# Modeling the Personality of Dyads and Groups

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**ABSTRACT** The paper presents a methodological approach for assessing the personality of a dyad or a group, a concept that is not equivalent to the sum, or mean, of the individual scores. We illustrate how the logic of the multitrait multimethod approach, which is a familiar technique for establishing construct validity, can be extended to assess the construct of a relationship "personality." The model, which we call the latent group model, provides a decomposition and comparison of individual-level and group-level variance in a given trait, and the individual-level and group-level covariance or correlation between two traits. The model is also extended to the assessment of stability of the individual and group level traits. Throughout the paper, we draw connections between related methods and show how the latent group model can be estimated through hierarchical linear modeling.

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## Modeling the Personality of Dyads and Groups

It is common to measure the personality of individuals; it is more complex, but not impossible, to measure the personality of situations; it appears almost inconceivable to measure the personality of dyads and groups. Nonetheless, in daily speech, people talk about narcissistic couples, sociable groups, and polite or aggressive nations. What do people mean by such statements, and can these concepts be captured by measures and statistics? Can we distinguish the personality of an interpersonal relationship from the personality of the individuals in the relationship? Is the former more than the sum of the parts? Can the personality of a dyad or group be modeled as a function of the context created by the people in the relationship?

Gonzalez and Griffin (2001) reviewed a social psychological debate about the use of group-level concepts such as "group mind" in theory construction. The debate can be characterized by placing George Herbert Mead (1934), who gave explanatory priority to the group, on one side and Floyd Allport (1924), who argued that explanations for social phenomena must ultimately reside in the individual, on the other. Gonzalez and Griffin (2001) provided a statistical structure that mirrored this conceptual debate: a statistical framework that permits the modeling of group-level processes from individual-level data. We called the model the *latent group model*. The model deals with Allport's concern that measurement and theory about groups should be bottom-up (i.e., it should derive from the individual because the responses of the individuals in the same group are modelled as indicators of a group-level latent variable). The model simultaneously deals with Mead's concern that group-level explanations not be ignored in social science. The underlying logic of the latent group model is to construct group-level variance from the shared tendencies exhibited by the group members and then use that group-level variance in subsequent analyses.

In this paper we argue that the common meaning of "group personality" can indeed be measured, though not through standard statistical techniques. We describe the latent group model in a way that builds on standard methodological techniques from the personality literature. We show how those techniques can be adapted to measure the "personality of a relationship." The framework permits data collected both at the level of the individual and at the level of the couple. We show how to use modern personality theory to inform our understanding of relationships (e.g., notions of coherence) and also show how the study of relationships presents new challenges to personality theory (e.g., studying the effects of the unique situational context created by the personality of the specific individuals in a relationship).

## Latent Multitrait Multimethod Analysis

We build upon the logic of the multitrait-multimethod technique (MTMM) proposed by Campbell and Fiske (1959). Campbell and Fiske had two themes guiding their framework. First, they considered the model in causal terms, in the sense that unobserved constructs are expressed in observed variables. Observed measures are viewed as a combination of an underlying trait, giving rise to observed similarity, and specific unshared causes (often termed method factors), giving rise to observed uniqueness. Second, they viewed the model as a set of conditions for an observed measure to be an indicator of an underlying construct. These conditions are convergence (confirmation) and discrimination (falsification). Depending on the traits chosen, construct validity requires the trait-level relation either to be large (for conceptually related traits—yielding convergent validity) or small (for conceptually unrelated traits—yielding discriminant validity). In the end, construct validity requires a "nomological net" of variables and unmeasured constructs (Cronbach & Meehl, 1955).

In the MTMM approach each trait is measured with multiple methods. The analysis of the covariance matrix of such traits measured with multiple methods allows the assessment of reliability, convergent validity, and discriminant validity (Campbell & Fiske, 1959). The structure of the covariance matrix that is needed for MTMM is depicted in Table 1.

The modern analysis of such matrices is typically done within the framework of structural equations modeling where each trait is represented by a latent variable and method variance is represented by correlated error (see Figure 1). We emphasize three key aspects of this latent variable MTMM. First, the paths from the trait latent variable to the indicators in this structural equations model provide reliability estimates (the square of the standardized path estimates are reliability estimates). This measure of reliability provides, for each trait, the ratio of true score variance to total variance. This is consistent with classical test theory, where reliability refers to the correlation between parallel measures of the same trait. Under the assumption of parallel tests (same scale, same error variance), further constraints need to be included, such

**Table 1**
The Multitrait-Multimethod Covariance Matrix

| | Trait A | | Trait B | |
|---|---|---|---|---|
| | Method 1 | Method 2 | Method 1 | Method 2 |
| Trait A Method 1 | | | | |
| Trait A Method 2 | | | | |
| Trait B Method 1 | | | | |
| Trait B Method 2 | | | | |

*Note*: The diagonal of this matrix contains variances and the off-diagonal contains covariances.

as constraining common paths to be equal or setting error variances to be equal. Second, the correlation between the two latent variables is the estimate of the "true" correlation between the two traits, given that the effects of random measurement error and systematic method error have been removed. That is, the correlation between the two latent variables is automatically corrected for unreliability in the observed data, yielding an appropriate test of convergent validity (between theoretically related traits) or discriminant validity (between theoretically unrelated traits). This automatic disattenuation for (un)reliability is one advantage of testing MTMM models in the context of structural equations modeling. Third, the correlations between the unique error terms implicitly model the method factors, and allow the separation of

