r}_Y}\right]^{1/2} \bar{r}_{XY} \quad . \tag{4}$$

It is obvious from Equation 4 that the correlation between two composites increases if n_X and/or

n_Y are increased, while all rs are constant and greater than zero.

Disaggregation reverses the effect that results from increasing n_X and/or n_Y. It determines the magnitude of $r_{\dot{X}\dot{Y}}$ that results if both n_X and n_Y are set to 1. This may be achieved by making different assumptions concerning the relationships between $\bar{r}_X$, $\bar{r}_Y$ and $\bar{r}_{YX}$. First, it may be assumed that the actual mean correlations are valid estimates for other mean correlations based on composites of larger numbers of variables. For this assumption, the estimates are obtainable from the intercorrelations of the items. Second, in some situations it may be useful to assume that there are latent mean correlations of equal magnitude. If all the items are of equal variance and are selected to measure the same trait or the same method, this assumption is appropriate. However, sufficient reason should be provided to justify this assumption in every investigation.

The assumption of equality among the mean correlations leads to the problem of determining an overall mean. A method is presented here for solving this problem in item-composite correlations. This special case is represented by Equation 5:

$$r_{\dot{X}X} = \left[\frac{n}{1 + (n - 1)r}\right]^{1/2} r \quad . \tag{5}$$

(Subscripts are omitted in Equation 5 because of the equality assumption.)

If the effect of an increase in test length is to be predicted, r must be known and $r_{\dot{X}X}$ is to be predicted. In contrast, if $r_{\dot{X}X}$ is known and r is missing, disaggregation should be applied to obtain a disaggregated correlation. For this purpose, Equation 5 is transformed in such a way that a polynomial of the second degree is finally obtained. First, both parts of Equation 5 are squared,

$$\frac{n}{1 + (n - 1)r} r^2 = r^2_{\dot{X}X} \quad , \tag{6}$$

and successively reordered:

$$nr^2 = r^2_{\dot{X}X}[1 + (n - 1)r] \quad ,$$

$$nr^2 = r^2_{\dot{X}X} + r^2_{\dot{X}X}(n - 1)r \quad ,$$

$$nr^2 - r^2_{\dot{X}X}(n - 1)r - r^2_{\dot{X}X}r^0 = 0 \quad . \tag{7}$$

Two well-known solutions are available for the quadratic equation finally obtained:

$$r_{1,2} = \frac{-(-r^2_{\dot{X}X})(n - 1) + \{[-r^2_{\dot{X}X}(n - 1)]^2 - 4n(-r^2_{\dot{X}X})\}^{1/2}}{2n} \quad . \tag{8}$$

Either one or two real numbers results from the application of Equation 8. One solution is usually positive and the other negative. Exploratory investigations lead to the conclusion that the positive value should be selected for r.

The Elimination of Effects Resulting From Aggregation and Partial Self-Correlation

According to Equation 4, the difference between the magnitudes of two correlations may result from differences between the mean correlations and/or from differences between the numbers of variables comprising the corresponding composites (composite "size"). Therefore, comparisons among correlations should be regarded with caution if composites of unequal size are included in an MTMM design. A difference between correlations may indicate a difference in data-level but not a difference in the basic properties. Two main types of unequal sizes of composites should be considered in MTMM designs.

The first type of composites with unequal sizes results from representing traits and methods by different numbers of items. Whereas trait composites and method composites usually include the same number of items, there are many studies in which the number of items included in a trait composite is smaller than the number of items included in a method composite. In such a case, the magnitudes of the correlations between item and method are increased more due to aggregation than the magnitudes of the corresponding correlations between item and trait. Despite the formal correctness of the result obtained in correlating the composites, differences resulting from unequal data-levels should be regarded as inaccurate for an evaluation of the composition of the variance of a composite or item. Proper adjustment of n_X and n_Y helps to avoid this.

The second type of unequal size composites may result from the elimination of partial self-correlation. If an item is correlated with a composite to which it is assigned, or if two composites have one item in common, the correlation is increased further by partial self-correlation. Comparisons among correlations might be regarded as invalid if some of them include partial self-correlation and others do not. This problem can be avoided either by removing the item from the composite before computing a correlation or by applying a correction scheme. The correction scheme restricts the contribution of the crucial item to the communality of the item with respect to the corresponding composite.[1] This is achieved by replacing the self-correlation (r_{ij} = 1.00) in Equation 2 with the communality. This correction scheme assures that all of the correlational information available is retained, whereas the removal of an item leads to a loss of information. This loss of information is regarded as especially serious for small numbers of items. Furthermore, the removal of an item leads to unequal composite sizes that must be compensated for by a proper adjustment of either n_X or n_Y according to Equation 4. However, in this case, problems concerning communality estimation are avoided.

