A CTC(M-1) Model for Different Types of Raters

Nussbeck, F W ; Eid, M ; Geiser, C ; Courvoisier, D S ; Lischetzke, T

DOI: https://doi.org/10.1027/1614-2241.5.3.88

Originally published at:
Nussbeck, F W; Eid, M; Geiser, C; Courvoisier, D S; Lischetzke, T (2009). A CTC(M-1) Model for Different Types of Raters. Methodology, 5(3):88-98.
DOI: https://doi.org/10.1027/1614-2241.5.3.88

A CTC(M–1) model for different types of raters

Fridtjof W. Nussbeck

Michael Eid

Christian Geiser

Delphine S. Courvoisier

Tanja Lischetzke

Abstract

Many psychologists collect multitrait multimethod (MTMM) data to assess the convergent and discriminant validity of psychological measures. In order to choose the most appropriate model, the types of methods applied have to be considered. It is shown how the combination of interchangeable and structurally different raters can be analyzed with an extension of the Correlated Trait - Correlated Method minus One [CTC(M–1)] model. This extension allows for disentangling individual rater biases (unique method effects) from shared rater biases (common method effects). The basic ideas of this model are presented and illustrated by an empirical example.

The analysis of convergent and discriminant validity of psychological measures plays a major role in the development of diagnostic instruments in the behavioral sciences. Campbell and Fiske (1959) introduced the multitrait-multimethod (MTMM) matrix to determine the degree to which psychological measures represent a particular construct (trait) rather than method-specific influences. During the last fifty years, many new and sophisticated approaches have been developed to refine the analysis of the correlation matrix proposed by Campbell and Fiske. Models of confirmatory factor analysis (CFA) and structural equation modeling (SEM) are the most prominent modern approaches to analyze MTMM data (Eid, 2000; Eid, Lischetzke, & Nussbeck, 2006; Eid, Lischetzke, Nussbeck, & Trierweiler, 2003; Marsh, 1989; Marsh & Grayson, 1995; Saris & van Meurs, 1991; Widaman, 1985).

Based on the seminal work of Campbell and Fiske (1959), modern MTMM approaches have three major aims: (1) Determining the convergent validity, (2) determining the discriminant validity, and (3) defining latent variables representing trait-specific, method-specific, and error-specific influences (e.g., Eid et al., 2006). *Convergent validity* represents the degree to which different methods and indicators aiming to measure the same trait converge. *Discriminant validity*, in contrast, is high when measurements of different traits show low associations.

Recently, Eid and colleagues (2006; Eid, Nussbeck, Geiser, Cole, Gollwitzer, & Lischetzke, 2008) distinguished between different types of methods and their implication for (1) choosing an appropriate MTMM model and (2) interpreting method factors. A major distinction is whether different methods are *interchangeable* or *structurally different*.

The distinction between interchangeable and structurally different raters resembles the distinction between random and fixed factors in the analysis of variance (e.g., Hays, 1994). In the case of random factors, the different factorial groups are considered as randomly chosen from a population, and the researcher aims to estimate the mean and the variance of the factor. In contrast, the fixed effect model aims at analyzing the specific effects of different groups that are not randomly chosen and to contrast them.

A typical example of interchangeable methods is the analysis of teaching quality by students. Students' ratings of a teacher's performance can be conceived of as interchangeable since all students attend the same classes and share the same information about the teacher's performance. Therefore, a random sampling of some of the students adequately represents the whole population of students attending the same class. The main interest in this situation is in measuring a trait (e.g., a dimension of teaching ability) and estimating the precision with which this trait is measured (convergent validity).

If the teacher additionally rates her or his own performance, the teacher rating will differ structurally from the students' ratings since teachers naturally have another point of view with respect to the educational processes in classes. Moreover, the teacher would provide a self-report whereas students' ratings are other reports. The specific effects of the students’ ratings compared to the teacher ratings are important in this design. It is of interest to measure a trait (e.g., a dimension of teaching quality) and to estimate the convergence of student and teacher ratings of this trait (convergent validity) as well as to estimate the specific effects of the students’ ratings (method effects).

Eid et al. (2008) have shown how an MTMM model for interchangeable and structurally different raters can be defined using multilevel factor analysis. However, the same type of data can also be analyzed using traditional CFA. Curran (2003) has shown that for some types of data models of traditional CFA and multilevel models can be applied yielding identical results. The aim of the present contribution is to extend the Correlated Trait-Correlated Method minus One (CTC(M-1) Model to a model that allows for the analysis of method effects when the methods are a combination of structurally different and interchangeable methods relying on the traditional CFA approach. Applying specific equality restrictions on model parameters the model is equivalent to the multilevel model proposed by Eid et al. (2008). Moreover, without these equality restrictions the CFA-CTC(M-1) model is an even more general model than the multilevel model. We will provide the psychometric definition of the model and simultaneously use an example to conceptually describe the model. Finally, we will illustrate the model and the meaning of the model parameters using an empirical application.

Development of the CTC(M–1) model for structurally different and interchangeable methods

We will first review the standard CT-C(M-1) Model and then show its extension to the combination of structurally different and interchangeable methods.

The standard multiple indicator CTC (M-1) Model

Figure 1 depicts the CTC(M–1) model for structurally different raters (Eid et al., 2003) with indicator-specific trait variables. In many applications multiple indicators are not perfectly homogeneous representations of one single construct. In order to account for this specificity (heterogeneity), there is one trait variable for each indicator. Since there are two indicators for each trait-method combination (trait-method unit; TMU) in Figure

1 there are two latent trait variables for each construct. We will shortly review the major properties of the multiple indicator CTC(M–1) model based on the empirical application presented below. In this application, three traits (Extraversion j = 1, Neuroticism j = 2, and Conscientiousness j = 3) are assessed by one self-report (k = 1) and two peer reports (k = 2, 3). We consider the two peer reports interchangeable (i.e., we assume that there is no structural difference between the two raters) the self-report differs structurally from them. Each TMU consists of two indicators (i = 1, 2).

Eid et al. (2003) formulated the CTC(M–1) model based on principles of true-score theory (see Lord & Novick, 1968). In a first step, an observed variable $\left(Y_{ijk}\right)$ is decomposed into a true-score variable $\left(\tau_{ijk}\right)$ and measurement error $\left(\varepsilon_{ijk}\right)$ for each indicator (i) of a trait (j) measured by a specific method (k): $Y_{ijk} = \tau_{ijk} + \varepsilon_{ijk}$. The true-score comprises all systematic influences. These can be influences of the trait, the method, the measurement situation and the item contents for example (for an overview about possible systematic influences on measurement scores, see Burns & Haynes, 2006). Since the CTC(M–1) model relies on the idea of contrasting methods, one method has to be taken as the reference method (the "gold standard"). No method factor is specified for the reference method, thus, all systematic variance of all indicators belonging to the reference method is captured by the indicator-specific trait variables. Therefore, the true-scores of the reference-method indicators are the trait-scores in the CTC(M-1) model with indicator-specific trait-variables. All other indicators (of non-reference methods) are contrasted against these trait-variables.

In the present empirical example, the self-report stands out because it structurally differs from the peer reports. Choosing the self-report as reference method implies that the trait variables in Figure 1 are defined as the true-score variables of the self-report indicators:

$T_{ij1} = \tau_{ij1}$, and (1)

$Y_{ij1} = T_{ij1} + \varepsilon_{ij1}$.