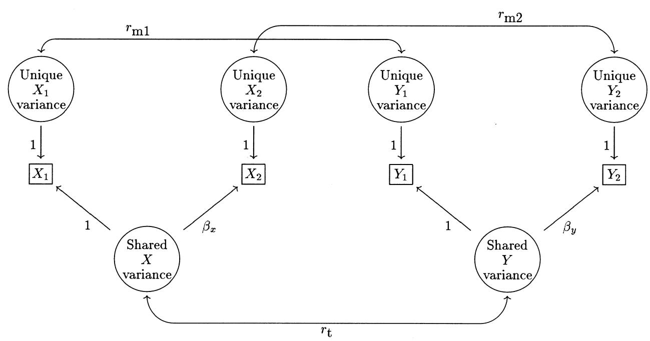


**Figure 1**
Classic Mulitrait Multimethod Model.
*Note: X* and *Y* refer to two traits, subscripts 1 and 2 refer to two methods for measuring a trait, $\beta$'s refer to indicator paths, 1's are identification constraints, and subscripts m and t refer to method and trait, respectively.

unique random variance from method variance. See Kenny (1976) and Wothke (1996) for more details.

In standard personality applications, the logic of the latent variable MTMM approach permits the researcher to separate method variance (reflected in the covariance between error variables), unique random variance (reflected in the error variance), and "true-score" trait variance (reflected in the latent variable), to estimate reliability and to evaluate construct validity. Most important to our perspective, this logical procedure provides a path for "going beyond" observed similarity and estimating a theory-based "deep structure" of the interrelationships among the variables. Suppose the researcher wished to use the logic of MTMM on the two traits of neuroticism and sociability, each measured by using two methods (self-report and behavioral observation). In this case, the latent variable MTMM model would have a latent variable for neuroticism identified by two observed indicators—one for the self-report neuroticism scale and another for the behavioral observation of neuroticism. Similarly, sociability would be a latent variable with two indicators (self-report and behavioral). The model would also have a correlation between the latent variables neuroticism and sociability, which is an estimate of the disattenuated (i.e., corrected for measurement error) correlation between the two traits. Method variance would be modeled by having a correlated path between the error variances of the two self-report scales (estimating the shared variance due to "self-report") and a correlated path between the error variances of the two behavioral observations (estimating the shared variance due to "behavioral observation"). This model is presented graphically in Figure 1.

The deep structure of the MTMM technique is simple: decompose the observed variances and covariances using a linear model. The linear model has each observed variable as a weighted sum of the latent variable and the method variable. Indeed, the graph in Figure 1 is identical to a system of linear equations that have correlations imposed between parameters. The decomposition of variance occurs because the design of the MTMM framework crosses (in a factorial sense) the method factor with the trait factor. In equation form Figure 1 becomes

$$\begin{array}{ccccccc} \text{neuroticism}_m & = & \beta_{n0} & + & \beta_n \text{trait}_n & + & \text{error}_{nm} \\ & & & & \Updownarrow = r_t & & \Updownarrow = r_m \\ \text{sociability}_m & = & \beta_{s0} & + & \beta_s \text{trait}_s & + & \text{error}_{sm} \end{array} \qquad (1)$$

The subscripts *n*, *s*, *t*, and *m* refer to neuroticism, sociability, trait, and method, respectively. According to this model, the two neuroticism observed scales have an identical linear structure but are allowed to have different error variances (one error variance for the behavioral measure and one for the self-report measure; hence, the subscript *m*). Thus, there are actually two equations for neuroticism, with each equation having its own error term. Similarly, the two observed scales for sociability have an identical linear structure. In addition to these equations, the model has a correlation imposed between the two latent traits and a correlation imposed between the two errors (denoted by the vertical doubleheaded arrows; note that there are two sets of error covariances, one for each method). The intercepts are not depicted in Figure 1 because we are modeling the covariance matrix; consequently, the variables are centered and the intercepts do not play a role in standard MTMM testing.

When testing this model, there are several constraints that may be tested. For example, one may test whether the correlated error between the two self-report scales is the same as the correlated error between the two behavioral observations. This provides a test of whether the variances of the two method factors are identical; such a test will become useful in the next section when we apply the MTMM framework to dyads. With only two indicators per latent variable, the analyst runs into the problem that more general models (i.e., models with fewer constraints) may not be identified. Applications of MTMM, therefore, usually have more than two indicators per latent variable, but we will keep our example at two indicators for simplicity and to maintain the connection to the dyadic research.

We now turn to the latent group model of relationships, and show its connection to the MTMM model. We then place the latent group model within the framework of a hierarchical linear model.

## Latent Variable Model of a Relationship

The common meaning of group personality, we argue, is analogous to the latent variable version of a nomological net—a network of variables and relationships, observed and unobserved, that define a construct. In particular, the lay conception of group personality is based on similarity that is more than skin deep. Members of an "entity" with a "personality" should act similarly (observed similarity within groups on some response), but this action level should reflect a deeper level of organization and coherence. This coherence should be reflected in correlated similarities across related traits. Thus, a dyadic or group personality must fulfill two measurement conditions: (1) similarity on each trait and (2) correlated similarity across related traits. The former is indexed by the intraclass correlation within a trait and the latter is indexed by the group-level correlation between latent group-level traits. In (2) we highlight the notion of convergent validity, but divergent validity (low correlated similarity across unrelated traits) applies as well. Note that in answering the question of whether an aggregate of people act like an entity, we are focusing on one of the four dimensions that Campbell (1958) suggested people use to decide if an aggregate looks like an entity: similarity, common fate, proximity, and boundedness.

