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The correlational analysis of dyad-level data in the distinguishable case

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Abstract
Many theories of interpersonal relationships distinguish between individual-level processes and dyadic or group-level processes. This suggests that two-person relationships should be studied at the level of the dyad as well as at the level of the individual. We discuss correlational methods for dyads when each dyad contains two different types of individuals (e.g., a husband and wife, a mother and child, or an expert and a novice). In such dyadic interaction designs, the dyad members are said to be *distinguishable.* We present a method for computing the overall correlation for distinguishable dyads, and we discuss a model for separating the dyad-level and individual-level components of such a correlation. The computational techniques and their interpretation are described using data from 98 heterosexual couples.

By definition, interpersonal interaction involves more than one person. The simplest interaction to study, and likely the most common (Bakeman & Beck, 1974), involves two people. However, despite their relative simplicity, dyadic designs present both conceptual and methodological challenges (Kenny, 1996; Gonzalez & Griffin, 1997). Dyadic designs, like all group designs, pose a conceptual "levels of analysis" problem (Robinson, 1950). One could test theory at either the level of the individual, the level of the dyad, or both. Statistically, correlational methods developed for independent individuals are not appropriate for designs featuring interdependent dyad members (Griffin & Gonzalez, 1995; Kenny, 1995). Instead, the degree of relatedness, or "statistical nonindependence," between dyadic partners must be taken into account when correlations are tested and interpreted.

Furthermore, the statistical analysis depends on whether the dyadic partners are *exchangeable* (i.e., the two members of each dyad are drawn from the same class or category) or *distinguishable* (i.e., the two members of each dyad are drawn from different classes or categories).[1] Two examples will help make this distinction clear. Research on romantic relationships might focus on male homosexual couples (which contain exchangeable dyad members) or heterosexual couples (which contain distinguishable dyad members). Research on social development might focus on dyadic play in same-sex children (exchangeable dyad members) or dyadic play between fathers and sons

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1. Kenny (1996) uses the terms "interchangeable" and "noninterchangeable" to denote this distinction.

(distinguishable dyad members). In the exchangeable case, each partner is drawn from the same category or type (e.g., adult males), and thus both scores are treated as though they are sampled from the same statistical distribution. In the distinguishable case, each partner belongs to a *different* category or type (e.g., fathers vs. sons), and their scores on each variable are drawn from distributions that may differ, yielding the possibility that these two samples may differ in their means, their variances, or their covariances.

The decision to treat dyadic partners as distinguishable or exchangeable should be guided by theoretical assumptions rather than empirical tests. Thus, even if the two types of partners do not differ in mean, variance, or covariance terms, they should be treated as distinguishable rather than exchangeable if they are distinguished in the relevant theory. When other variables are tested, the two types of partners may well differ. Furthermore, no power is lost by treating the partners as distinguishable as long as the relevant parameter estimates are pooled across both types of partners.

We now turn to a specific research example that we will use throughout this article. Murray, Holmes, and Griffin (1996) collected trust and conflict ratings from both members of 98 heterosexual couples. One question of interest addressed by this study is: Across the entire sample of men and women, do ratings of trust relate to reports of conflict? In other words, is there a significant *overall within-partner correlation* between trust and conflict? A second question of interest involves a different overall correlation: Across the entire sample, do ratings of an individual's trust relate to the partner's report of conflict? In other words, is there a significant *overall cross-partner correlation* between trust and conflict?

The meaning of these "overall" correlations could then be examined in light of a model of the underlying process that gave rise to it. Although the data could be modeled in a number of ways (Kenny, 1996), two specific underlying models seem of greatest relevance: a dyadic version of the group effects model (Kenny & La Voie, 1985) that decomposes the observed overall within-partner correlation into latent dyadic and individual-level components, and the generalized actor-partner model (Gonzalez & Griffin, 1997; Kenny, 1996) that decomposes the observed relations into partial path coefficients (beta weights). The latter model was used by Murray et al. (1996). This article will focus on the dyadic effects model and discuss the meaning and computation of couple-level and individual-level correlations. However, it must be emphasized that the choice of an underlying model is a theoretical rather than a statistical question (Kenny, 1996).

We now turn to a more detailed discussion of these overall correlations. We will review the pairwise coding, show how to estimate these two overall correlations, provide tests of significance, compare the SEM (structural equation modeling) approach to the pairwise approach, and provide a concrete example. We will then review the dyadic model that decomposes the observed overall within-partner correlation into latent dyadic and individual-level components. This multilevel model will not only provide new insight for the overall correlations, but will also be a useful model in many research settings.

Estimating and Testing the Overall Correlations in the Distinguishable Case

Suppose a researcher collected two variables, X and Y, from each individual in a sample of heterosexual couples. For instance, as in Murray et al. (1996), a researcher could collect trust ratings (variable X) from both the husband and the wife, and reports of conflict (variable Y) from both the husband and the wife. This results in four variables: X_h, X_w, Y_h, and Y_w, where the subscript h represents husband and the subscript w represents wife. There are a total of six correlations that can be computed in this situation; these correlations are shown in Figure 1.

The correlation between X_h and Y_h, denoted $\text{cor}(X_h, Y_h)$ in Figure 1, is the within-partner correlation between trust and conflict for husbands, and the correlation

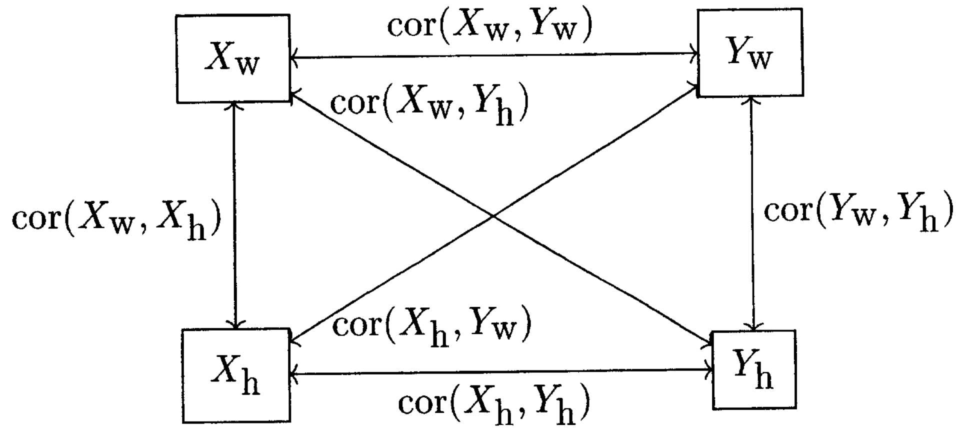

Figure 1. The six possible pairwise correlations in the distinguishable case.

between X_w and Y_w is the within-partner correlation between trust and conflict for the wives. Under some conditions (described below) it is possible to pool these two correlations to form a single index, the *overall within-partner correlation* between trust and conflict.