The self-reported trait variables are used in a latent regression to predict the true-scores of the peer reports (the non-reference methods). The latent (true) residual of this regression corresponds to the peer specific method effect. It is the part of the true peer rating that cannot be explained by the self report — it is, thus, the peer-specific effect. This prediction will generally be far from perfect yielding a substantial residual variable. This residual — the over- or underestimation of a given peer from the expected score — is conceived as the peer-specific effect inherent in this particular indicator. The indicators of the peer reports (as non-reference method), thus, depend on three sources of variance: i) the trait variable representing the "true" (error-free) self-report (T_{ij}), and two residual components ii) a (peer-specific) method effect (M_{jk}), and iii) measurement error (ε_{ijk}):

$Y_{ijk} = \alpha_{ijk} + \lambda_{\mathrm{T}ijk} T_{ij1} + M_{ijk} + \varepsilon_{ijk}$, for non-reference methods $(k \neq 1)$, (2)

with $M_{ijk} = \tau_{ijk} - E\left(Y_{ijk} \mid T_{ij1}\right)$, and

$$E(Y_{ijk} | T_{il1}) = \alpha_{ijk} + \lambda_{\mathrm{T}ijk} T_{ij1} .$$

The method effects belonging to the same TMU are generally assumed to depend on one trait-specific method factor to identify the model (i.e., all method-specific residuals $\left(M_{ijk}\right)$ are assumed to be unidimensional for a given trait-method unit *jk*):

$$M_{ijk} = \lambda_{\mathrm{M}ijk} M_{jk} , \tag{3}$$

which yields the final CTC(*M*–1) model equation for non-reference methods:

$$Y_{ijk} = \alpha_{ijk} + \lambda_{\mathrm{T}ijk} T_{ij1} + \lambda_{\mathrm{M}ijk} M_{jk} + \varepsilon_{ijk} \text{, for non-reference methods } \left(k \neq 1\right). \tag{4}$$

In the standard CTC(*M*–1) model all trait variables are allowed to covary. Correlations between trait variables of the same construct (e.g., the two facets of extraversion) reflect convergent validity; correlations across constructs (e.g., a facet of extraversion with a facet of neuroticism) reflect discriminant validity. Method effects may covary within and across methods. Correlations between the method factors belonging to the same method indicate the degree to which method effects generalize across traits. Between methods, correlations of method factors indicate if there are common parts of variance of the non-reference methods. Particularly interesting are correlations of different method factors (for the two peers) belonging to the same construct (e.g., extraversion). These correlations show if the two peers deviate in the same way from the predicted scores based on the self-report; a high correlation would indicate a common method effect.

Besides the clear meaning of the latent variables and, thus, the very clear interpretation of the latent correlations, another strength of the CTC(*M*–1) model is that it allows quantifying different variance components (see Eid et al., 2003, 2006, 2008; Nussbeck, Eid, & Lischetzke, 2006). The consistency coefficient (*CO*) identifies the part of the variance that can be predicted by the trait variable (the self-reported trait):

$$CO(\tau_{ijk}) = \frac{\lambda^2_{\mathrm{T}ijk} Var(T_{ij1})}{Var(\tau_{ijk})}. \tag{5}$$

Necessarily, this coefficient equals 1 for the self-reports since the self-reported true scores *are* the trait-scores. In the same way, the (true) variance components due to the method factors can be determined as:

$$MS(\tau_{ijk}) = \frac{\lambda^2_{\mathrm{M}ijk} Var(M_{jk})}{Var(\tau_{ijk})}. \tag{6}$$

The method specificity coefficient (*MS*) provides an estimate of the variance due to an individual rater. The consistency and method-specificity coefficients can also be defined for the observed variables (see Eid et al., 2003).

In some cases, researchers are interested in method effects that are common to peers and not unique to specific peers. Therefore they aggregate across peer ratings to have scores free of specificities to one rater (cf. Spain, Eaton, & Funder, 2000; Watson &

Clark, 1991). In the standard CT(*M*-1)model this common method effect is reflected in the latent correlation between method factors. Yet, there is no variable in the CTC(*M*–1) model representing this common method effec. It is thus not easily feasible to estimate the common method variance components which are shared between peer raters (variance due to a common method effect).

The CTC(M-1) Model with common method effects

The CTC(*M*–1) model can easily be extended to a CTC(*M*–1) model *with common method effects* (*CM*). The common method effects reflect the parts of method effects, which are shared by peers (the common deviation of peers from the prediction based on the trait variable only). Figure 2 presents this model for three traits and three methods. The model equation for the self-reports does not change:

$$Y_{ij1} = \alpha_{ij1} + T_{ij1} + \varepsilon_{ij1}\,. \qquad \text{(1, repeated)}$$

The model equation for the peer reports is extended by splitting the method-specific effect into two parts:

$$M_{ijk} = \lambda_{\mathrm{M}ijk} M_{jk} = \lambda_{\mathrm{CM}ijk} CM_j + \lambda_{\mathrm{UM}ijk} UM_{jk}\,, \qquad (7)$$

which yields $Y_{ijk} = \alpha_{ijk} + \lambda_{\mathrm{T}ijk} T_{ij1} + \lambda_{\mathrm{CM}ijk} CM_j + \lambda_{\mathrm{UM}ijk} UM_{jk} + \varepsilon_{ijk}\,.$ (8)

The method specific effect $\left(M_{ijk}\right)$ in the traditional CTC(*M*–1) model is now additively decomposed into one part which is common to the two peers (CM_j) and a second part which is unique to a particular peer (UM_{jk}). Thus, peer-report indicators are influenced by four sources of variance. These influences can be quantified calculating the variance components:

$$CO(\tau_{ijk}) = \frac{\lambda^2_{\mathrm{T}ijk} Var(T_{ij})}{Var(\tau_{ijk})}, \tag{9}$$

as consistency coefficient and the method-specificity coefficient:

$$MS(\tau_{ijk}) = \frac{Var(M_{ijk})}{Var(\tau_{ijk})} = \frac{\lambda^2_{\mathrm{CM}ijk} Var(CM_j) + \lambda^2_{\mathrm{UM}ijk} Var(UM_{jk})}{Var(\tau_{ijk})}, \tag{10}$$

as the combination of common and unique method effects. The common method-specificity coefficient:

$$CMS(\tau_{ijk}) = \frac{\lambda^2_{\mathrm{CM}ijk} Var(CM_j)}{Var(\tau_{ijk})}, \tag{11}$$

represents the part of variance due to the common method factor. The unique method specificity coefficient:

$$UMS(\tau_{ijk}) = \frac{\lambda^2_{\mathrm{UM}ijk} Var(UM_{jk})}{Var(\tau_{ijk})}, \tag{12}$$

represents the variation of a true-score which is only due to the unique method effect. Replacing the true-variance $\left[Var(\tau_{ijk})\right]$ by the model-implied variance of the observed variables $\left[Var(Y_{ijk})\right]$ in the denominators of Equations 9 to 12 yields the manifest variance components (see Eid et al., 2003).

The definition of the model via latent regressions implies the interpretation of the different model components. The trait variable $\left(T_{ij1}\right)$ is the true-score of the self-report for a particular indicator. It comprises trait effects as well as method effects specific to the self-report (i.e., the trait factor is confounded with the self-report / reference method). This variable is used as a predictor in a latent regression to predict the scores of the peer-report indicators. The loading parameter $\left(\lambda_{\mathrm{T}ijk}\right)$ can be interpreted as the regression coefficient. The latent residual of this regression (belonging to the peer reports) can be split into two parts. The first part (i) is *common* to the two peer reports, whereas the second part (ii) is *unique* to a given peer report. (i) The first part of this residual is represented by the *common method factor* (CM_j). This component can be interpreted as the *general peer-specific effect* with respect to a particular trait — it answers the question of whether the common part of the rating of the peers is an over- or underestimation of the predicted score given the trait score. Given its definition as a residual variable, its mean value has to be 0. (ii) The second part of the latent residual is represented by the *unique method factor* $\left(UM_{jk}\right)$. This component comprises the individual (unique) deviation of the true-score for a given peer from the predicted score when trait and common method-specific influences are already considered. The unique method factor is the part of the peer-specific effect that is unique to a particular peer rater and not shared with the other peer raters.