A model with an analogous structure to the MTMM model can be used in the analysis of interpersonal relationship data, and it provides a framework for testing the two measurement conditions. Here the trait resides within the couple instead of the individual because, for each couple, there are two measurements on each variable. For example, if each member of the couple completes a neuroticism scale, then we can construct a latent variable having two indicators for the group-level latent variable: the neuroticism scale score from the husband and the neuroticism scale score from the wife. Such a latent variable can be interpreted as the dyad level effect. We construct such a latent variable structure for each variable and allow correlation between pairs of latent groups.

Because each individual dyad member is measured on multiple variables, we also need to allow for individual-level correlations across variables. For example, the male provides both neuroticism and sociability scores; thus, there could be a correlation between the male's unique score neuroticism and his unique score on sociability (i.e., the unique variance of each scale could be correlated because the same individual responds to both scales). Similarly, there would be a correlation between the wife's unique terms for neuroticism and sociability. These individual-level correlations indicate that the underlying dyadic relation is not enough to explain the observed relationships. Even if neurotic couples tend to be more (or less)

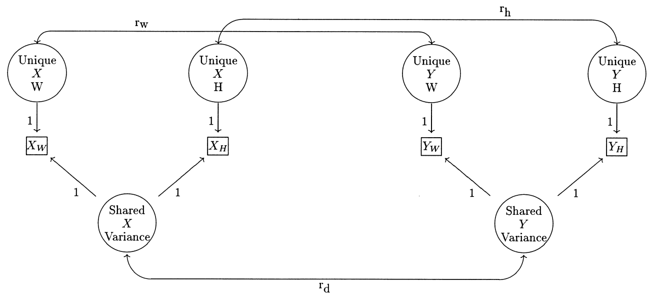


**Figure 2**
Latent Group Dyad Model. *X* and *Y* refer to two traits, subscripts w and h refer to wife and husband (respectively), 1's are identification constraints, and subscripts d refer to dyad-level.

sociable couples, the more neurotic individual within a couple may also be more (or less) sociable.

The latent group model for dyads is depicted in Figure 2, which is identical to Figure 1, except for the labels and constraints. Instead of multiple measures of a trait converging as indicators of an underlying latent trait, we have multiple individuals converging as indicators of an underlying group trait. Instead of unique method causes creating differences among measures of the same trait, we have unique individual trait causes creating differences among measures of the same trait. Instead of unique method causes that correlate across different traits, we have unique individual effects that correlate across different traits. Put together, we have a multilevel model that decomposes the set of observed relationships into group-level relations and individual-level relations.

This latent variable dyad model was developed in detail by Gonzalez and Griffin (1999, see also Kenny & La Voie, 1985), where we showed the connection between the latent variable approach and an identical, though easier to compute and understand, pairwise approach. Most of the examples we use in the present paper focus on distinguishable dyads, or dyads where the two members can be categorized into different classes (e.g., males and females, doctor and patient, mentor and student). For examples involving exchangeable couples, such as same-sex romantic couples where couple membership is not distinguishable, see Griffin and Gonzalez (1995). We use couples in our examples for simplicity, but the techniques are not limited to couples and easily extend to groups.

The graphical representation in Figure 2 can also be expressed in equation form.

$$\begin{array}{rcccccc} \text{neuroticism}_i & = & \beta_{n0} & + & \text{group}_n & + & \text{individual}_n \\ & & & & \Updownarrow = r_g & & \Updownarrow = r_i \\ \text{sociability}_i & = & \beta_{s0} & + & \text{group}_s & + & \text{individual}_s \end{array} \quad (2)$$

where subscript $i$ denotes individual (say, husband and wife), subscript $g$ denotes group, and subscripts $n$ and $s$ denote neuroticism and sociability, respectively. Again, there are two equations for the neuroticism observed variable (one for each couple member) and two equations for the sociability observed variable.

There are some crucial differences between Figures 1 and 2. The key issue is that in MTMM the same person provides two observations under different methods for one trait. There are also MTMM applications where multiple people, or raters, provide data about the same target individual, such as when parents, teachers, and peers rate a target individual. In either case, the data all refer to the same unit. However, in the latent dyad model, a dyad-level "trait" is indicated by scores from two different individuals. While there is an analogy to be made between the role of "method" in MTMM and the role of "individual" in the latent dyad model, there is an important distinction. The MTMM permits the two methods of the same trait to have different scales (e.g., the self-report can be a likert scale, and the behavioral observation can be a frequency measure). But, because the latent dyad model defines group level variance as a function of the similarity between the individual members, the indicators (i.e., individuals) must be measured on the same scale. The latent group model makes the strong assumption of "parallel tests." The implication of this difference is that additional constraints need to be imposed on the latent group model that are not required in the more general MTMM model (see Gonzalez & Griffin, 1999). Further, some tests make more sense in the latent variable group model than in the MTMM framework. For example, one can test whether the individual-level correlation between the two traits for the husbands is the same as the individual-level correlation for the wives.