The purpose of the overall within-partner correlation is to index the strength of the linear relation between two variables, X and Y, across *all* individuals in the sample. With N dyads, the overall within-partner correlation involves $2N$ scores on each variable. The practice of computing the overall correlation has a number of advantages over the more common practice of computing separate correlations within the two types of dyadic partners (e.g., computing the correlation between trust and conflict separately for men and for women). First, if the correlational structure is identical across the two types, then the overall correlation serves as a more efficient estimate of the true correlation between variable X and variable Y than either of the separate estimates. Second, the overall correlation will usually have substantially more power to reject the null hypothesis relative to either one of the separate correlations. The procedure described here includes an explicit test of whether the correlational structure is the same within both classes, a step often ignored by researchers looking at each type of partner separately.

Returning to Figure 1, the correlation between X_h and Y_w is the cross-partner correlation between the husband's trust and his wife's report of conflict, and the correlation between X_w and Y_h is the cross-partner correlation between the wife's trust and the husband's report of conflict. Again, under some conditions, it is possible to pool these two "cross" correlations to form the *overall cross-partner correlation,* which has advantages similar to that of the overall within-partner correlation discussed above.

Computing the overall within-partner correlation between trust and conflict in the exchangeable case is relatively straightforward, because the distributions of each partner's scores are by definition equivalent. With N dyads, the $2N$ individual scores on trust are correlated with the $2N$ individual scores on conflict, and the result is evaluated using a significance test that corrects for the degree of intradyadic similarity on each variable (see Griffin & Gonzalez, 1995, for the development of this test). However, when each dyad is made up of two different types of individuals (e.g., men and women), additional complications arise because of the possibility of between-partner differences in means, variances, and covariances. In this article we extend the pairwise correlational model (Griffin & Gonzalez, 1995) to the more complicated case of distinguishable dyads and compare the pairwise approach with structural equation modeling.

Whenever possible, we relegate statistical details to the Appendix, allowing us to focus the text on the conceptual "big picture."

In the distinguishable case, computing and testing the overall within-partner and cross-partner correlations can be achieved either through the pairwise correlation method or through structural equation modeling (SEM) programs. When SEM is estimated through the maximum likelihood approach, the two approaches yield identical parameter estimates because the pairwise approach also provides the maximum likelihood estimate, and the two approaches provided asymptotically equal significance tests under the null hypothesis. For those comfortable with SEM programs, the SEM approach offers substantial advantages in terms of flexibility and adaptability. However, the pairwise correlational approach is a useful tutorial method and provides a unified framework across the distinguishable and exchangeable cases. After discussing the assumptions common to both approaches, we first describe the SEM method and then describe the pairwise method, which does not require special software.

Assumptions of the overall within-partner, cross-partner correlations

The overall within-partner correlation r_{xy} is a summary of the strength of the linear relation between variables X and Y across all partners of *both* types. Because the overall within-partner correlation is essentially a weighted average of the two within-partner correlations (e.g., the correlations between trust and conflict for men and women separately), it is necessary to examine whether the components of the separate within-partner correlations are similar enough to be combined. For an overall within-partner correlation to be a legitimate summary of the linear relation between the two variables across both types of dyad members, the following conditions must hold: (a) the two within-category population variances on X must be equal (e.g., the population variance on variable X for men equals the population variance on X for women), (b) the two within-category population variances on Y must be equal, and (c) the two within-category population covariances between X and Y must be equal (e.g., the population covariance between X and Y for women must equal the population covariance between X and Y for men). For the overall cross-partner correlation conditions (a) and (b) must hold, and in addition (d), the population covariances between one partner's X and the other partner's Y, must be equal across the two classes (e.g., the population covariance between the wife's X and the husband's Y must equal the population covariance between the husband's X and the wife's Y). Methods for testing each assumption separately are presented in the Appendix. Below we present a method for testing all four assumptions simultaneously using SEM.

These equality assumptions have *conceptual* meaning and are more important than mere statistical worries. First, a difference in variances between the two types of partners might suggest that different processes may be operating in each type or category. Second, a difference in variances may lead to differences in the observed correlations even when the population covariances are equivalent. Third, when the assumption of equal covariances is violated for the within-partner comparison, the pooled correlation no longer represents the relation within either type of partner (e.g., women or men). When pooling is appropriate, the conceptual focus should be on the general processes occurring for both partners. When the pooling is not appropriate, the conceptual focus should be on the difference between the types of partners. As these arguments suggest, the tests of the assumptions have implications for the direction the theory should take.

Using SEM to estimate the overall correlations

The overall within-partner correlation and the overall cross-partner correlation can be estimated within SEM (using covariances or raw data as input; see Footnote 4). The

SEM model presented in Figure 1 constrains the two X variables to have equal variances, and also constrains the two Y variables to have equal variances. Of the six observed covariances, the two within-partner covariances between variables X and Y are constrained to be equal as are the two cross-partner cross-variable covariances. The resulting SEM analysis yields a χ^2 with 4 degrees of freedom (*df*) that provides an omnibus test on all four constraints. Note that it is also possible to test each assumption separately within SEM by relaxing each assumption and comparing the difference in χ^2s from the full model ($df = 4$) to each reduced model ($df = 3$).

If the omnibus χ^2 test is nonsignificant, then the pooled covariance between X and Y is an appropriate estimate of the "overall within-partner covariance," and the significance test associated with this parameter tests the overall correlation against the null hypothesis. Similarly, the pooled covariance between an individual's X and the partner's Y is an estimate of the "overall cross-partner covariance," and the significance test associated with this parameter tests the overall cross-partner correlation against the null hypothesis.[2] In the SEM output, the overall within-partner and cross-partner correlations will appear as standardized coefficients.

Using the pairwise approach to estimate the overall correlations

The pairwise approach offers an alternative method for estimating the overall correlations; it provides parameter estimates that are identical to those given by SEM under maximum likelihood. In the pairwise correlation approach, the estimation of the overall within-partner and overall cross-partner correlations proceeds in four steps. First, the data are arranged in the pairwise manner (Griffin & Gonzalez, 1995). Second, the assumptions necessary for pooling the correlations across the two categories of individuals (i.e., equality of variances within variables and equality of covariances within and across categories) are checked. Third, the overall within-partner and cross-partner correlations are computed as partial correlations with between-class mean differences (e.g., sex differences) partialled out. Fourth, the overall within-partner and overall cross-partner correlations are tested for significance by a method that takes into account the degree of nonindependence within dyad members.