Integrating the common method factor into the model also has consequences with respect to the correlations in the model (for an overview on admissible and non-admissible variances and covariances see Appendix A):

- The common method factor as well as the unique method factor are residuals with respect to the trait variable of the same trait method unit. Therefore, these variables are not correlated with the trait variables sharing the same index j — their predictors in the latent regressions.
- Since all common parts of the non-reference methods are captured by the trait and the common method factor, the unique method factors of different methods must not correlate across methods. Unique method factors are only allowed to covary within one method indicating the degree of generalizability of the unique method-specific effects. These correlations show if peers produce a stable method effect irrespective of the trait under consideration or trait-specific method effects.
- Correlations between common method factors are allowed reflecting general method effects of non-reference methods across traits.
- Traits are allowed to covary with common method factors as well as with unique method factors of different trait-method-units. These correlations show if trait scores can predict the over- or underestimation of aggregated peer ratings and / or of particular methods with respect to another trait.

The CTC (M-1) Model for Structurally Different and Interchangeable Methods

Interchangeable methods. Interchangeable raters are randomly chosen out of a set of possible raters. Random samples out of one population should not differ with respect to their distributions. Thus, some restrictions should be incorporated into the model concerning the following parameters: the intercepts $\left(\alpha_{ijk}\right)$, the loading parameters $\left(\lambda_{\mathrm{T}ijk}, \lambda_{\mathrm{CM}ijk}, \text{ and } \lambda_{\mathrm{UM}ijk}\right)$, and the variances of the latent variables $\left(\sigma^2_{UM_{jk}} \text{ and } \sigma^2_{\varepsilon_{ijk}}\right)$ have to be identical across all interchangeable methods measuring the same trait. This results in the following model equation for interchangeable (non-reference) methods:

$$\begin{aligned}
&Y_{ijk} = \alpha_{ijk} + \lambda_{\mathrm{T}ijk} T_{ij1} + \lambda_{\mathrm{CM}ijk} CM_j + \lambda_{\mathrm{UM}ijk} UM_{jk} + \varepsilon_{ijk}, \text{ with} \\
&\alpha_{ij2} = \alpha_{ij3} \\
&\lambda_{\mathrm{T}ij2} = \lambda_{\mathrm{T}ij3} \\
&\lambda_{\mathrm{CM}ij2} = \lambda_{\mathrm{CM}ij3} \\
&\lambda_{\mathrm{UM}ij2} = \lambda_{\mathrm{UM}ij3} \\
&\sigma^2_{\varepsilon_{ij2}} = \sigma^2_{\varepsilon_{ij3}} \\
&\sigma^2_{UM_{j2}} = \sigma^2_{UM_{j3}},
\end{aligned} \tag{13}$$

In the current data situation, for example, these coefficients have to be identical for the two peer groups because the two peer raters are randomly selected out of the same set of possible peer raters given the self-rater. Note that these are constraints concerning the distributions of the latent and manifest variables as well as the links between these variables. The restrictions do not imply that a pair of peers must have the same scores on latent or manifest variables.

Figure 3 shows a trait unit for one structurally different method (self-report) and two interchangeable methods. Model parameters constrained to be equal are marked with Roman letters.

Convergent and discriminant validity. The CTC(M–1) model for structurally different and interchangeable methods allows analyzing the convergent and discriminant validity of self- and peer reports. The convergent validity can be analyzed by inspecting the correlation of the testhalf-specific trait variables of one construct $\left[Corr\left(T_{ij1}, T_{i'j1}\right)\right]$. These correlations should, generally, be close to 1 indicating that the indicators measure exactly the same construct. Additionally, the convergent validity can be determined by regarding different measurement methods. The proportion of the true-score variance of the peer report indicators that can be explained by the trait variables determines the *convergence* of these two methods (*consistency coefficient*). Moreover, the model allows determining the proportion of variance of the peer report indicators that is explained by the common method factor (*common method specificity coefficient*) and by the unique method factors (*unique method specificity coefficient*; see Eq. 10–12). These coefficients indicate whether peer-specific effects represent mainly common effects shared across peers or whether peer-specific effects are mainly due to an individual rater-specific perspective.

The discriminant validity is represented by the correlations between trait variables of different constructs $\left[Corr\left(T_{ij1}, T_{i'j'1}\right)\right]$. The generalizability of the common peer bias across constructs is reflected by the correlations of the common method factors

$\left[Corr\left(CM_{j},CM_{j'}\right)\right]$. The generalizability of the unique method effects across constructs is reflected by the correlations of the unique method factors $\left[Corr\left(UM_{jk},UM_{j'k}\right)\right]$.

Empirical Application

We will present an empirical application in order to show how the model can be estimated and how to interpret the findings with respect to questions of convergent and discriminant validity. The empirical data correspond to the classical MTMM data situation which consists of three traits [Extraversion (j = 1), Neuroticism (j = 2), and Conscientiousness (j = 3)] measured by three different methods [one self-report (k = 1) and two (interchangeable) peer reports (k = 2, 3)] using self- and peer-report questionnaires. Each trait-method combination consists of four items with 5 categories. For ease of presentation, we created testhalves by calculating the mean of two indicators in order to have metric indicators (see Appendix B). The sample consists of 481 self-raters who were enrolled as students at the University of Trier and the University of Applied Sciences of Trier (Germany) and two of their peers who also filled in the same questionnaire but in the peer report version. The two peers were arbitrarily assigned to be Peer A or B. The peers can be regarded interchangeable since they were random samples of the set of possible peers given the self-report.

The CTC(*M*–1) model for structurally different and interchangeable methods was analyzed using Mplus 4 (Muthén & Muthén, 2006). In order to have the most parsimonious and most simple illustration, we applied the very restricted version of the model as presented in Figure 2 (with the restrictions depicted in Figure 3 for each trait-method-unit). The model fits well to the data (χ^2 = 138.45; *df* = 111; *p* = .04; CFI = .99; RMSEA = .02).

The intercepts, loading parameters, and residual variances for all indicators can be found in Table 1. The loading parameters of the reference method on the trait variable have been fixed to unity in order to define the true-score of these indicators as trait score. Additionally, the first loadings of the common method factors and all loadings on the unique method factors have been fixed to unity in order to identify the model[1]. The intercepts of the self-report variables have been fixed to 0 in order to estimate the mean value of the latent trait variable.

The reliabilities of the indicators differ vastly across and within scales. The conscientiousness indicators show acceptable reliabilities. All reliabilities are higher than .68. The extraversion indicators have lower reliabilities $\left(.63 \leq R^2 \leq .75\right)$. Dissatisfying results are obtained for the neuroticism indicators with reliabilities around .50 (except for the first indicator)[2].

Table 2 shows the decomposition of the true variances for all indicators. In general, around 40% to 50% of the variation of the peer indicators is due to the unique method factor, 15% to 34% of the variance is shared between the peers and between 17% and 44% of the variance is due to the trait variable (shared with the self-report). Thus, the true variance depends substantially on all three variance components. Moreover, the consistency coefficient can be interpreted as an indicator of convergent validity between structurally different raters. The square-root of this coefficient corresponds to the latent correlation between trait and indicator. Thus, the latent correlations between self-reported latent traits and peer-rated indicators range from .41 to .66.