It is also possible to merge the MTMM model with the latent group model, allowing for multiple measures to indicate a latent variable for each individual and latent variables to characterize individual-level and group-level effects. That is, one uses MTMM to find latent traits for each individual. Those latent traits are then subjected to the latent group model to separate the (second order) individual-level and group-level latent variables.

## The Latent Group Approach in the Context of a Hierarchical Linear Model

In this section we connect concepts from the previous section to hierarchical linear modeling (HLM; also known as multi-level modeling), a technique that is growing in popularity. HLM is a technique that allows the estimation of random and nested effects in a more general way than traditional analysis of variance treatments (see, e.g., Bryk & Raudenbush, 1992). There are now several computer programs that can do HLM analyses; the most well-known are HLM (Bryk & Raudenbush, 1992; the program and the technique are not synonymous), MLwin, and PROC MIXED.

### *Sampling and Factorial Decomposition*

There are additional similarities and differences to highlight between the MTMM and the latent variable dyadic models. The MTMM model is based on the standard psychometric assumption that each observation is modeled as a sum of intercept plus true score plus a method term. Thus, under MTMM we have

$$\text{observed score} = \text{intercept} + \text{true score} + \text{method score} \quad (3)$$

The latent variable dyad model has the same underlying mathematical structure, but there are some minor differences in interpretation. The sampling model is that there is a population of dyad effects rather than a population of true scores for each individual. Each dyad that is sampled into the study brings a group-level score, and each member of the dyad has an individual effect (analogous to the method effect in the MTMM).[1] Thus, under the latent variable dyad model

$$\text{observed score} = \text{intercept} + \text{group score} + \text{individual score} \quad (4)$$

1. In the simplest case, where each member of the couple provides one score, it is not possible to separate measurement error related to the scale from individual-level variance. However, when each individual provides more than one observation of the same trait, then additional decomposition is possible. The section of this paper examining temporal stability provides one framework for dealing with such multiple observations.

The structure of these equations is identical to a two-level model in the context of HLM. Those familiar with the logic of HLM will recognize the classic "slopes as outcomes" model. In the classic model, a slope is estimated at level one (e.g., the regression of an individual's reported well-being on the individual's level of daily stress, using data collected over several days; intuitively, running a regression separately for each subject). At level two the slopes from each individual serve as an outcome for yet another regression on an individual-difference variable (e.g., self-esteem).

In our simple model, there is no slope, only an intercept. As shown below, level one is the random intercept, and the second level is a linear model of that random intercept term. For example, in the case of the latent group model the two levels would be:

$$Y = \mu + \text{individual effect} \tag{5}$$

$$\mu = \beta_0 + \text{group effect} \tag{6}$$

with Y being the dependent variable, $\mu$ the random effect group mean, and $\beta_0$ the fixed constant (or grand mean term). The "group effect" is equivalent to the group mean minus the grand mean, much like treatment effects in the context of an ANOVA. But keep in mind that in the present model the group is treated as a random effect. This is known as a random intercept model because at level one $\mu$ plays the role of an intercept that varies by group (each group has its own $\mu$).[2] Additional individual-level predictors, or covariates, can be added in Equation 5; additional group-level predictors, or covariates can be added in Equation 6.

Statistical programs provide several methods to estimate the parameters, with the two most popular being maximum likelihood (ML) and restricted maximum likelihood (REML). As far as the choice between these two estimation procedures (ML and REML), they are asymptotically equivalent. But, for small numbers of dyads (say, less than 20 dyads), the two methods tend to yield different parameter estimates. Because REML takes degrees of freedom into account, it is the preferred method in the case of few dyads (this

2. Subscripts can be distracting when discussing HLM models, so we omit them for sake of expositional clarity (even though we sacrifice mathematical rigor).

advice is especially relevant in applications where there are few data points to parameters).

*The Intraclass Correlation*

The previous subsection reviewed two equations (Equations 3 and 4) that had parallel structures. This simple structure leads to the well-known intraclass correlation (ICC), which is a natural measure of similarity or reliability. The ICC is a ratio of true-score variance divided by the sum of the true-score variance plus error variance. In different applications, the true-score variance can take on different interpretations, and the computation of the error variance can also differ. The general formulation of the intraclass correlation in symbols takes on the following form: if $\alpha$ denotes the term of interest (e.g., true-score variance) and $\epsilon$ denotes the error term, then the ICC is given by

$$\frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\epsilon^2} \tag{7}$$

The intraclass correlation provides a normalization of the (shared) variance of interest. In the MTMM context (Equation 3) the term of interest is the individual's "true score" on a trait. Consider the case when neuroticism is measured both by self-report and by a behavioral measure, and the researcher acknowledges that each method has specific systematic effects. By using two methods, he or she hopes to cancel the unique impact of both methods, thus arriving at a better estimate of the underlying neuroticism score. Reporting the true score variance by itself would be difficult to interpret; hence it is normalized by Equation 7.