The effects of partial self-correlations as well as the methods for eliminating them can be illustrated by the following example: Assume that there are nine items that all correlate exactly r = .30 with each other and that composite 1 consists of items 1 to 3, composite 2 consists of items 4 to 6, and items 7 to 9 comprise composite 3. Assume further that composites are computed for these sets of items, and that these composites are correlated with each of the nine items. The results are presented in Table 1, which also shows partial self-correlation coefficients for reduced composites and coefficients adjusted for avoiding partial self-correlation. In this type of data both methods lead to coefficients of the same magnitude.

The correlations including partial self-correlation are r = .730, whereas the other correlations are r = .411. The correlations with a reduced composite for avoiding partial self-correlations are r = .372. If the data-level is adjusted according to Equation 5 and the correction scheme is applied, all correlations are equal. This result is as expected, because uniformity of item-item correlations justifies uniformity of item-composite correlations.

Evaluating MTMM Matrices by Means of Disaggregated Correlations

Campbell and Fiske (1959) proposed a strategy for the evaluation of MTMM matrices that only applies to correlations between the smallest organizational units—the item-item correlations. Their method requires a large number of comparisons between correlations. The number of comparisons

[1]The author is indebted to an anonymous reviewer for pointing out this scheme.

Table 1
Correlations Between Items and Composites for a Uniform Matrix of Correlations: Self Correlations, Correlations With Reduced Composite, and Adjusted Correlations

	Composite 1			Composite 2			Composite 3		
Item	Self	Red.	Adj.	Self	Red.	Adj.	Self	Red.	Adj.
1	.730	.372	.411		.411			.411	
2	.730	.372	.411		.411			.411	
3	.730	.372	.411		.411			.411	
4		.411		.730	.372	.411		.411	
5		.411		.730	.372	.411		.411	
6		.411		.730	.372	.411		.411	
7		.411			.411		.730	.372	.411
8		.411			.411		.730	.372	.411
9		.411			.411		.730	.372	.411

is reduced if item-composite correlations are used for the evaluation of an MTMM matrix instead of item-item correlations, because the computation of composites according to the MTMM design leads to a further organizational unit connected with an increase in data-level. Effects resulting from partial self-correlations and differences in sizes of composites can be avoided by appropriate adjustments, which are described above. Furthermore, it is proposed that disaggregation be applied to correlations between items and composites as well as to correlations between composites and composites. This leads to a reduction in data-level, but the organizational unit is retained. Although disaggregation is not essential, there are two reasons to prefer disaggregated correlations, r_d:

1. In many cases, the difference between two correlations reaches its highest value if the data-level approaches its lower limit. Consequently, the discrimination is usually better for low data-level than for high data-level.
2. By disaggregation, coefficients are obtained that may be submitted to every type of comparison. Even item-composite correlations may be compared with composite-composite correlations.

The guidelines for the evaluation of convergent and discriminant validity proposed by Campbell and Fiske (1959) must be modified for evaluating item-composite correlations. For ease of exposition, items belonging to the same trait or method are called "congeneric" (Jöreskog, 1971) with respect to this trait or method. Convergent validity is regarded as a matter of consistency of composites. A composite is consistent if all the item-composite correlations for congeneric combinations are larger than all the item-composite correlations that are noncongeneric. The following inequality relation represents this condition for convergent validity,

$$r_{d_{x_i s_k}} > r_{d_{x_j s_k}} \text{ for all } x_i, s_k \quad , \tag{9}$$

under the condition that x_i and s_k are congeneric, and that x_j and s_k are noncongeneric. The notation $x_i s_k$ indicates a congeneric combination, whereas the notation $x_j s_k$ indicates a noncongeneric combination. If the inequality relation does not hold for all congeneric combinations, a trait is not well-represented by the composite.