The analysis reveals some interesting results concerning the trait variables. The consistency coefficients are higher for extraversion than for neuroticism and conscientiousness. This might be due to the fact that extraversion is a more visible attribute than the other two traits. On the other hand, the common method specificity is relatively high for neuroticism and conscientiousness. A relatively strong part of a peer´s view of these two attributes is shared with the other peer, but not with the self. This part is at least as large as the common part shared with the selves. The CTC(*M*–1) model enables researchers to identify these variance components, yet, additional research must be conducted to examine why self-reports and peer reports differ (see e.g., John & Robins, 1993). This may be due to several possible reasons:

1) Self-raters may have a tendency to show socially desirable behavior in situations with social interactions. Peers must generally rely on these situations to build up their view of another person. Self-raters may not have this tendency when filling in a questionnaire. Since for some traits there are stronger norms than for others, the tendency to show socially desirable behavior will produce different amounts of over- or underestimations for different traits in peer ratings.
2) Social desirability may inflict the self-rating. Self-raters may answer the questionnaire trying to meet the wishes of the investigator or to show themselves in a favorable light. Peer raters may not show the same tendency.
3) Some pairs of peer-raters may also have a tendency to show their friends (self-raters) in a favorable light.

4) The self-rater may feel that her or his behavior is not neurotic at all whereas both peers think that she or he shows clear neurotic tendencies. If the two peers are correct, this would correspond to the bias of self-deception.

This list of possible biases is by far not exclusive. Depending on the research domain different biases may occur. Therefore, the large parts of variances that are due to the unique method factors indicate that the peers—although they are interchangeable—have a unique view of the target person. High values on the unique method specificity coefficient thus indicate that the self-ratings cannot be used to predict the peer ratings very well, however, the values of the latent consistency coefficients are in line with prior research results (see e.g., Colvin, 1993; Funder, 1995).

Table 3 presents the mean values, variances, and correlations of the latent variables. All latent mean values of trait variables correspond to the mean values of the manifest self-report indicators. Table 3 also presents the latent correlation matrix. The correlation matrix reveals some interesting results. The test-halves measuring the same trait $\left[COR(T_{ij1}, T_{i'j1});\ i \neq i'\right]$ are highly correlated $\left(r \geq .75\right)$ indicating high albeit not perfect convergent validity (these parameters are underlined in Table 3). The items forming the indicators seem to measure two slightly different facets of the trait under consideration (except for the very homogeneous indicators of conscientiousness, $r = .96$). The correlations between trait variables of different constructs $\left(COR(T_{ij1}, T_{i'j'1});\ i \neq i' \ \vee \ i = i';\ j \neq j'\right)$ are very small indicating high discriminant validity (all $|r| \leq .16$).

The correlations between common method factors $\left[COR(CM_j, CM_{j'});\ j \neq j'\right]$ indicate the generalizability of the common method effect. None of these correlations (grey shaded cells in Table 3) is significant showing that common method effects are trait-specific. In other words, knowing the deviation of a pair of peers for one trait does not tell us anything about their deviation with respect to another trait. Correlations between trait variables and common method factors $\left[COR(T_{ij}, CM_{j'});\ j \neq j'\right]$ are allowed for variables belonging to different traits. These correlations show whether common method effects can be explained by other trait variables. Extraverted individuals tend to be judged more neurotic (one of the two correlations is positive, the other one is not significant). Extraverted individuals are also judged less conscientious (the two negative correlations are significant). More conscientious individuals tend to be judged more neurotic (two significant positive correlations) and less extraverted (two significant negative correlations).

Covariances between unique method effects of the same method but different traits were set equal across methods. The results show that only the unique method effects for extraversion and conscientiousness are significantly correlated $(r = .14)$. A peer who judges the target higher on extraversion than predicted by the trait and the common method specific variable also tends to judge the target higher on conscientiousness. The correlations between common method factors and the correlations between unique method factors show that method effects do by far not generalize across traits. No correlations are allowed between unique method factors and any other factors except for unique method factors of the same method.

Discussion

The CTC(*M*–1) model has proven to be a very versatile tool to analyze the convergent and discriminant validity of psychological scales. Extending the standard CTC(*M*–1) model to the CTC(*M*–1) model with common method effects additionally allows inspecting to which degree method effects are shared across interchangeable methods. The specification of common and unique method factors allows examining these two effects in one single analysis. Often, researchers aggregate across peer raters to have scores free of specificities to one rater (cf. Spain et al., 2000; Watson & Clark, 1991). In the CTC(*M*–1) model with common method effects, researchers can simultaneously analyze the aggregated peer-specific method effect (*CM*) and the specific or unique peer-specific method effect (*UM*).

The model for structurally different and interchangeable methods is defined by specific restrictions on the parameters. These restrictions are reasonable because the peer raters are randomly selected from a group of peers. The model is equivalent to the multilevel MTMM model for structurally different and interchangeable methods proposed by Eid et al. (2008). An advantage of the model defined as a classical CFA model is, that the hypothesis that the methods are interchangeable can be tested by comparing the model with restrictions and the model without these restrictions. In our example the $\chi2$-difference test showed that the models do not differ in their fit [$\chi2$-difference (scaled) = 20.95 df = 27 p = .79). A disadvantage of the model compared to the multilevel model is that the number of interchangeable methods must not differ between targets. This, however, is possible in the multilevel model.

If the CTC(*M*-1) model for structurally different and interchangeable methods holds this indicates that i) there is a substantial common method effect and ii) the observed variables of the presumably interchangeable methods follow the same distribution and are (at least) statistically interchangeable. However, it may occur that the unique variance components (*UMS*) are much higher than the shared variance components (*CO* and *CMS*); this indicates that although the methods are statistically interchangeable, they do not converge to a large extent. Therefore, the scores of one interchangeable method (e.g. Peer A) are not trustworthy as indicators of the general peer-specific view (because these scores rather represent a unique peer-specific view). To obtain a general peer rating (an aggregated peer view) the scores of several peers have to be considered. In contrast, if the common method specificity is very high, the scores of one peer may be sufficient to represent the general (common) peer-view (see also Eid et al., 2008).

The meaning of latent variables in the context of SEM and MTMM models is an issue that requires careful consideration (see e.g., Geiser, Eid, & Nussbeck, 2008). Defining the CTC(*M*–1) model and its variants relying on principles of true-score theory determines the meaning of the latent variables in a psychometrically very clear way. The trait score, for example, is the true-score of the reference method.

In the CTC(*M*-1) model with common method effects as in the model for structurally different and interchangeable methods, two systematic method-specific effects can be separated from the true-score of the reference method: The common and the unique deviation of non-reference methods from the reference method. The common method factors (*CM*) represent the variance that is shared by the peers, but that is not shared with the self. The unique method factors represent the variance that is unique to a peer rater and that is not shared with another rater neither with the other peer nor with the self.

The CTC(*M*–1) model and its variations are best suited for the analysis of MTMM data when one method is theoretically outstanding with respect to the other methods. Researchers should apply the CTC(*M*–1) model for structurally different and interchangeable methods when a group of methods is assumed to be interchangeable. The empirical example shown here corresponds to this case. If one exclusively deals with structurally different methods, one should apply the standard CTC(*M*–1) model. If one is interested in general effects of non-reference methods the CTC(*M*–1) model with common method effects should be applied. A typical example for this case may be to investigate the common deviation of mothers and fathers from the scores predicted by their child's self-report.

The choice between the many different MTMM models should be driven by theoretical considerations. If one is interested in a common trait score, the CTUM model should be applied. If one is interested in contrasting several methods against each other, one should choose the CTC(*M*–1) model. If one is interested in common method biases, the CTC(*M*–1) model with common method effects should be applied. If, moreover, there is at least one group of methods that can be conceived as interchangeable, the CTC(*M*–1) model for structurally different and interchangeable methods should be applied.

References

Burns, G. L. & Haynes, S. N. (2006). Clinical Psychology: Construct validation with multiple sources of information and multiple settings. In M. Eid and E. Diener (Eds.) *Handbook of Multimethod Measurement in Psychology*. Washington, DC: American Psychological Association.

Campbell, D. T., & Fiske, D. W. (1959). Convergent and discriminant validation by the multitrait-multimethod matrix. *Psychological Bulletin*, *56*, 81-105.