In the distinguishable case, the pairwise correlation model requires five columns of data (see Griffin & Gonzalez, 1995, for a general discussion of the pairwise model). As shown in Table 1, the first column (labeled *C*) consists of binary codes representing the "category" variable (e.g., sex of subject). If the researcher decided to code wives as "1" and husbands as "2" the first column would consist of "1" in the first row and "2" in the second row. This pattern would be repeated for each of the N dyads in the sample, yielding a column containing $2N$ binary codes. The second column (labeled X) contains the scores on variable X corresponding to the dyad member represented by the category code in column one. For example, the first woman's score on trust is adjacent to the first "1" in column one. Below that, the first man's score on trust is adjacent to the first "2" in column one. This pattern continues, yielding a total of $2N$ scores.

Column three is created by the pairwise reversal of column two. For example, adjacent to each person's score on trust in column two is placed her or his *partner's* score on trust in column three. This "reversed" column of scores on X is referred to as X'. Columns four and five consist of the scores on variable Y (e.g., conflict), which are also coded in the "pairwise" format and labeled Y and Y', respectively. Table 1 presents

2. One possible generalization of this model is a relaxation of the variance constraints (i.e., a model that has all four variances as free parameters). On the surface this generalized model may appear attractive; however, it is difficult to interpret because the resulting parameters are standardized according to the particular variances involved. Thus, even when the covariances are set equal across classes, the standardized solutions for each class (e.g., the correlations for men and women) will be unequal.

Table 1. *Symbolic representation for the pairwise data setup for two variables in the distinguishable case*

Dyad No.	Variable				
	C	*X*	*X'*	*Y*	*Y'*
1	1	X_{11}	X_{12}	Y_{11}	Y_{12}
	2	X_{12}	X_{11}	Y_{12}	Y_{11}
2	1	X_{21}	X_{22}	Y_{21}	Y_{22}
	2	X_{22}	X_{21}	Y_{22}	Y_{21}
3	1	X_{31}	X_{32}	Y_{31}	Y_{32}
	2	X_{32}	X_{31}	Y_{32}	Y_{31}
4	1	X_{41}	X_{42}	Y_{41}	Y_{42}
	2	X_{42}	X_{41}	Y_{42}	Y_{41}

Note: The first subscript represents the dyad and the second subscript represents the individual. Categorization of individuals as 1 or 2 is based on the class variable *C*. Primes denote the reverse coding described in the text.

these five columns in symbolic form. The reasoning behind the pairwise coding is that interdependence is built directly into the data matrix. By constructing such links between data points, subsequent analyses become relatively straightforward.

The Appendix provides statistical tests for each of the assumptions discussed in the previous section. Note that the pairwise approach tests assumptions separately, whereas above we described an omnibus test for the set of assumptions in SEM. Those concerned about inflated Type 1 error rates for the separate tests of the assumptions in the pairwise approach may wish to use a Bonferroni corrected α-level. Separate tests may be desirable because the omnibus test could mask violations (e.g., an assumption may be violated even when the omnibus test is not statistically significant).

Given that the assumptions are met, the overall within-partner correlation is computed using all 2*N* individual scores in columns two (*X*) and four (*Y*) of Table 1—or equivalently, columns three (*X'*) and five (*Y'*). However, the simple correlation between column *X* and column *Y* does not, in general, estimate the "true" overall within-partner correlation. Instead, if there are between-category *mean differences* on one or both variables (e.g., men have a higher score on trust than do women or vice versa), these mean differences will bias the observed overall within-partner correlation, with the direction of the bias controlled by the magnitudes and directions of the two mean differences. The overall within-partner correlation must be corrected for these mean differences by partialling on the category variable. Thus, the appropriate estimate of the overall within-partner correlation is

$$r_{xy\cdot c} = \frac{r_{xy} - r_{cx}r_{cy}}{\sqrt{1 - r_{cx}^2}\sqrt{1 - r_{cy}^2}} \qquad (1)$$

This equation is simply the partial correlation between variables *X* and *Y*, holding *C* constant, denoted by $r_{xy.c}$ (where variables to the right of the dot have been partialled out). In our ongoing example, the corrected estimate of the overall within-partner correlation would be the partial correlation between trust and conflict with sex of subject partialled out. Most statistical packages have procedures for computing partial correlations.

The computation of the overall cross-partner correlation proceeds in a similar manner. The "partial" overall cross-partner correlation is given by

$$r_{xy'\cdot c} = \frac{r_{xy'} - r_{cx}r_{cy'}}{\sqrt{1 - r_{cx}^2}\sqrt{1 - r_{cy'}^2}} \qquad (2)$$

Again, this is simply the partial correlation between an individual's X (column 2) and his or her partner's Y (column 5, or Y') holding C constant.

Significance tests for the two overall correlations are presented in the Appendix. The reader may examine the symbolic form of the significance test to develop intuition for how interdependence influences these tests. Even though significance tests for the pairwise approach are asymptotically equivalent to the Z-tests in SEM under the null hypothesis, in a single sample the two tests will not be identical. A Monte Carlo simulation that assesses the performance of the pairwise and SEM tests for r_{xy} is given in the Appendix. The simulation suggests that the pairwise approach performs at least as well as the SEM approach with respect to the effective Type I error rate, with the SEM approach tending to be slightly liberal.

Illustrating the overall within-partner and cross-partner correlations for the distinguishable case

In the following section we use data collected by Murray et al. (1996) to illustrate the pairwise analysis of the overall within-partner correlation when dyadic partners are distinguishable. Murray and colleagues collected data from both members of 98 heterosexual couples. We chose two variables from their data: trust (Holmes & Rempel, 1989) and conflict (a 5-item index adapted from Braiker & Kelley, 1979, indexing the self-rating of the frequency of overt behavioral conflict). The relevant means, variances, covariances, and correlations are presented in Table 2. The relevant partial pairwise correlations needed for testing the overall within-partner correlation r_{xy} and the overall cross-partner correlation $r_{xy'}$ are presented in Table 3. Each entry in Table 3 is a partial correlation in that the category variable C has been partialled out. The information needed to compute all statistics and tests presented in this article is contained in those two tables.

The SEM analysis estimating the overall within-partner and cross-partner correlations tests all assumptions simultaneously; the omnibus test with 4 degrees of freedom was nonsignificant ($\chi^2 = 7.98, p = .09$), indicating that it was appropriate to interpret the pooled overall correlations as summaries of the relation between trust and conflict across the entire sample.

In the pairwise approach, the assumptions are tested individually. An examination of the diagonal elements in Table 2 reveals that men and women had approximately equal variances on each variable. The t values corresponding to the dependent variances test presented in the Appendix were 1.31 for trust and 1.04 for conflict, neither of which is statistically significant at $\alpha = .05$ with 96 degrees of freedom. The

Table 2. *Correlations, variances, and covariances from 98 couples*

	Trust		Conflict	
	Female	Male	Female	Male
Female Trust	1.351	0.440	− 0.857	− 0.443
Male Trust	0.287	1.743	− 0.365	− 0.438
Female Conflict	− 0.474	− 0.178	2.421	1.025
Male Conflict	− 0.269	− 0.234	0.465	2.006
Means	7.631	7.509	2.992	2.882

Note: Correlations appear below the diagonal, variances on the diagonal, and covariances above the diagonal. The means on each variable (e.g., the mean female trust score) are presented in the last row. From Murray et al., 1996.