Discriminant validity concerns the ability of items to discriminate between the various composites. This requires a comparison of the correlations of every item with the alternative composites. In every case the item-composite correlation for the congeneric combination should be higher than the item-composite correlations that are noncongeneric. A formal representation of this condition is provided by the inequality relation,

$$r_{d_{x_i s_j}} > r_{d_{x_i s_k}} \text{ for all } x_i, s_k \quad , \tag{10}$$

under the condition that x_i and s_j are congeneric and that x_i and s_k are noncongeneric. The notation $x_i s_j$ indicated a congeneric combination, whereas the notation $x_i s_k$ indicates a noncongeneric combination.

Disaggregation Applied to an Empirical Example

An example taken from the classic study by Campbell and Fiske (1959) was analyzed for a demonstration. The MTMM matrix presented in Table 12 by Campbell and Fiske was originally reported by Kelly and Fiske (1951), and it has been used in a number of other studies (e.g., Boruch & Wolins, 1970; Browne, 1984; Jackson, 1969; Jöreskog, 1971, 1974; Ray & Heeler, 1975). The correlations are available from 15 items arranged in three blocks of five trait measures (assertive, cheerful, serious, unshakable poise, broad interests). The measures of every block have one method of measurement (staff rating, teammate rating, self rating) in common. The procedure applied to these correlations includes two steps: (1) computation of item-composite correlations, and (2) disaggregation of item-composite correlations.

The item-composite correlations are obtained from the original correlations on the assumption of equal variance of items that may be obtained by standardization. The disaggregated correlations for all item-trait combinations are presented in Table 2. Although in most cases the conditions of convergent and discriminant validity hold, there are also some deviations. The requirements of convergent validity for composite 4 (unshakable poise) as well as composite 5 (broad interests) are not met. The disaggregated correlations between composite 5 and items 1 (.291) and 6 (.331) are higher than the disaggregated correlation with item 15 (.285) that is congeneric. The disaggregated correlations between composite 4 and items 2 (.234), 7 (.268), and 10 (.183) are higher than the disaggregated correlations with items 4 (.217), 9 (.166), and 14 (.178) that are congeneric. In particular, in the case of composite 4, the corresponding trait is not well represented. This deficiency is also noted by Campbell and Fiske (1959). The investigation of the correlations with regard to discriminant validity yields two items that do not meet the requirements. The correlation between item 4 and composite 2 (.295)

Table 2
Disaggregated Correlations Between Items and Trait Composites for the Correlations Presented in Table 12 of Campbell and Fiske (1959)

	Composite				
Item	1	2	3	4	5
1	>.628	.291	−.165	.131	.291
2	.300	>.527	−.175	.234	.109
3	−.170	−.107	>.327	.023	−.023
4	.189	.295	−.029	>.217	.209
5	.247	.125	.019	.107	>.367
6	>.610	.246	−.106	.153	.331
7	.332	>.379	−.132	.268	.188
8	−.149	−.225	>.396	.038	.040
9	.063	.018	.078	>.166	.116
10	.205	.063	.081	.183	>.438
11	>.430	.280	−.122	.153	.164
12	.126	>.305	−.138	.076	.023
13	−.031	−.098	>.248	.012	.048
14	.098	.200	.021	>.178	.065
15	.237	.116	−.032	.145	>.285

is higher than the correlation between item 4 and composite 4 (.217) that is congeneric. Also, the correlation between item 14 and composite 2 (.200) is higher than the correlation between item 14 and composite 4 (.178) that is congeneric.

Campbell and Fiske (1959) were especially concerned about the influence of methods of measurement. The importance that is attached to the methods demands an investigation of the relations between items and methods according to the procedure that was applied to correlations with the trait composites. The disaggregated correlations for combinations of items and method composites are presented in Table 3. These results suggest that the method composites have little convergent and discriminant validity.

Investigating the Intercorrelations Among the Composites

Several authors stress the importance of the correlations between the traits and the methods for the evaluation of an MTMM matrix (e.g., Browne, 1984; Schmitt & Stults, 1986). The trait-method correlations are of special interest because they are necessary for estimating the amount of method variance in trait composites. Because every trait composite has one item in common with a method composite, the correlation is overestimated due to partial self-correlation. In order to avoid self-correlation, the correction scheme described above was applied. Subsequently, the correlations were submitted to disaggregation to obtain comparability between item-composite correlations and composite-composite correlations. Disaggregation was applied on the assumption of independent mean correlations.