Colvin, C. R. (1993). Judgable people: Personality, behavior, and competing explanations. *Journal of Personality and Social Psychology*, *64, 861–873.*

Courvoisier, D.S., Nussbeck, F. W., Eid, M., Geiser, C., & Cole, D. A. (2008).Analyzing the convergent validity of states and traits: Development and application of multimethod latent state trait models. *Psychological Assessment, 20*, 270-280.

Curran, P. J. (2003). Have multilevel models been structural equation models all along? *Multivariate Behavioral Research, 38*, 529-569.

Eid, M. (2000). A multitrait-multimethod model with minimal assumptions. *Psychometrika*, *65*, 241-261.

Eid, M., Lischetzke, T., & Nussbeck, F.W. (2006). Structural equation models for multitrait-multimethod data. In M. Eid & E. Diener (Eds.), *Handbook of psychological measurement: A multimethod perspective* (pp. 283-299). Washington, DC: American Psychological Association.

Eid, M., Lischetzke, T., Nussbeck, F. W., & Trierweiler, L. I. (2003). Separating trait effects from trait-specific method effects in multitrait-multimethod models: A multiple-indicator CT-C(M–1) model. *Psychological Methods*, *8*, 38-60.

Eid, M., Nussbeck, F. W., Geiser, C., Cole, D. A., Gollwitzer, M., & Lischetzke, T. (2008). Structural equation modeling of multitrait-multimethod data: Different models for different types of methods. *Psychological Methods, 13*, 230-253.

Funder, D. C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological Review*, *102*, 652–670.

Geiser, C., Eid, M., & Nussbeck, F. W. (2008). On the meaning of the latent variables in the CT-C(M–1) model: A comment on Maydeu-Olivares and Coffman (2006). *Psychological Methods, 13,* 49-57.

Hays, W. L. (1994). *Statistics (5th ed.)*. Orlando, FL, US: Harcourt Brace College Publishers.

John, O. P. & Robins, R. W. (1993). Determinants of interjudge agreement on personality traits: The Big Five domains, observability, evaluativness, and the unique perspective of the self. *Journal of Personality*, *61*, 521 - 551.

Lord, F. M., & Novick, M. R. (1968). *Statistical theories of mental test scores*. Reading, MA: Addison-Wesley.

Marsh, H. W. (1989). Confirmatory factor analyses of multitrait-multimethod data: Many problems and a few solutions. *Applied Psychological Measurement*, *13*, 335-361.

Marsh, H. W. & Grayson, D. (1995). Latent variable models of multitrait-multimethod data. In R. H. Hoyle (Ed.), *Structural equation modeling: Concepts, issues, and applications* (pp. 177-198). Thousands Oaks: Sage Publications.

Muthén, L. K. & Muthén, B. O. (2006). *Mplus user's guide*. Los Angeles, CA: Muthén & Muthén.

Nussbeck, F. W., Eid, M., & Lischetzke, T. (2006). Analyzing MTMM data with SEM for ordinal variables applying the WLSMV-estimator: What is the sample size needed for valid results? *British Journal of Mathematical and Statistical Psychology*, *59*, 195-213.

Saris, W. E. & van Meurs, A. (1991). Evaluation of measurement instruments using a structural modeling approach. In P. P. Biemer, R. M. Groves, L. E. Lyberg, N. A. Mathiowetz & S. Sudman (Eds.), *Measurement errors in surveys* (pp. 575-597). New York: Wiley.

Spain, J. S., Eaton, L. G., & Funder, D. C. (2000). Perspectives on personality: The relative accuracy of self versus others for the prediction of emotion and behavior. *Journal of Personality, 68*, 837-867.

Watson, D., & Clark, L. A. (1991). Self- versus peer ratings of specific emotional traits: Evidence of convergent and discriminant validity. *Journal of Personality and Social Psychology, 60*, 927-940.

Widaman, K. F. (1985). Hierarchically nested covariance structure models for multitrait-multimethod data. *Applied Psychological Measurement*, *9*, 1-26.

Appendix A

Table A1.

*Admissible (x) and non-admissible (–) variances and covariances in the CTC(*M*–1) model with common method effects depicted in Figure 2.*

	Variances and Covariances														
	T_{111}	T_{211}	T_{121}	T_{221}	T_{131}	T_{231}	CM_1	CM_2	CM_3	UM_{12}	UM_{22}	UM_{32}	UM_{13}	UM_{23}	UM_{33}
T_{111} (1st TH Extraversion)	x														
T_{211} (2nd TH Extraversion)	x	x													
T_{121} (1st TH Neuroticism)	x	x	x												
T_{221} (2nd TH Neuroticism)	x	x	x	x											
T_{131} (1st TH Conscient.[a]).	x	x	x	x	x										
T_{231} (2nd TH Conscient.[a])	x	x	x	x	x	x									
CM_1 (CMF Extraversion)	–	–	x	x	x	x	x								
CM_2 (CMF Neuroticism)	x	x	–	–	x	x	x	x							
CM_3 (CMF Conscient.[a])	x	x	x	x	–	–	x	x	x						
UM_{12} (MF Extraversion)	–	–	–	–	–	–	–	–	–	x					
UM_{22} (MF Neuroticism)	–	–	–	–	–	–	–	–	–	x	x				
UM_{32} (MF Conscient.[a])	–	–	–	–	–	–	–	–	–	x	x	x			
UM_{13} (MF Extraversion)	–	–	–	–	–	–	–	–	–	–	–	–	x		
UM_{23} (MF Neuroticism)	–	–	–	–	–	–	–	–	–	–	–	–	x	x	
UM_{33} (MF Conscient.[a])	–	–	–	–	–	–	–	–	–	–	–	–	x	x	x

Notes. T_{ijk}: Trait; CM_j: Common Method Factor; UM_{jk}: Unique Method Factor; TH: testhalf; [a] Conscient. = Conscientiousness.

Appendix B

Table B1.

Construction of indicators

Indicator	Item (English translation)	German original item
	Extraversion	
1st	sociable	kontaktfreudig
	companionable	gesellig
2nd	vivacious	lebhaft
	spirited	temperamentvoll
	Neuroticism	
1st	vulnerable	verletzbar
	sensitive	empfindlich
2nd	moody	launenhaft
	self-doubtful	selbstzweiflerisch
	Conscientiousness	
1st	industrious	arbeitsam
	diligent	fleissig
2nd	dutiful	pflichtbewusst
	ambitious	strebsam

Author Note

Fridtjof W. Nussbeck, Department of Psychology, University of Zurich, Switzerland.

Michael Eid, Christian Geiser, Tanja Lischetzke, Department of Psychology, Free University of Berlin. Delphine S. Courvoisier, Department of Epidemiology, Faculty of Medicine, University of Geneva

This research was funded by Grant 101411-103771/1 from the Swiss National Science Foundation.

Correspondence concerning this article should be addressed to Fridtjof W. Nussbeck, Department of Psychology, University of Zurich, Binzmuehlestrasse 14/23, 8050 Zurich, Switzerland. Phone: 0041-44-6357544. Fax: 0041-43-6357552. E-mail: fridtjof.nussbeck@psychologie.uzh.ch

Footnotes

[1] An annotated Mplus-input can be obtained from the first author upon request..

[2] For illustrative reasons, we decided to create indicators consisting of two items only. Therefore, one may not expect high reliabilities.

Table 1

Intercepts, Loading Parameters, Error Variances, and Reliabilities in the CTC(M-1) model for structurally different and interchangeable methods.