In the context of interpersonal research (Equation 4), the term of interest is the "group true score," inferred from the similarity of responses for individuals in the same group. Again, the intraclass correlation provides a normalization of the group-level variance and, in this context, carries the interpretation of true similarity, convergence, or resemblance. For example, when neuroticism is measured for both the wife and the husband, the researcher wishes to arrive at a measure of convergence in the neuroticism scores. Here convergence, or "shared variance," has a very special meaning because it refers to absolute similarity (Gonzalez & Griffin, 2001). Similarity is high when both members of the couple respond identically. This differs from, say, the Pearson correlation between the husband and wife, which could be perfect even when the scores from the two individuals do not perfectly agree (e.g., the wife always responds some amount higher than the husband).

Equation 7 provides a general formulation of the intraclass correlation that can also be used in the case of hierarchical linear models. The output of an HLM program provides both variance terms needed to compute Equation 7. Current HLM programs do not compute the ICC automatically, nor do they print the ICC in the output; the ICC must be computed by the user, using the variance component terms that appear in the output and Equation 7.

Recall that HLM programs tend to have two options for the estimation of variance components: maximum likelihood and restricted maximum likelihood. These two estimation routines lead to different variance estimates, but Equation 7 is used to compute the ICC regardless of which estimation technique was used. The pairwise ICC that we reviewed in our previous work (Griffin & Gonzalez, 1995; Gonzalez & Griffin, 1999) is identical to the maximum likelihood ICC; the ANOVA ICC, which may be more familiar to psychologists (see, e.g., Kenny & La Voie, 1985), is identical to the restricted maximum likelihood ICC. Both of these exact equivalences hold only when all groups of are equal size, such as couples of size 2, families of size 5, or juries of size 12.

### *Multivariate Latent Group Model*

Our discussion of the intraclass correlation and its corresponding linear model (e.g., Equation 4) focused on one dependent variable. We began the paper by discussing an example involving two traits (neuroticism and sociability), and, of course, psychological research frequently involves multiple dependent variables. Furthermore, we have argued that the concept of a relationship personality is fundamentally based on a coherent network of shared tendencies (a multivariate concept). We now extend the models we have presented to the multivariate case (for expositional clarity, we illustrate the model for two variables, but any number of variables is possible).

Let's look at a concrete example. Each individual in a study of same-sex roommate pairs is given an neuroticism scale and a self-report sociability scale. For each scale, we can compute the intraclass correlation using the techniques presented in the previous section. We now seek to extend the HLM formulation to handle the multivariate latent group model depicted in Figure 2.

This extension is not straightforward because the current version of HLM is usually formulated as having a single dependent variable. We need a way to trick the HLM program into handling two dependent variables within its univariate framework. A simple use of dummy codes plus an extra level added to the HLM framework provides a solution.

In order to compute the multivariate latent group model within an HLM program, the data must be organized in a particular way. Data are assumed to be distributed as multivariate normal and are stored in one long column of numbers, which we denote Y. That is, we would have a single column of data that includes the neuroticism score of the husband, the neuroticism score of the wife, the sociability score of the husband, the sociability score of the wife, and so on for each couple. It may seem strange to place data from different people, even different variables, into the same column, but through the use of dummy codes and the hierarchical structure of HLM, we will be able to recreate for each score which person and which variable the score is associated with.

First, we will need two columns of dummy codes. One dummy code $D1$ assigns a 1 to all neuroticism scores and a 0 for all sociability scores. The other dummy code $D2$ assigns a 1 to all sociability scores and a 0 to all neuroticism scores. Thus, each of the two variables is perfectly selected by these two dummy codes. We also need a column of identifiers for each dyad member (which is internally transformed into dummy codes by the program).

The first level in the HLM framework uses these two dummy codes as predictors of the data column Y.

$$Y = \beta_n D1 + \beta_s D2 \tag{8}$$

This regression equation says that Y is a weighted sum of these two dummy codes, but the role of these two dummy codes is to inform the regression whether a particular Y score is a neuroticism score (D1 = 1) or a sociability score (D2 = 1).

We point out two additional features about this first-level equation (Equation 8). There is no intercept term because the two dummy codes are full-rank; the addition of an intercept would create a linear dependence problem. The other observation is that there is no error term. The reason there is no error term is that we will move the usual $\epsilon$ term to the next level in the HLM framework. The reason for this move will become obvious below. Thus, the regression equation depicted in

Equation 8 can be viewed as a "switching regression" because the only purpose it serves is to estimate either $\beta_n$ if a particular Y score is an neuroticism score or $\beta_s$ if a particular Y score is a sociability score. One needs to be careful when dealing with specific HLM programs. For example, note that in Equation 8 there is no error term. In the program MLwin, it is easy to omit the usual $\epsilon$ term at level 1; whereas, in the HLM program, one needs to use the latent variable feature available within the program in order to omit the $\epsilon$ term at a level 1.

These two $\beta$'s from level 1 are then modeled as random effects, which is how the error term $\epsilon$ works its way into the regression. Recall the linear form of "group score + individual score" that we reviewed above. Conceptually, each of the $\beta_s$ (one corresponding to neuroticism and the other corresponding to sociability) will be modeled in terms of this simple linear form. That is,

$$\beta_n = \text{intercept}_n + v_{ng} + u_{ni} \tag{9}$$

$$\beta_s = \text{intercept}_s + v_{sg} + u_{si} \tag{10}$$

where $v$ and $u$ are random effects that code group and individual terms (respectively), each equation has its own fixed effect intercept term, the subscripts $n$, $s$, $g$, and $i$ refer to neuroticism, sociability, group and individual, respectively. The random effect $v$ is defined with respect to a classification variable that codes group number and the random effect $u$ is defined with respect to a classification variable that codes individuals. In short, the switching regression (level 1) serves to isolate the two variables; then, the next level builds a linear regression separately for each variable.