Table 3. *Partial pairwise correlation matrices for trust (T) and conflict (C) from Murray et al. (1996)*

	Trust and Conflict		
	T	T′	C
T′	**.284**		
C	−.350	−.218	
C′	−.218	−.350	**.463**

Note: The prime denotes the "reverse" coding of the variable as described in the text. Boldfaced values are the partial intraclass correlations.

assumption that cov_{xy} for women equals cov_{xy} for men is tested next[3] (again, see the Appendix for details on tests of dependent covariances). For trust and conflict, cov_{xy} equaled −.857 for women and −.438 for men. This difference was not statistically significant by the test on dependent covariances given in the Appendix, $Z = -1.64$. The final assumption tested is that the two cross-partner covariances are equal. The assumption that $cov_{xy'}$ for one partner (e.g., the population covariance between women's trust and partner's report of conflict) equals $cov_{xy'}$ for the other partner (e.g., the population covariance between men's trust and partner's report of conflict) appears to fit. The difference between the trust–conflict covariances across partners was not statistically significant by the covariance test presented in the Appendix, $Z = -.33$.

Estimates of the two overall correlations are identical for the SEM and pairwise approaches, although the tests of significance differ slightly. The overall within-partner correlation (partialled on sex) between trust and conflict was −.350. Thus, a negative correlation existed between trust and reports of conflict when pooling both sexes and controlling for mean differences. In the pairwise analysis, the effective sample size $N_{*1} = 166.24$, and the Z value was −4.51, $p < .001$. The SEM Z was −4.27. The overall cross-partner correlation was −.218, with an effective sample size of 175.0 and a pairwise Z of −2.88. The SEM Z was −2.67 for the identical standardized estimate.

3. Note that when the variances are equal across classes, the equality of covariance assumption can be tested using either covariances or correlations.

Separating Dyad-Level and Individual-Level Effects

In contrast to the overall correlations discussed above, the dyadic effects model focuses on three different questions. First, are dyadic members similar to each other on each variable? That is, is there significant *dyad-level* variance in each variable? Second, if there is dyad-level variance in each variable, are the two variables correlated at the dyadic level? That is, is there a significant *dyad-level* correlation between the trust ratings and the reports of conflict? Third, within each dyad, does the relative standing of the two individuals on one variable relate to their relative standing on the second variable? That is, is there a significant *individual-level* correlation between trust and conflict? These questions assess whether the overall within-partner correlation reflects dyad-level processes, individual-level processes, or both.

The overall within-partner correlation serves as a summary of the relation between variables X and Y across all individuals, but it does not reveal whether the relation between variables X and Y exists at the level of the individual, at the level of the dyad, or both. Figure 2 presents one model of the sources of the linear relation between X and Y that allows the separation of individual-level and dyad-level effects (Kenny & La Voie, 1985). Once again, we emphasize that the appropriateness of this model is not provable by statistical means; alternate structural models (e.g., Kenny, 1996) may be theoretically justified. In the dyadic effects model for the distinguishable case, the variance of a given observed variable is assumed to result from three different sources: variation due to category membership (which is partialled out from the model

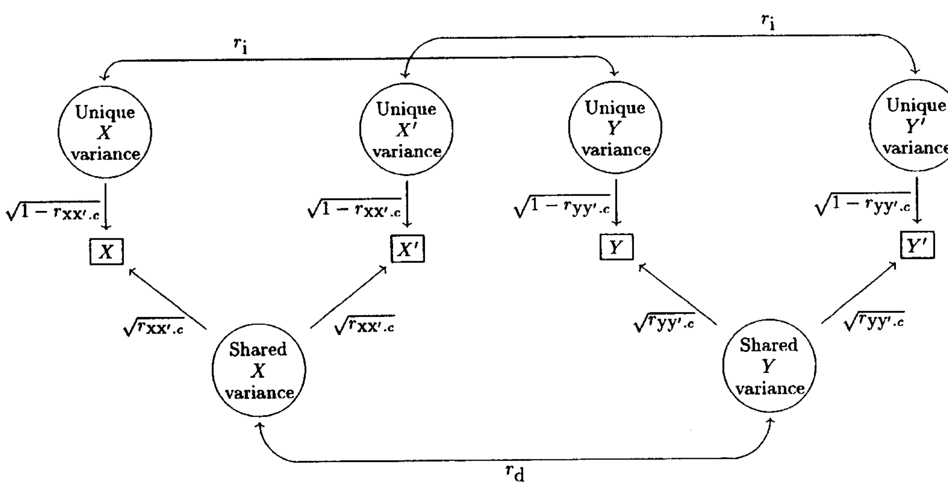

Figure 2. A latent variable model separating individual-level (unique) and dyad-level (shared) effects using the pairwise approach.

shown here), variation due to dyads, and variation due to individuals within dyads. The dyadic component of a given variable is the portion of that variable that is *shared* between dyadic partners; the individual component is the portion of a variable that is *unshared* between dyadic partners.

As Figure 2 illustrates, in this model the *covariation* of two variables is also assumed to result from the same three sources. First, mean category differences on X and Y (which are held constant in the pairwise model) give rise to one portion of the observed overall correlation. Second, the dyadic (shared) portions of X and Y are related through the dyadic correlation r_d. Finally, the individual (unshared or unique) portions of X and Y are related through the individual-level correlation r_i. After the class differences are partialled out, the corrected overall within-partner correlation can be decomposed into the remaining two parts:

$$r_{xy \cdot c} = \sqrt{r_{xx' \cdot c}}\sqrt{r_{yy' \cdot c}}\, r_d + \sqrt{1 - r_{xx' \cdot c}}\sqrt{1 - r_{yy' \cdot c}}\; r_i \qquad (3)$$

In words, the overall within-partner partial correlation between all X scores and all Y scores in a distinguishable dyadic design is modeled as a weighted sum of the dyad-level correlation (r_d) and the individual-within-dyad correlation (r_i). The dyad level correlation contributes more to the overall within-partner partial correlation when the shared variance between partners is large (as indexed by the partial intraclass correlations $r_{xx'.c}$ and $r_{yy'.c}$), whereas the individual-level correlation contributes more to the overall within-partner partial correlation when the shared dyadic variance is small.