Indicator	α	Loading Parameters			Var(ε)	Rel.
		Trait	*CM*	*UM*		
Extraversion						
Y_{111}	0	1			0.18	.75
Y_{211}	0	1			0.27	.63
Y_{112}	2.05	0.55	1	1	0.24	.65
Y_{212}	0.88	0.75	1.32	1	0.29	.67
Y_{113}	2.05	0.55	1	1	0.24	.65
Y_{213}	0.88	0.75	1.32	1	0.29	.67
Neuroticism						
Y_{121}	0	1			0.22	.74
Y_{221}	0	1			0.41	.60
Y_{122}	2.19	0.32	1	1	0.47	.44
Y_{222}	1.48	0.35	1.13	1	0.40	.51
Y_{123}	2.19	0.32	1	1	0.47	.44
Y_{223}	1.48	0.35	1.13	1	0.40	.51
Conscientiousness						
Y_{131}	0	1			0.20	.79
Y_{231}	0	1			0.22	.68
Y_{132}	1.67	0.59	1	1	0.24	.78
Y_{232}	1.53	0.57	0.93	1	0.12	.85
Y_{133}	1.67	0.59	1	1	0.24	.78
Y_{233}	1.53	0.57	0.93	1	0.12	.85

Notes. α: Intercept; Var(ε): residual variance; Rel.: reliability; CM: common method factor; UM: unique method factor. All parameters with values of 0 and 1 are fixed parameters.

Table 2

Variance Components in the CTC(M-1) model for structurally different and interchangeable methods.

	Variance Components			
	Consistency Coefficient	Method Specificity Coefficient	Common Method Specificity coefficient	Unique Method Specificity Coefficient
Extraversion				
τ_{111}	1			
τ_{211}	1			
τ_{112}	.36	.64	.15	.49
τ_{212}	.44	.56	.19	.37
τ_{113}	.36	.64	.15	.49
τ_{213}	.44	.56	.19	.37
Neuroticism				
τ_{121}	1			
τ_{221}	1			
τ_{122}	.17	.83	.29	.54
τ_{222}	.18	.82	.34	.48
τ_{123}	.17	.83	.29	.54
τ_{223}	.18	.82	.34	.48
Conscientiousness				
τ_{131}	1			
τ_{231}	1			
τ_{132}	.32	.68	.30	.39
τ_{232}	.22	.78	.31	.47
τ_{133}	.32	.68	.30	.39
τ_{233}	.22	.78	.31	.47

Note. Manifest variance components can be obtained by multiplying the latent variance components by the reliabilities of the manifest indicators. The variance components can be determined according to Equations 5, 11, and 12.

Table 3

Means, Variances, and Correlations of the CTC(M-1) model for structurally different and interchangeable methods.

		Variances and Correlations														
	Mean Val.	T_{111}	T_{211}	T_{121}	T_{221}	T_{131}	T_{231}	CM_1	CM_2	CM_3	UM_{12}	UM_{22}	UM_{32}	UM_{13}	UM_{23}	UM_{33}
T_{111} (1st TH Extraversion)	3.90	***.52***														
T_{211} (2nd TH Extraversion)	3.67	<u>**.75**</u>	***.46***													
T_{121} (1st TH Neuroticism)	3.96	.05	.11	***.61***												
T_{221} (2nd TH Neuroticism)	3.29	**-.16**	.08	<u>**.75**</u>	***.62***											
T_{131} (1st TH Conscient.[a]).	3.32	.08	**.15**	.07	-.06	***.76***										
T_{231} (2nd TH Conscient. [a])	3.63	.04	.12	.12	-.07	<u>**.96**</u>	***.45***									
CM_1 (CMF Extraversion)	0			**-.35**	-.20	**-.29**	**-.44**	***.07***								
CM_2 (CMF Neuroticism)	0	.02	**.23**			**.20**	**.21**	-.15	*.11*							
CM_3 (CMF Conscient. [a])	0	**-.19**	**-.24**	.02	-.09			-.13	.04	***.24***						
UM_{12} (MF Extraversion)	0										***.22***					
UM_{22} (MF Neuroticism)	0										–.02	***.20***				
UM_{32} (MF Conscient. [a])	0										**.14**	.10	***.32***			
UM_{13} (MF Extraversion)	0													***.22***		
UM_{23} (MF Neuroticism)	0													–.02	***.20***	
UM_{33} (MF Conscient. [a])	0													**.14**	.10	***.32***

Notes. T_{ijk}: Trait; CM_j: Common Method Factor; UM_{jk}: Unique Method Factor; TH: testhalf; [a] Conscient. = Conscientiousness; The variances of the latent variables are italicized on the main diagonal of the correlations matrix. Values with t-values larger than 2 are typed in bold face.

Figure Captions

Figure 1.

Standard CTC(M-1) model with indicator-specific trait variables. Y_{ijk} : observed variable; i: Indicator; j: Trait; k: Method; ε_{ijk}: Error variable (only depicted for the first indicator). For ease of presentation, no loading parameters are presented.

Figure 2.

The CTC(M-1) model with common method factors for two traits and three methods. Y_{ijk} : observed variable; i: Indicator; j: Trait; k: Method; ε_{ijk}: Error variable (only depicted for the first indicator). For ease of presentation, no loading parameters are presented.

Figure 3.

One trait unit of the CTC(M-1) model for structurally different and interchangeable raters. Y_{ijk} : observed variable; i: Indicator; j: Trait; k: Method; ε_{ijk}. Identical parameters are marked with identical roman letters.