The correlations between the composites of the example are of special interest because they have been the subject of previous investigations (Browne, 1984; Jöreskog, 1971). The disaggregated composite-composite correlations are presented in Table 4. The disaggregated correlations between the composites are rather modest. The correlations between trait composites and method composites are lower than the corresponding correlations between items and trait composites in Table 2. Only in the case of the fourth trait composite are the differences quite small.

Table 3
Disaggregated Correlations Between Items and Method Composites for the Correlations in Table 12 of Campbell and Fiske (1959)

	Composite		
Item	1	2	3
1	>.177	.227	.251
2	>.220	.106	.224
3	>-.040	.028	-.062
4	>.289	.232	.087
5	>.230	.293	.045
6	.378	>.155	.185
7	.341	>.148	.154
8	-.029	>.008	-.027
9	.047	>.197	.045
10	.219	>.273	.111
11	.177	.218	>.130
12	.102	-.010	>.124
13	-.021	.048	>.022
14	.100	.063	>.224
15	.122	.141	>.224

Table 4
Disaggregated Intercorrelations Between Trait Composites and Method Composites for the Correlations in Table 12 of Campbell and Fiske (1959)

	Trait Composite					Method Composite	
Composite	1	2	3	4	5	1	2
Trait							
2	.29	1.00					
3	−.15	−.17	1.00				
4	.15	.19	.03	1.00			
5	.28	.12	.03	.15	1.00		
Method							
1	.23	.20	−.04	.14	.18	1.00	
2	.19	.08	.04	.16	.21	.16	1.00
3	.18	.16	−.03	.11	.12	.10	.09

Investigating Trait and Method Composites

One of the most characteristic features of a composite is its variance, because the amount of variance is an indication of the consistency of the items of the composite. Comparability of variances is achievable by relating actual variances, Var_{ac}, to maximum variances, Var_{max}, as well as to minimum variances, Var_{min}. All the item variances are assumed to be 1. Var_{max} is obtained under the condition of correlations of $r = 1.0$ among the items, whereas for Var_{min}, the correlations among the items are set to $r = 0.0$. A first degree of comparability is achieved by computing $\mathrm{Var}_{ac}/\mathrm{Var}_{max}$. The magnitude of this ratio varies between 1 and 0. In the next step, the Var_{min} that does not result from covariation between the items of a composite ($r = 0.0$) is eliminated. Finally, the proportion of systematic variance, V_s, is defined by

$$V_s = \frac{\mathrm{Var}_{ac} - \mathrm{Var}_{min}}{\mathrm{Var}_{max} - \mathrm{Var}_{min}} \quad . \tag{11}$$

V_s is independent of the number of items. If there is systematic covariation between the items included in a composite, V_s is larger than 0. An adequate representation of a trait requires a V_s that is considerably higher than 0. Cronbach's alpha (Cronbach, 1951) is another coefficient for measuring consistency. However, it depends on the number of items as well as on the variances of the items.

The V_s of various composites may be contrasted. Of special interest are comparisons of V_ss for alternative allocations of items. The overall composite provides the most general alternative, because in this case it is assumed that there is only one source of covariation that is common to all items. The proportion of V_s of the overall composite is indicated by V_o. A composite representing a substantial source of covariation that is trait specific is expected to obtain a V_s that exceeds V_o considerably. The ratio of the proportions of V_ss is defined as

$$V = V_s/V_o \quad . \tag{12}$$

If the value of V for a composite is considerably larger than 1, this can be regarded as an indication for the validity of the composite. The results of the investigation of the composite variances for the example are presented in Table 5. The V_ss for the traits and the methods vary in magnitude considerably. The V_s of the fourth trait composite is rather low, as are all the V_ss for the method com-

Table 5
Variance Coefficients for the Trait and Method Composites of the Example

Composite	$\frac{Var_{ac}}{Var_{max}}$	V_s	V
Trait			
1	.700	.550	4.231
2	.598	.397	3.054
3	.547	.320	2.462
4	.458	.187	1.438
5	.573	.359	2.762
Method			
1	.338	.172	1.323
2	.327	.159	1.223
3	.314	.142	1.092
Overall	.188	.130	

posites. The V coefficients show analogous results, although these differences are larger than the others.