Assumptions of the dyadic model

The assumptions for the distinguishable dyadic model are identical to the assumptions for the overall correlations (equal variances on X, equal variances on Y, equal covariances between an individual's X and the partner's Y, and equal covariances between X and Y within each class). As with the overall case, these assumptions can be tested either separately with the tests provided in the or simultaneously with SEM. The omnibus test in SEM is the 4-degrees-of-freedom χ^2 test given by the model in Figure 2 with the observed covariance matrix as input. Note that this is the identical χ^2 from the omnibus test of the assumptions for the overall correlations.

The dyadic effects model has one additional assumption that must be examined as well: The intraclass correlations must both be significant (Kenny & La Voie, 1985). The partial intraclass correlation yields the proportion of shared or dyad-level variance in each variable. Stated another way, the square root of the intraclass correlations define the "reliability coefficients" for the underlying dyadic latent variables. If the intraclass correlations are zero, then there is no dyad-level variance, and r_d is meaningless. A simple asymptotic test for the partial intraclass correlation is provided in the Appendix.

The SEM framework offers more flexibility than does the pairwise approach because it permits a relaxed model with different individual-level correlations for each member. If the χ^2 is significant, then the pooled dyadic structural model does not fit the data. One option available in that case is to refit the model with separate individual-level correlations, and examine the change in χ^2 between the full and reduced model (see the Appendix for the necessary EQS syntax).

Using SEM to estimate the dyadic model

Figure 2 also illustrates the structural model used to estimate the two underlying correlations r_d and r_i in the SEM approach. Sample EQS syntax and guidelines for AMOS are presented in the Appendix. The SEM approach involves three important changes from the pairwise structural model. First, instead of the pairwise data setup (e.g., columns X and X' each with the entire $2N$ set of observations differing only in order), the observed variables are coded separately by categories (e.g., X_w represents the wife's score on trust and X_h represents the husband's score on trust, each column with N observations). Second, and following from the first point, the category effect is not directly partialled out from the SEM structural model. Instead, this model is based on the six covariances[4] presented in Table 2. Third, when using SEM the model in Figure 2 could be generalized to allow for separate individual-level correlations r_i for each class (i.e., separate individual-level correlations for men and women), whereas the pairwise model can only estimate a pooled individual-level correlation.

The output from an SEM program will provide the estimates of r_d and r_i, as well as tests of significance for these parameters. We identified the model by setting the variances of all latent variables to 1 (there are two latent dyadic variables and four latent individual variables) and requiring the two individual-level loadings on each variable to be equal (e.g., the individual loading on trust is set equal for men and women) and the two dyadic loadings on each variable to be equal (e.g., the dyadic loading on trust is set equal for men and women). This parameterization facilitates generalization to more variables and groups of larger size, as discussed later in this article. Under the present identification scheme, the unstandardized coefficients are the correlations. For different identification schemes, one would need to use the standardized coefficients rather than the unstandardized coefficients. See Bentler (1995) for an illustration of different methods of identifying such a model; Gonzalez and Griffin (1998)

4. For some simple SEM models, a correlation matrix or a covariance matrix as input leads to identical solutions (see Bollen, 1989, or Long, 1983, for a nontechnical discussion of this issue). However, a covariance matrix should be used as input whenever there are *equality constraints* in the model. In the present models, the two dyadic loadings from each latent variable leading to the two individual scores are constrained to be equal and the two individual loadings leading to a given variable are constrained to be equal. Thus, the models presented here must be evaluated by using unstandardized input. Note also that the individual-level correlations are identical to correlated errors provided by standard SEM models; however, the parameterization provided here is slightly different from usual to make the multilevel nature of the data clearer and to allow easy generalization to more than two variables.

discuss the implications that different identification schemes have on the Z tests.

Parameter estimation and significance testing

In this section we show how the dyad-level and individual-level correlations can be computed from the partial pairwise correlations given in Table 3. These estimates are identical to those given in SEM under maximum likelihood estimation (i.e., the pairwise approach also provides maximum likelihood estimators).

The dyad-level correlation addresses the following question: Does the similarity of the members of a dyad on X (i.e., both tending to be high on X or both tending to be low on X) relate to the similarity of the members of that dyad on Y (i.e., both tending to be high on Y or both tending to be low on Y)? Following the logic developed in Griffin and Gonzalez (1995), the dyad-level correlation in the distinguishable case is

$$r_d = \frac{r_{xy'\cdot c}}{\sqrt{r_{xx'\cdot c}}\sqrt{r_{yy'\cdot c}}} \qquad (4)$$

Because dyad-level correlations represent the degree of linear relation between the shared dyadic components of each variable, there can be no dyad-level correlation without within-dyad similarity on both variables, as indexed by a significant intraclass correlation (or equivalently, by a significant amount of variance in the latent variable). Therefore, the partial intraclass correlations $r_{xx'\cdot c}$ and $r_{yy'\cdot c}$ need to be nonzero.

Note that the dyad-level correlation is quite different from the correlation between the dyad means because the mean-level correlation is not constrained by the dyadic similarity within each variable, and instead contains a mix of dyad-level and individual-level effects (see Griffin & Gonzalez, 1995, for an extended discussion). This problem can be seen most clearly in a "pseudo-dyadic" design where individuals participate individually but are randomly collected into dyads by the experimenter after the data have been collected. In this situation, as long as there is a significant individual-level correlation, correlations computed on "dyadic" means could be substantial, even though the dyads never existed! This is because the dyad average combines the unique qualities of the individuals with the "emergent properties" of the dyad. A dyad-level correlation should represent only the relation between the shared or emergent properties of the dyad on two variables.

The individual-level correlation addresses the following question: Does the residual of an individual's score on variable X (beyond what would be expected by membership in a particular dyad) relate to the residual of that individual's score on variable Y (beyond what would be expected by membership in a particular dyad)? Under the dyadic model, the individual-level correlation can be expressed as

$$r_i = \frac{r_{xy\cdot c} - r_{xy'\cdot c}}{\sqrt{1 - r_{xx'\cdot c}}\sqrt{1 - r_{yy'\cdot c}}} \qquad (5)$$

Individual-level correlations represent the degree of relation between the unique variance on variable X (how a person differs from his or her partner on X) and the *unique* variance on variable Y (how a person differs from his or her partner on Y). The individual-level correlation can exist whether or not there is intra-dyadic similarity, as long as the intra-dyadic similarity is not perfect. The individual-level correlation differs from the overall within-partner correlation because the latter correlation is not constrained by the *unique* portion of an individual's score, and instead contains (like the mean-level correlation) a mix of individual and dyadic effects (see Equation 3).

Both r_d and r_i are estimated latent variable correlations and are "disattenuated" for the proportion of dyad-level and individual-level variance, respectively, in each variable. The disattenuation interpretation is driven by the denominators of Equations 4 and 5. The numerator of r_d is the overall cross-partner correlation $r_{xy'\cdot c}$, which indexes the strength of the dyadic relation in raw score terms. When $r_{xy'\cdot c}$ is 0, then r_d must be 0.