We next need to force a covariance structure on each of the random effects $v$ (group level) and $u$ (individual level). Let the group-level $v$'s be bivariate normally distributed with covariance matrix

$$\Omega_v = \begin{bmatrix} \sigma^2_{vn} & \\ \sigma_{vns} & \sigma^2_{vs} \end{bmatrix} \tag{11}$$

where $n$ and $s$ denote neuroticism and sociability, respectively. This means that the random effect $v$ associated with neuroticism has variance $\sigma^2_{vn}$, random effect $v$ associated with sociability has variance $\sigma^2_{vs}$ and the two $v$'s have covariance $\sigma_{vns}$. Similarly, an analogous covariance is imposed on the two individual-level $u$'s

$$\Omega_u = \begin{bmatrix} \sigma^2_{un} & \\ \sigma_{uns} & \sigma^2_{us} \end{bmatrix} \tag{12}$$

This covariance matrix $\Omega_u$ gives the variances and covariance between neuroticism and sociability at the individual level. In this formulation, we require equality of all individual-level correlations (i.e., referring back to Figure 2, this HLM implementation forces the two individual-level correlations to be identical). In sum, these two covariance matrices contain information about group level and individual level variance for, and covariance between, the two variables. We next show how the information given in these matrices can be used to compute the terms in the latent group model.

While the notation of the model may appear complicated, the setup automatically provides the four critical terms in the latent model: the intraclass correlations for each variable (which provide a measure of agreement within each variable), the group level correlation $r_g$, and the individual level correlation $r_i$. These four correlations are computed as follows:

**intraclass correlation for neuroticism:**

$$\frac{\sigma_{vn}^2}{\sigma_{vn}^2 + \sigma_{un}^2}$$

**intraclass correlation for sociability:**

$$\frac{\sigma_{vs}^2}{\sigma_{vs}^2 + \sigma_{us}^2}$$

**individual level correlation between neuroticism and sociability:**

$$\frac{\sigma_{uns}}{\sqrt{\sigma_{un}^2 \sigma_{us}^2}}$$

**dyad level correlation between neuroticism and sociability:**

$$\frac{\sigma_{vns}}{\sqrt{\sigma_{vn}^2 \sigma_{vs}^2}}$$

The two intraclass definitions are identical to what we presented in a previous section. The form of the individual and dyad level correlations is the usual correlation (a covariance divided by the square root of a product of variables). The individual-level correlation uses terms from the individual-level covariance matrix $u$, and the group-level correlation uses terms from the group-level covariance matrix $v$. Thus, these two covariance matrices yield the intraclass correlations, the variances of the individual and group-level latent variables, and also yield the two doubleheaded arrows of Equation 2 indicating individual and group-level correlation between two variables, or traits. The HLM framework maps onto the latent group relationship model we presented earlier.

Technically, this is a three-level HLM model. The first level is the switching regression (Equation 8). The way we wrote the next part (Equation 9) may suggest that it is only one level. But recall how we implemented the intraclass correlation in the context of HLM above (Equation 5): the "group variance plus individual variance" logic itself required two levels. Thus, the way we wrote the second level (Equation 9) implies two levels. In the context of the switching regression (which is level 1), these two new levels become levels 2 and 3.

To provide some intuition to the various terms that are involved in the model, we refer to Figure 3, which is designed to illustrate the concepts with a demonstration data set of four couples. These plots

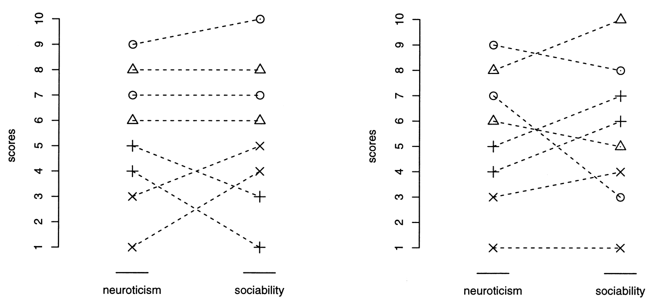


**Figure 3**
Demonstration data set with four couples. Left panel has high intraclass correlations on both variables (0.75), high individual-level correlation (0.90) and high dyad-level correlation (0.80). Right panel has high intraclass on neuroticism (0.75), zero intraclass on sociability, high individual-level correlation (0.95), and zero dyad-level correlation. Different symbols are used to indicate couples. Line segments connecting symbols represent the same individual's score on neuroticism and sociability.

illustrate different combinations of the two necessary conditions for the latent group model to hold: similarity within groups, or dyads, on each variable and a correlated similarity across variables. Note that an individual-level correlation can occur regardless of whether the two conditions are fulfilled and can even be of opposite sign to the dyad correlation; that is, the individual and dyad levels are conceptually independent. In the plot, each couple is denoted by a unique symbol (such as a square) and the scores of an individual on the two traits are linked by a line segment. The panel on the left portrays a set of data with high intraclass correlations on both neuroticism and sociability (0.75 on each variable). A high level of similarity on neuroticism can be seen because the two members of each dyad are "near" each other—the members of the x dyad are lowest, the members of the + dyad are next lowest, and the two other dyads share the upper scores. In other words, the scores tend to cluster within dyads. Clustering is also seen on the sociability scores in the left panel. Thus, the first condition is satisfied here. The second condition is also satisfied because the shared orderings on neuroticism are largely matched by shared orderings on sociability: couples who are both low on neuroticism tend to be both low on sociability. The panel on the right fails both conditions; it shows within-dyad clustering on neuroticism, but not sociability. Furthermore, the shared tendency for a dyad to be large or small on neurotism is not matched by any dyadic tendency on sociability (and indeed, the group-level correlation is meaningless in the absence of similarity on both variables). However, in both panels the individual-level correlation is high and positive, reflecting the fact that, within a dyad, the individual higher on neuroticism is almost invariably also higher on sociability.