Investigating Traits and Methods on the Facet Level

The facets of the MTMM design that imply the allocation of all items to composites are selected for the largest organizational unit that is included in the equal-level approach. At this level, a statistical test is proposed in order to arrive at a final conclusion. This test is designed to summarize the findings obtained on the lower levels of organization, and is based on the item-composite correlations for congeneric combinations because they represent the design of an MTMM matrix. Item-composite correlations that are based on another allocation of all items to composites pose an alternative to the structuring according to the design. Among the various alternatives, the allocation of items to an overall composite is regarded as the most important, because it represents the hypothesis of no underlying structure. Therefore, the item-composite correlations for the traits and for the methods were compared with the item-composite correlations for the overall composite.

The use of disaggregated correlations ensures comparability over differing composite sizes. Additionally, Fisher's z transformation was applied to the disaggregated correlations in order to compensate for skewness (Silver & Dunlap, 1987). t tests for independent groups were used to investigate the difference between the coefficients, because the data could be assumed to be metric and normally distributed. The results are presented in Table 6. Obviously, the traits differed from the methods as well as from the overall structure [$t(28) = 4.498, p = 0.0, t(28) = 5.249, p = 0.0$], whereas methods and overall structure did not differ.

Thus far, structures according to the traits as well as the methods were separately investigated. However, it is the validity of the traits that is to be evaluated. The methods of measurement are regarded as a potential danger to their validity. Therefore, the effect of the method composites was partialed out from the correlations between items and traits on the basis of disaggregated correlations. Again the t test was used to investigate the difference between the coefficients leading to results that are presented in the lower section of Table 6. The difference between trait structure and uniformity structure was still very significant [$t(28) = 4.9, p = 0.0$].

Discussion

The equal-level approach allows for an evaluation of MTMM matrices with respect to various

Table 6
t Test Results for the Comparisons Between Item-Trait Correlations (T), Item-Method Correlations (M), and Item-Overall-Composite Correlations (O), Based on Correlations and Partial Correlations

Contrast	*t*	*df*	*p*
Correlations			
T vs. O	5.249	28	0.000
M vs. O	.924	28	0.363
T vs. M	4.498	28	0.000
Partial Correlations			
T vs. O	4.900	28	0.000

organizational units while retaining the confirmatory character of an MTMM investigation. The higher the level of organization, the lower the number of coefficients needed to be investigated. Furthermore, units of different size can be analyzed separately. In this way, it is possible to locate deviations from the requirements of validity for individual items, composites, or entire facets. The evaluation is mainly based on comparisons between coefficients to avoid a large number of significance tests. Only for the organizational unit including all the variables is a statistical test included; all the statistics obtained at lower levels of organization are summarized in such a test.

The induction of equality in data-level is an essential part of the equal-level approach because conclusions based on coefficients differing in data-level may be regarded as inaccurate. Inequality in data-level can, for example, lead to an overestimation of the importance of method variance in comparison with trait variance if more items per method are available than items per trait. Achieving equality in data-level either by disaggregation to the basic data-level or by an appropriate adjustment using disaggregation was proposed. Disaggregation may also be used to eliminate partial self-correlations that pose another problem to be solved within the equal-level approach. However, this problem may also be solved by a correction scheme that even allows retention of all the correlational information.

Because one of the main aims of this approach is also to contribute to the investigation of convergent and discriminant validity of an MTMM matrix, applying disaggregation to the basic data-level is recommended. At the basic data-level, differences between coefficients are usually larger than at all higher data-levels. Furthermore, at this data-level, comparisons between item-composite correlations and composite-composite correlations are possible. However, disaggregation is not without weaknesses. The magnitudes of disaggregated coefficients are low so that they might possibly be regarded as unimportant. There is the danger that this observation might discourage researchers from increasing the number of items per trait. Therefore, the evaluation of the contribution of an item to a composite should not be based on a disaggregated correlation. The result achieved by means of the equal-level approach concerning the matrix of correlations adopted from Kelly and Fiske (1951) closely agrees with the original assessment made by Campbell and Fiske (1959). In both studies the validity of the trait "unshakable poise" was questioned. Deficiencies were obvious in the item-item correlations, the item-composite correlations, and the variances. The representation of the trait "broad interests," the validity of which was questioned in another study (Ray & Heeler, 1975), also proved to be weak.

The equal-level approach should be regarded as an attempt to extend the MTMM methodology presented by Campbell and Fiske (1959). The comparisons between coefficients of correlations are still an important part of the evaluation of an MTMM matrix. However, different levels of organization are added to reduce the number of comparisons and, consequently, to reduce the ambiguity of an evaluation. A test based on all the coefficients of an MTMM matrix serves to reach a final conclusion.

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