Figure 1

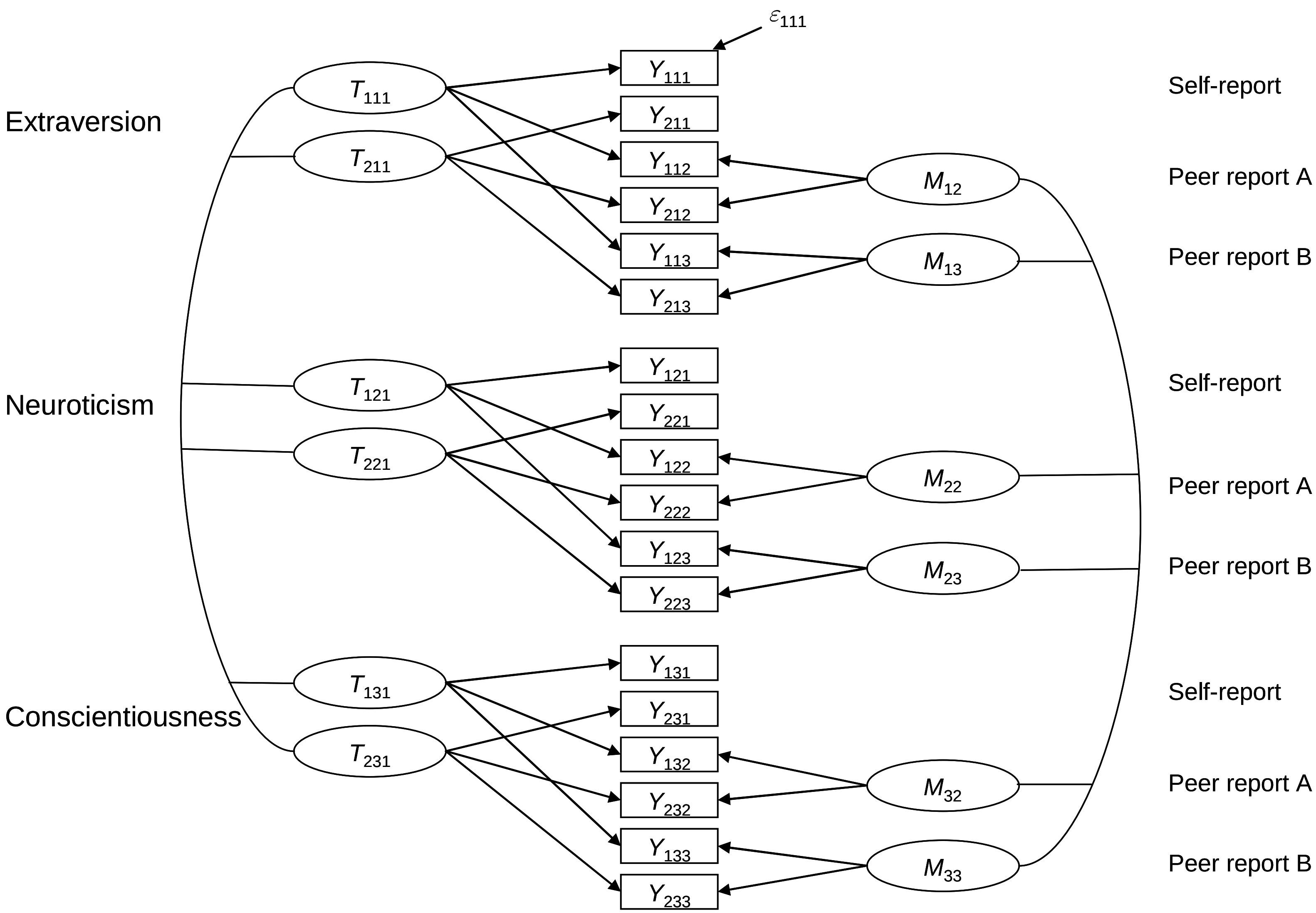

ε111
Y111
Y211
Y112
Y212
Y113
Y213
Y121
Y221
Y122
Y222
Y123
Y223
Y131
Y231
Y132
Y232
Y133
Y233
T111
T211
T121
T221
T131
T231
M12
M13
M22
M23
M32
M33
Extraversion
Neuroticism
Conscientiousness
Self-report
Peer report A
Peer report B
Self-report
Peer report A
Peer report B
Self-report
Peer report A
Peer report B

Figure 2

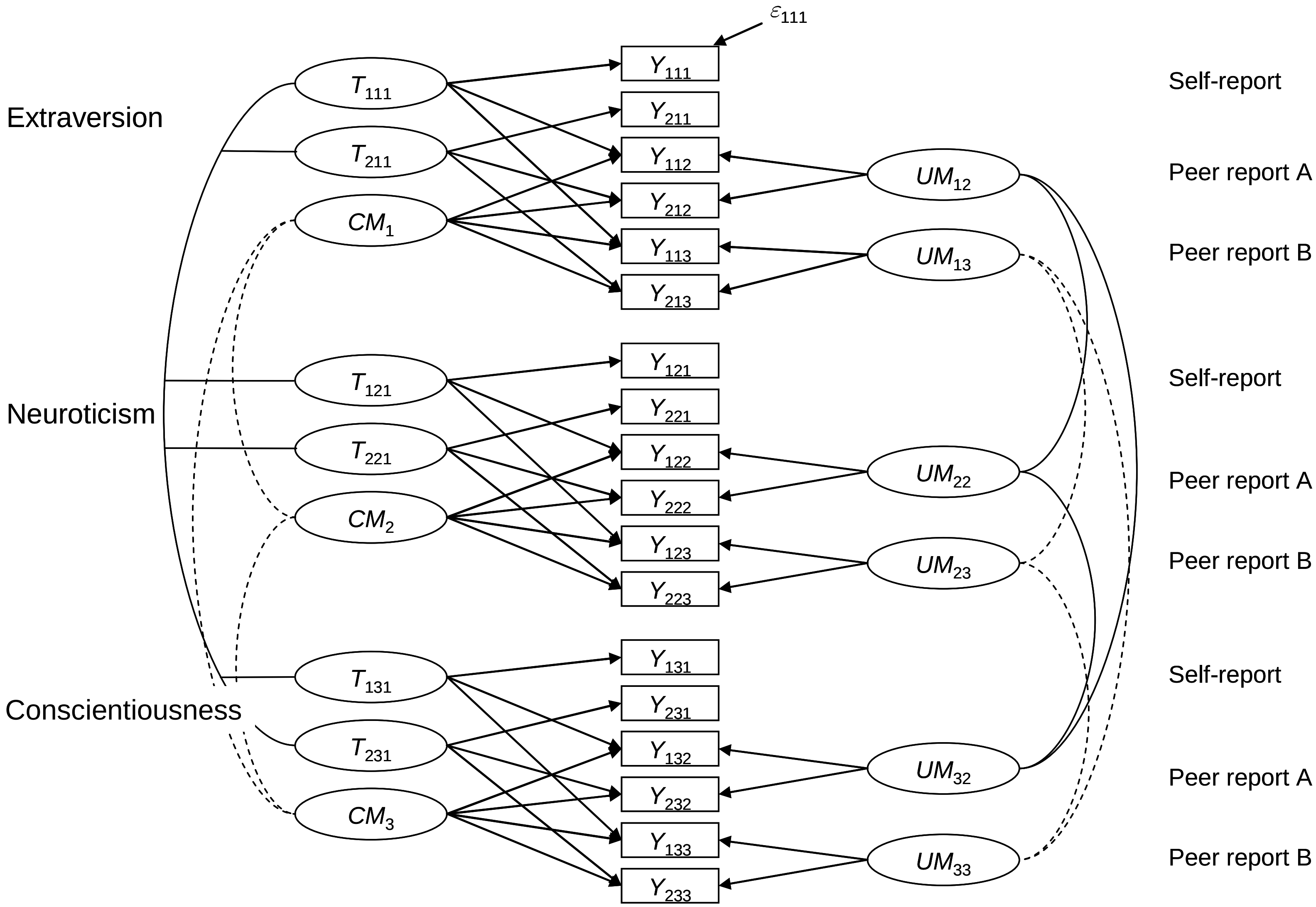
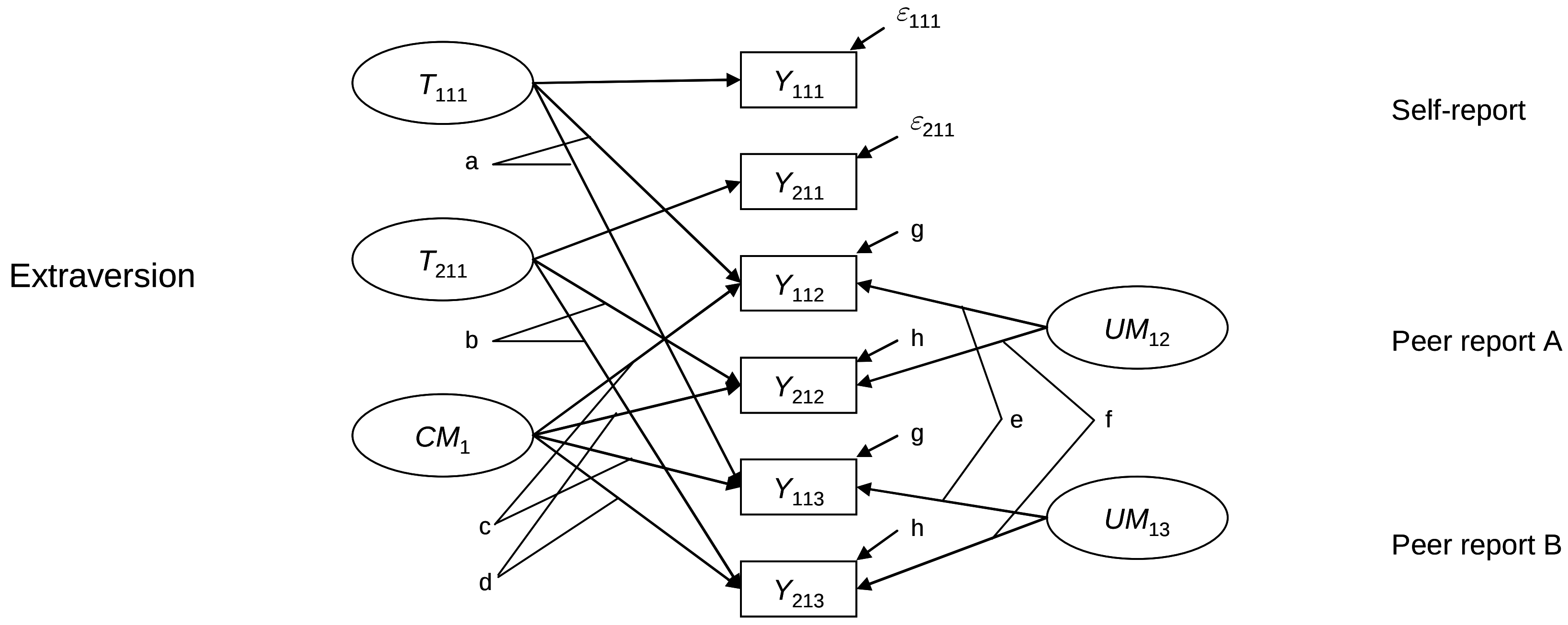