As with the intraclass correlation, there is connection between the type of estimation used and familiar frameworks. If one implements this HLM model using the maximum likelihood estimation option, then the results are identical to the pairwise approach when group sizes are equal (Griffin & Gonzalez, 1995; Gonzalez & Griffin, 1999). If one implements this model using the restricted maximum likelihood estimation option, then the results are identical to the ANOVA model given by Kenny and La Voie (1985). Note that Kenny and La Voie (1985) did not provide a test of significance for their group-level correlation. Recasting their model into the language of HLM leads directly to a test of significance—one tests whether the covariance term $\sigma_{uns}$ is statistically significant (a test that appears in the output of all HLM programs; see also Gollob, 1991). Again, the exact equivalence of the pairwise latent group model and maximum likelihood HLM on the one hand and the equivalence of the ANOVA-based group-level model and restricted maximum likelihood on the other hand holds only when all groups have the identical size. A benefit of the HLM framework is that it can handle groups of unequal size.

Readers familiar with HLM may recognize another dummy code technique that has appeared in the literature (Barnett, Marshall, Raudenbush, & Brennan, 1993). Their method is a special case of the one proposed in this paper. In the Barnett et al. framework, each member of the couple provided two parallel scales of the same trait. Barnett et al. used the switching regression technique to have separate regression equations for each dyad member (unlike in our case, where we used the switching regression to code for variable). That is, they created a dummy code for women and another dummy code for men. Because their design had parallel scales they assumed the individual error variances were the same for the two scales, and they placed the usual error term $\epsilon$ at level 1 (the level of the switching regression). This forced men and women subjects to have the same error variance on the scale (and the parallel versions of the scale to also have equal and independent variances). The effect of this assumption was to eliminate the individual $v$ covariance matrix (i.e., the variances were assumed equal, and errors were assumed independent, so the covariance was fixed at zero). Thus, their model does not permit an estimation of the analog to the individual-level correlation. This is the reason the specification we suggest places the $\epsilon$ terms at a higher level, so a covariance matrix can be estimated, thus allowing different variances and nonindependence of error terms.

## Time Passages: Latent Variable Dyadic Model Over Time

One of the fundamental contributions of personality theories has been to alert psychologists to the importance of measuring and theorizing about stability. Stability, or temporal consistency, has become a necessary criterion for the establishment of a trait. Given that the present paper argues that there is psychological meaning to the group level variance and covariance, it is important to establish the stability of the group level variance when doing empirical work.

A design feature that must be added in order to assess the stability of the group level variance is *time*—participants need to be assessed more than once. For simplicity in exposition, we assume that the investigator has two time points and each member of the couple responds to neuroticism and sociability scales at each of those two points in time. Conceptually, we can estimate the latent group model (i.e., the model depicted in Figure 2) separately at each time. But rather than doing two separate estimations (one for time 1 and one for time 2), it is appropriate to estimate the entire model simultaneously (i.e., the latent group model at both times together). The benefit of such a simultaneous model is that one can estimate the stability of the latent variable terms. This can be done by allowing correlations between all time 1 latent variables and all time 2 latent variables.

Figure 4 shows the group-level subset of this complicated model. Note that at time 1 there is the group-level correlation between X and Y, and at time 2 there is also a group-level correlation between X and Y. Thus, within the two times separately, we are recreating the group-level portion we have already discussed (e.g., Figure 2). The new feature in Figure 4 is that there are now across-time correlations between group-level latent variables—a correlation between the two X latent variables and another correlation between the two Y latent variables. These two correlations provide estimates of the group-level stability for each variable. As is customary within the SEM framework, it is possible to perform additional analyses (such as moderation and mediation) to get a deeper understanding of the contributors to group-level stability. What we show here is how to measure stability of group-level variance, but once it is measured, then the usual statistical techniques can be used (e.g., testing whether different types of groups have, or different manipulations lead to, more group-level stability).

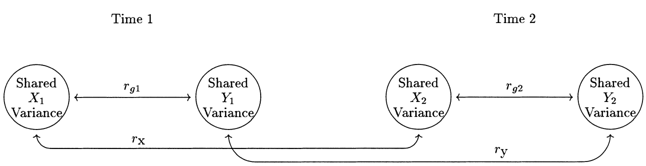


**Figure 4**
Stability of the Shared Variance Components.

*Note:* the Figure displays the group level variance for variables $X$ and $Y$, for each of two times. The correlations $r_{g1}$ and $r_{g2}$ are the group level correlations between variables $X$ and $Y$ at time 1 and time 2, respectively; the correlations $r_X$ and $r_Y$ measure the stability of the group-level variance for variables $X$ and $Y$, respectively.