Significance tests for the distinguishable pairwise case are, with one slight exception, identical to those presented in Griffin and Gonzalez (1995) for the exchangeable case. The asymptotic tests include those for the partial intraclass correlations $r_{xx'\cdot c}$ and $r_{yy'\cdot c}$, which index the amount of dyadic or shared variance in each variable, the partial raw-score dyadic correlation $r_{xy'\cdot c}$, which indexes the dyadic relation uncorrected for the degree of shared variance, and the latent dyadic correlation r_d. The individual-level correlation r_i is tested using a standard t test for Pearson correlations, and this test loses a degree of freedom relative to the exchangeable case owing to the partialling of variable C. Details of the tests can be found in the Appendix.

Although the significance tests from the SEM and pairwise approaches are equivalent under the null hypothesis, in practice the null hypothesis will not be exactly true and the significance tests from the two methods will differ. In the Appendix we present simulation data comparing the tests of significance provided by the two models. Note that the significance test from the pairwise approach is slightly more well-behaved than the SEM version (see Gonzalez & Griffin, 1998, for a discussion of the limitations in SEM significance tests).

An illustration of the dyadic effects model

We use the Murray et al. (1996) data to illustrate the distinguishable dyadic effects model. For trust, the observed partial intraclass correlation of .284 indicates that about 28% of the variance in trust was shared between dyadic partners.[5] Similarly, for conflict, the observed partial intraclass correlation of .463 represents the proportion of variance in conflict that was shared between the partners. The same information is obtained from the standardized path coefficients of the SEM model after they are squared. When the two partial intraclass correlations are tested by the asymptotic Z tests, both are significant: $Z = 3.06, p < .01$ for trust, and $Z = 5.83, p < .001$, for conflict. The relevant tests from the SEM output are 5.39 and 8.28, again statistically significant. Recall that the two tests will not coincide except asymptotically under the null hypothesis.

Turning to the multilevel correlations, the pairwise analysis yields a dyad-level correlation between trust and conflict of $-.601$. This value is obtained by disattenuating the overall cross-partner correlation $r_{xy'} = -.218$ by the amount of dyad-level variance in each variable, $r_{xx'} = .284$ and $r_{yy'} = .463$. In this case, $r_d = \frac{-.218}{\sqrt{.284}\sqrt{.463}} = -.601$. Note that exactly the same estimate is obtained from SEM. Under special circumstances the estimated latent correlation can obtain "out of bounds" values greater than 1.0. Some programs such as EQS automatically restrict the possible values of correlations to fall between -1 and 1, and then the pairwise and SEM values will diverge. When tested by the pairwise significance test, r_d is statistically significant, $Z = -2.88$, $p < .01$ (the SEM Z value is -3.49).

Finally, the individual-level correlation is obtained by correcting the difference between the combined individual and dyadic correlation r_{xy} and the pure dyadic correlation $r_{xy'}$ for the amount of unique individual-level variance in each variable, $1\text{-}r_{xx'}$ and $1\text{-}r_{yy'}$. In this case, the individual-level correlation between trust and conflict is $-.212$, yielding a $t(96) = 2.12, p < .05$ (the SEM the corresponding estimate of r_i is identical and the Z value is 2.19).

Interpreting these results

How should these results be interpreted? First, the relations across men and women between trust and conflict were symmetric.

5. Note that for the intraclass, the percentage of variance explained is given by r not r^2.

That is, the relation between men's trust and women's report of conflict was roughly equal to the relation between women's trust and men's report of conflict. This is an important conclusion in itself, but is also a necessary assumption for the dyadic effects model to be appropriate. Second, the members of heterosexual romantic couples were moderately similar (at a correlational, but not necessarily at a mean level, because mean sex differences were partialled out of this analysis) on levels of both trust and conflict. The significant intraclass correlations indicated that men and women within a couple tended to resemble each other, although the proportions of variance were only moderate (28% and 46% dyad-level variance for trust and conflict, respectively).

Finally, and most important, trust and conflict were related at both the level of the dyad and the level of the individual. This situation is by no means preordained. Substantial correlations may be observed at only one level of analysis, and in special cases, each of the two levels can have *opposite* signs. Recall that the dyad-level correlation represents dyadic processes because it indexes the extent to which the *similarity* between men and women on X (trust) relates to the *similarity* between men and women on Y (conflict). Conceptually, this suggests that the dyadic processes that give rise to shared positive trust are related to those dyadic processes that reduce shared perceptions of conflict. In this case, an individual who was relatively more trusting tended to report relatively less conflict, so that both levels moved in the same direction. But it is easy to imagine situations (theoretically justified) for an opposite result. If the individual-level relation primarily reflected neuroticism, for example, one might find that the more neurotic and enmeshed partner was both more trusting and more likely to report conflict.

Note the limitations provided by an *existing couples* design. We do not know whether the significant dyad-level correlations came about (a) because of dyadic processes that occurred between the dyad members, or (b) because of the selection principles that led couples to end up together, or (c) because of some third variable operating on both partners. Only when dyad members are randomly assigned can we conclude that the similarities on each variable, and the dyad-level correlation between each variable, reflect actual dyadic processes (or shared environments that have dyad-level effects).

Once again, we stress that multilevel conclusions cannot be reached by the common practice of (a) correlating dyad means on X and Y or (b) correlating individual scores on X and Y. As noted earlier, both the mean-level correlation r_m and the overall within-partner correlation are weighted combinations of the dyad-level and the individual-level correlation.

Extensions to Larger Groups and More Variables

Clearly, the two-person, two-variable problem we have demonstrated here is the simplest possible setup. In the distinguishable case, because of the multiple equality constraints, the pairwise approach becomes cumbersome when larger groups or multivariate analyses are desired. The SEM approach, however, is well-suited to such extensions. (Note that the standard SEM approach is not easy to implement in the exchangeable case.) For example, imagine that one collected trust and conflict scores on members of family units where each family consisted of a father, mother, daughter, and son, and where the four categories were treated as distinguishable. An SEM model generalized from Figure 2 could address such questions as: Are trust and conflict related overall, at the family level, and at the individual level? (See Cook, 1994, for a similar model of family functioning using a latent variable approach.) With four distinguishable family members, a step-down approach to the equality constraints should be used: For example, after testing for a common overall within-individual correlation, the constraints might be relaxed to allow the children to have a different overall correlation than the adults.

Or, as another example, one might wish to study whether the multilevel relations between trust and conflict in couples remain when a third variable, such as relationship satisfaction, is held constant. This could be accomplished by extending the model presented in Figure 2 so that the correlated latent dyadic variables underlying trust and satisfaction were used to predict the latent dyadic variable underlying conflict, and the correlated individual-level variables underlying trust and satisfaction were used to predict the individual-level variable underlying conflict. Examples of this extension (and others) are given in Gonzalez and Griffin (1997).