ε111
Extraversion
Neuroticism
Conscientiousness
T111
T211
CM1
T121
T221
CM2
T131
T231
CM3
Y111
Y211
Y112
Y212
Y113
Y213
Y121
Y221
Y122
Y222
Y123
Y223
Y131
Y231
Y132
Y232
Y133
Y233
UM12
UM13
UM22
UM23
UM32
UM33
Self-report
Peer report A
Peer report B
Self-report
Peer report A
Peer report B
Self-report
Peer report A
Peer report B

Figure 3



Extraversion
T_{111}
T_{211}
CM_1
a
b
c
d
ε_{111}
ε_{211}
Y_{111}
Y_{211}
Y_{112}
Y_{212}
Y_{113}
Y_{213}
g
h
g
h
e
f
UM_{12}
UM_{13}
Self-report
Peer report A
Peer report B

Supplementary Material to be provided on the web-page www.XY.net

Mplus specification of the ML-MTMM and CFA-MTMM models depicted in Figures 1 and 2.

Parameters with identical values in parentheses are restricted to be equal.

INPUT:

TITLE: Mplus input for the CFA-CTC(M-1) model for structurally different and interchangeable methods

! Specification of data file

DATA: FILE IS IMPS.dat;

FORMAT IS 71F8.2;

TYPE IS Individual;

! Definition of the manifest variables in the data file

VARIABLE: NAMES ARE

! The following variables are not used in the analysis

ID zbf01 zbf03 zbf04 zbf06 zbf07 zbf10 zbf11 zbf12

zbf13 zbf16 zbf19 zbf20 abf01 abf03 abf04 abf06 abf07

abf10 abf11 abf12 abf13 abf16 abf19 abf20 bbf01 bbf03

bbf04 bbf06 bbf07 bbf10 bbf11 bbf12 bbf13 bbf16 bbf19

bbf20 zdaua zvera zkenna zdaub zverb zkennb zgesch

adauz averz akennz agesch aalter bdauz bverz bkennz bgesch

! Extraversion (self)

```
zex1 zex2
! Neuroticism (self)
zneu1 zneu2
! Conscientiousness (self)
zcon1 zcon2
! Extraversion (peer A)
aex1 aex2
! Neuroticism (peer A)
aneu1 aneu2
! Conscientiousness (peer A)
acon1 acon2
! Extraversion (peer B)
bex1 bex2
! Neuroticism (peer B)
bneu1 bneu2
! Conscientiousness (peer B)
bcon1 bcon2;

! Variables to be used in the analysis
usevariables =
zex1 zex2 zneu1 zneu2 zcon1 zcon2 aex1 aex2 aneu1
aneu2 acon1 acon2 bex1 bex2 bneu1 bneu2 bcon1 bcon2;

! Missing value flag
```

MISSING ARE ALL (999.00);

! A standard SEM meanstructure analysis is requested

ANALYSIS:

TYPE IS MEANSTRUCTURE;

! Specification of the estimator

ESTIMATOR IS MLR;

! Model specification

MODEL:

! The complete model is estimated on one level

! The trait factors are identified

! EX1 and EX2 trait factors for extraversion

! NEU1 and NEU2 trait factors for neuroticism

! CON1 and CON2 trait factors for conscientiousness

! The loading parameters are resticted to be equal for the two peers

EX1 by zex1

aex1 bex1(1);

EX2 by zex2

aex2 bex2(2);

NEU1 by zneu1

aneu1 bneu1(3);

NEU2 by zneu2

```
aneu2 bneu2(4);
CON1 by zcon1
acon1 bcon1(5);
CON2 by zcon2
  acon2 bcon2(6);

! The mean values of the trait factors are freely estimated
[EX1];
[NEU1];
[CON1];
[EX2];
[NEU2];
[CON2];

! The intercepts of the self-report indicators are set to 0 to identifiy the trait means
[zex1@0];
[zneu1@0];
[zcon1@0];
[zex2@0];
[zneu2@0];
[zcon2@0];

! The intercepts of the peer reported indicators are set equal to each other
[aex1](7);
```

```
[bex1](7);
[aex2](8);
[bex2](8);
[aneu1](9);
[bneu1](9);
[aneu2](10);
[bneu2](10);
[acon1](11);
[bcon1](11);
[acon2](12);
[bcon2](12);

! The common method factors are specified
CMFEX by aex1 bex1@1
aex2 bex2(21);
MFNEU1 by aneu1 bneu1@1
aneu2 bneu2(22);
MFCON1 by acon1 bcon1@1
acon2 bcon2(23);

! The residual variances of the peer report indicators are restricted to be equal
aex1(31);
bex1(31);
aex2(32);
```

```
bex2(32);
aneu1(33);
bneu1(33);
aneu2(34);
bneu2(34);
acon1(35);
bcon1(35);
acon2(36);
bcon2(36);

! The mean of the common method factor is fixed to 0
[CMFEX@0];
[CMFNEU@0];
[CMFCON@0];

! The unique method factors are identified
AEX by aex1
aex2@1;
BEX by bex1
 bex2@1;
ANEU by aneu1
aneu2@1;
BNEU by bneu1
bneu2@1;
```

```
ACON by acon1
 acon2@1;
BCON by bcon1
 bcon2@1;

! The variances of the unique method factors are restricted to be equal
AEX(41);
BEX(41);
ANEU(42);
BNEU(42);
ACON(43);
BCON(43);

! The mean values of the unique method factors are fixed to 0
[AEX@0];
[BEX@0];
[ANEU@0];
[BNEU@0];
[ACON@0];
[BCON@0];

! The covariances of the unique method factors are set equal across methods
AEX with ANEU(51);
AEX with ACON(52);
```

```
ANEU with ACON(53);
BEX with BNEU(51);
BEX with BCON(52);
BNEU with BCON(53);

! Covariances between unique method factors of different methods are set to 0
AEX ANEU ACON with BEX@0 BNEU@0 BCON@0;

! Covariances between shared variables and the unique method factors  are set to 0
AEX ANEU ACON with EX1@0 NEU1@0 CON1@0 EX2@0 NEU2@0 CON2@0;
AEX ANEU ACON with CMFEX@0 MFNEU1@0 MFCON1@0;
BEX BNEU BCON with EX1@0 NEU1@0 CON1@0 EX2@0 NEU2@0 CON2@0;
BEX BNEU BCON with CMFEX@0 MFNEU1@0 MFCON1@0;

! Covariances of traits and common method factors of the same trait unit are set to 0
EX1 EX2 with CMFEX@0;
NEU1 NEU2 with MFNEU1@0;
CON1 CON2 with MFCON1@0;

! Sample statistics and the standardized solution are requested
OUTPUT: sampstat standardized;
```