The analogous stability coefficients would also be estimated for the individual-level variances, such as error for males' sociability at time 1 is allowed to be correlated with the error of males' sociability at time 2, etc. (Figure 4 only displays the group-level stability estimates).

This model can also be placed into an HLM format. This appears complicated because an extra level needs to be added to handle time; however, an important advantage of estimating stability in the context of HLM is the ability to handle missing data, which is one of the key methodological advances to come out of research on HLM. The analysis of the latent group model can even be conducted when some groups have data from only one member (e.g., Snijders & Bosker, 1999). These HLM techniques also permit "units" of unequal sizes. So, if the unit is the individual with up to, say, four time points, then one way to handle missing data would be to treat the "missingness" as something that yields unequal sized units. The general HLM framework can thus handle missing observations in a longitudinal design as well as groups of unequal sizes (as would be encountered, for example, in research where family is the unit of analysis); for a complete discussion, see Bryk and Raudenbush (1992). For an example of a longitudinal design in HLM for couple research using a single dependent variable, see Barnett, Raudenbush, Brennan, Pleck, and Marshall (1995).

## Limitations and Complications

We have presented the latent group model as a formal checklist of conditions that need to be satisfied to infer the existence of a "group personality." As we noted in the beginning, this logic corresponds to a lay theory rather than to personality theory more generally. In particular, although we have considered whether the underlying construct is a relatively enduring characteristic, we have neglected the second key question of whether that enduring characteristic is appropriately termed a disposition or even a predisposition. There is an alternative explanation for the coherence that we sought, one that cannot be dismissed with the types of data discussed so far—that is, that all members of a group respond similarly because of shared situational or environmental pressures. One particularly interesting version of this model is that the key environmental pressure is the presence of the other partner and that the observed coherence in fact represents mutual influence rather than a shared underlying disposition. These and related models are discussed in the context of personal relationships by Kenny (1996). Further, the source of the similarity needs to be established. Is group-level variance present at the beginning of the relationship or does it emerge over time? Clearly, there are variety of design tools that can be used to tease apart the various theoretical models of shared coherence (observations across multiple situations, observations across multiple time periods, observations when group members are interacting within, versus outside of, the group), and these models and manipulations will only serve to enrich the meeting point of personality theory and group theory.

The usual structural equations modeling considerations about sample size apply for the latent group model and its equivalent in the HLM context (see, e.g., Bollen, 1989). Our simulations (Griffin & Gonzalez, 1995; Gonzalez & Griffin, 1999) suggest that sample sizes as small as 30 dyads perform well with respect to Type I error rates and bias, but a complete analysis of sample size (especially under violations of distributional assumptions) has not yet been completed.

## Summary

Our goal for this paper was to present a methodology for assessing the personality of a relationship, a concept that is not equivalent to the "sum" of the individuals who make up the relationship. We showed how the logic of the MTMM technique, which is familiar in personality research to measure the reliability and validity of constructs, can be extend to model the similarity of the members in the relationship. Following Campbell and Fiske (1959), such similarity is a necessary condition for the measurement of a group-level personality. The latent group model permits the decomposition of individual-level and group-level variance. Once the latent variables at the different levels are identified, then covariances between such latent variables across different traits can then be examined. Our exposition focused on covariances between latent variables, but one can also model directed paths between such latent variables (e.g., the group-level latent variable of one trait mediating the group-level latent covariance between two traits). For an example of such an extension, see Gonzalez and Griffin (2000).

An important criterion in establishing the existence of a trait is the concept of stability, which is second nature to personality theorists. The present framework permits the assessment of stability at both the individual and group levels. We believe the capacity to assess stability at different levels will be a useful tool for researchers. For example, longitudinal analyses following the development of an intimate relationship (and perhaps the breakup) will be able to assess the time course of the individual-level and group-level variances. This will provide theorists new patterns to explain and may push the envelope of current theory of interpersonal relationships. We hope this will prompt researchers to ask new questions, such as, Does group-level variance at time $t$ predict individual-level variance at time $t + 1$? Does group-level variance, a measure of a particular relationship-level trait, predict subsequent breakup? How does the magnitude of group-level variance on a particular variable change as a nature of the relationship changes?

We presented several techniques and emphasized their similarity. For example, we showed how the latent group model can be estimated in the context of hierarchical linear modeling. Our hope was that by discussing the various techniques in the same paper, highlighting the similarity of the underlying logic, the reader would gain a better understanding of the methods. The reader should not be overwhelmed by the complexity of the menu of choices. Rather, our intention was to place several techniques in a common language to provide clarity for personality researchers wishing to enter relationships research. Many of the intuitions and techniques a personality researcher is familiar with from MTMM can be extended to the study of relationships. Armed with this analogy, techniques and theories from the personality literature can be applied to the study of relationship as well as to the study of whether there are separate individual-level and group-level personalities.

We hope that this paper has helped reframe the question "How should I analyze my relationship data" to the more meaningful question: "How can I bring personality methods and theory to bear in understanding interpersonal relationships?" We showed how a standard tool from personality research, the MTMM, can be adapted to the study of relationships. We await the interesting empirical and theoretical insights about relationships that we hope will emerge from the application of personality theory and its methodology to the study of relationships.

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