Summary and Conclusion

We have presented a technique for analyzing correlational data from distinguishable dyads. The pairwise correlation model has the advantage of simplicity, both conceptually and in the computer software required. Simulation results presented in the Appendix show that the pairwise approach is at least as accurate as SEM in protecting against Type I error when the null hypothesis is true. A benefit of the structural equations modeling approach is that it allows a test of whether separate individual-level correlations are needed for each class. Further benefits come when multiple distinguishable members and/or multiple variables are analyzed. However, we believe that contrasting the merits of the two approaches is not as important as illustrating their common abilities to separate dyadic and individual-level relations.

We hope that analytic methods that separate the relative contribution of dyad or group-level processes from individual-level processes may encourage the development of theory in interpersonal behavior. Every step of the model-testing procedure presented here may help to guide theory about the multilevel nature of interpersonal behavior. For example, the explicit testing of the equality of the two cross-partner correlations should encourage theory-building about when relations between variables across classes of individuals will be equal and when they are likely to be unequal.

We believe that the most important aspect of this model is the explicit separation of dyad-level and individual-level relations. At the moment, little theory in social psychology has been developed about how dyad-level or group-level processes differ from individual-level processes. However, in the present examples we found that in romantic couples the relations between trust and conflict appear at both levels. Perhaps empirical findings such as these will promote more precise and complex multilevel theories of interpersonal behavior.

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Appendix

This appendix summarizes several statistical tests that are mentioned in the text.

Testing the Difference Between Two Dependent Variances

To test the difference between the variance of each individual in the dyad, select only those cases coded with a "1" in column one and compare the variance of X (column two) with that of X' (column three), and compare the variance of Y (column four) with that of Y' (column five). We illustrate with an example from Murray et al. (1996). The variance for the women on trust was 1.35 and the variance for the men on trust was 1.74. These two samples are not independent because the women and men are paired as a function of their dyad. To test the null hypothesis that the population variance for the women equals the population variance for the men, one can use the t-test

$$t = \frac{(V_w - V_m)\sqrt{N-2}}{2\sqrt{V_w V_m (1 - r^2)}} \qquad \text{(A1)}$$

with $N - 2$ degrees of freedom where r is the cross-partner correlation on a given variable, V_w is the sample variance for the women, and V_m is the sample variance for the men. From Table 2, the correlation between the woman's trust and the man's trust is .287, yielding a nonsignificant test

$$t = \frac{(1.351 - 1.743)\sqrt{96}}{2\sqrt{(1.351)(1.743)(1 - .287^2)}} = -1.31$$

A computationally simpler method to test two dependent variances was given by Kenny (1979). One creates two new variables: a sum within dyads and a difference within dyads. That is, a new variable equal to the sum of the two scores within a dyad (denoted S) and a new variable equal to the difference of the two scores within the dyad (denoted D). The test for the correlation between S and D (i.e., the usual t-test for the Pearson correlation with $N - 2$ degrees of freedom as in Equation A4 below) is equivalent to the test for two correlated variances presented in Equation A1.

Testing the Difference Between Two Dependent Covariances

We present a simple asymptotic Z test that directly compares two dependent covariances (rather than correlations). Using the asymptotic property that

$$\mathrm{cov}(c_{12}, c_{34}) = (c_{13}c_{24} + c_{14}c_{23})/N$$

(Kendall & Stuart, 1966), a Z test for two dependent covariances can be constructed. We illustrate with an example from the Murray et al. (1996) data. Suppose the researcher wanted to test whether the covariance between a woman's trust and her conflict equaled the covariance between a man's trust and his conflict (i.e., the equality constraint necessary to justify the pooling in the overall within-partner correlation r_{xy}). Let C denote the sample covariance and V denote the sample variance. For convenience we denote the woman's trust as 1, the woman's conflict as 2, the man's trust as 3, and the man's conflict as 4. The necessary variances and covariances are denoted using subscripts (e.g., C_{12} denotes the covariance between the woman's trust and her conflict; V_1 denotes the variance of the woman's trust). The test for two dependent covariances (e.g., C_{12} and C_{34}) is given by

$$Z = \frac{(C_{12} - C_{34})\sqrt{N}}{\sqrt{V_1V_2 + V_3V_4 + 2C_o^2 - 2(C_{13}C_{24} + C_{14}C_{23})}}$$

where C_0 represents the average of the two sample covariances being tested (i.e. $(C_{12} + C_{34})/2$). This Z can be compared to the critical value of 1.96 for a two-tailed test at $\alpha = .05$.

Using the values from Table 2, we can test whether the covariance between the woman's trust and her conflict (−.857) differs from the covariance between the male's trust and his conflict (−.438). The resulting test statistic is

$$Z = \frac{(-.857 - (-.438))\sqrt{98}}{\sqrt{(1.351)(2.421) + (1.743)(2.006) + 2(-.6475^2) - 2[(.440)(1.025) + (-.443)(-.365)]}}$$
$$= -1.64,$$

which is not statistically significant by conventional standards.

Significance Testing for the Pairwise Approach

The significance test for the overall within-partner correlation requires four elements: the number of dyads and three indices of the degree of nonindependence within dyads (Griffin & Gonzalez, 1995). In the distinguishable case, the indices of nonindependence include the partial intraclass correlation on variable X ($r_{xx'.c}$, indexing the within-dyad similarity on X), the partial intraclass correlation on variable Y ($r_{yy'.c}$, indexing the within-dyad similarity on Y), and the partial overall cross-partner correlation between variables X and Y' ($r_{xy'.c}$, indexing the dependence of an individual's X on his or her partner's Y).

Given the four elements of the partial pairwise correlation matrix in the distinguishable case ($r_{xy.c}$, $r_{xx'.c}$, $r_{yy'.c}$, and $r_{xy'.c}$), significance testing of the overall within-partner correlation proceeds in the same manner as for the exchangeable case (Griffin & Gonzalez, 1995).[6] First, we consider the test for the overall within-partner correlation. Under the null hypothesis that $\rho_{xy.c} = 0$, the approximate large-sample variance of $r_{xy.c}$ is $\frac{1}{N_1^*}$, where

$$N_1^* = \frac{2N}{1 + r_{xx'\cdot c}r_{yy'\cdot c} + r^2_{xy'\cdot c}}. \quad \text{(A2)}$$

Thus, the overall (partial) correlation $r_{xy.c}$ can be tested using the critical ratio $Z = \frac{r_{xy\cdot c}}{\sqrt{\frac{1}{N_1^*}}}$, or more simply $Z = r_{xy\cdot c}\sqrt{N_1^*}$. The observed Z can be compared to the standard table of the normal distribution. Because this test is asymptotic we ignore the loss of one degree of freedom due to partialling the class variable C.

Intuitively, N_1^* can be thought of as the "effective sample size" for $r_{xy.c}$ adjusted for dependent observations, and it typically ranges between N (the number of dyads) and $2N$ (the number of individuals) depending on the degree of nonindependence within dyads (Griffin & Gonzalez, 1995).[7] Thus, under the null hypothesis, when there is complete dependence within dyads the overall within-partner correlation and its significance test reduce to the usual (par-

6. As in our previous article dealing with the exchangeable case, we focus on hypothesis testing rather than interval estimation. The hypothesis-testing approach has the advantage of simplifying the standard error under the null hypothesis (see the Appendix in Griffin & Gonzalez, 1995).

7. As discussed in our earlier report (Griffin & Gonzalez, 1995), when the two intraclass correlations differ in sign it is possible for the effective sample size to exceed $2N$.

tial) Pearson correlation using one individual from each dyad because the two individuals are essentially identical. When there is complete independence within dyads on both variables, the correlation and its significance test essentially reduce to the (partial) Pearson estimates obtained using both members of each dyad.

Similarly, the asymptotic variance of the overall cross-partner correlation $r_{xy'.c}$ under the null hypothesis is $\frac{1}{N_2^*}$ where $N_2^* = \frac{2N}{1 + r_{xx'\cdot c}r_{yy'\cdot c} + r^2_{xy'\cdot c}}$. N_2^* can be thought of as the "effective sample size" for the overall cross-partner correlation $r_{xy'.c}$ adjusted for dependent observations, and under the null hypothesis can range between N, the number of dyads, and $2N$, the number of individuals. The critical ratio $\frac{r_{xy'\cdot c}}{\sqrt{\frac{1}{N_2^*}}} = r_{xy'.c}\sqrt{N_2^*}$ is tested as a Z statistic. Note that these tests (and those following), despite being simplified, are asymptotically equivalent to the Z tests provided in an SEM program under maximum likelihood estimation.

The partial intraclass correlation (e.g., $r_{xx'\cdot c}$) can be tested against its standard error $\frac{1 - r^2_{xx'\cdot c}}{\sqrt{N}}$ as a Z test of the null hypothesis, where N is the number of dyads. The observed Z ratio of $(\sqrt{N}\, r_{xx'\cdot c})/(1 - r_{xx'\cdot c}{}^2)$ is compared to 1.96 for a two-tailed test at $\alpha = .05$.

The significance test for r_d is related to the test for $r_{xy'\cdot c}$ presented earlier. Under the null hypothesis that $\rho_d = 0$, the asymptotic variance of r_d is $\frac{1}{D^*}$ where

$$D^* = \frac{2N}{1 + r_{xx'\cdot c}r_{yy'\cdot c} + r^2_{xy\cdot c}}(r_{xx'\cdot c}r_{yy'\cdot c}) \quad \text{(A3)}$$

Thus, $Z = r_d\sqrt{D^*}$. Intuitively, D^* can be thought of as the "effective sample size" adjusted for dependent observations and disattenuation. When $r_{xx'.c}$ and/or $r_{yy'.c}$ are small, r_d will tend to be large and may even exceed 1.0. Under these circumstances, D^* will be small and so the "inflated" value of r_d will generally not be significant. Note that the p values for testing $r_{xy'.c}$ and r_d against their respective null hypotheses will always be identical in the pairwise approach.

The individual-level correlation r_i can be computed directly from the pairwise setup as per Equation 5, or equivalently by correlating the difference scores within a dyad (e.g., female minus male scores on trust correlated with female minus male scores on conflict). The significance of r_i can be tested using the usual Pearson correlation table (or the associated t test for a Pearson correlation

$$\frac{r\sqrt{N-2}}{\sqrt{1-r^2}} \quad \text{(A4)}$$

with $N - 2$ degrees of freedom).

Simulation Study on the Dyad-Level Correlation and the Overall Within-Partner Correlation

We conducted a small simulation study on the dyad-level correlation to compare the pairwise approach to the SEM approach. The simulation was based on the algorithm described by Eliasziw and Donner (1991) and was written in the S statistical language, making use of its built-in random number generator (Becker, Chambers, & Wilks, 1988). For each set of population values listed in Table 4, 500 samples of either $N = 30$ or $N = 200$ were drawn from a multivariate normal distribution with unit variances and a mean difference of 5 between the population μs for the two classes. Population correlation parameters were chosen to ensure a correlation matrix with full rank. All other details parallel the previous simulation performed on the exchangeable case (Griffin & Gonzalez, 1995).

Table 4. *Bias and effective Type I error rates for the latent variable model for the pairwise and SEM approaches*

		Null hypothesis that $\rho_d = 0$			No. of Samples Consistent with Model
$\rho_{xx'} = \rho_{yy'}$	ρ_i	Average Estimate r_d	Pairwise Type I Error	SEM Type I Error	
$N = 30$					
.50	−.5	.078	.039	.047	487
.50	0	−.010	.040	.058	497
.50	.5	−.055	.043	.070	486
.75	−.5	.016	.052	.080	500
.75	0	.006	.040	.080	500
.75	.5	.002	.050	.072	500
$N = 200$					
.50	−.5	.001	.060	.050	500
.50	0	−.002	.030	.036	500
.50	.5	−.004	.048	.060	500
.75	−.5	.001	.058	.064	500
.75	0	.001	.054	.060	500
.75	.5	−.001	.068	.074	500

Note: Number of dyads (N) was either 30 or 200. Details of the simulation are provided in the text.

Examination of Table 4 suggests that, for the population values examined in this simulation, the pairwise approach performed at least as well as the SEM approach (as implemented in EQS) with respect to Type I error rates, even with a small number of dyads ($N = 30$).[8] In all but one case the SEM approach had a greater effective Type I error than did the pairwise approach; in 8 out of the 12 combinations of population values, the pairwise approach had an effective Type I error rate that was closer (in an absolute difference sense) to 0.05 than was the SEM approach. We note that a different parameterization of the equivalent SEM model (i.e., variances of the latent variables as free parameters and indicator paths fixed to 1) leads to effective Type I errors that are quite close to rate from the pairwise approach (see Gonzalez & Griffin, 1998, for a discussion of the effects of parameterization on tests of significance).

We also performed an analogous simulation on the overall within-partner correlation r_{xy} to examine the Type I error rate of the asymptotic test presented here for the pairwise distinguishable case. Again, a population mean difference of 5, with unit variance, was introduced between the two classes. Table 5, based on $N = 30$ dyads, presents the average estimate over the 500 runs and the effective Type I error rate. As shown in Table 5, the asymptotic test for the pairwise approach performed well even with samples of 30 dyads. Again, the SEM approach produced effective Type I error rates that tended to be liberal.

8. With $N = 200$ there were no model-inconsistent estimates in the sense of out-of-bounds r_d. However, with $N = 30$ and the population intraclasses both set to .50, a few sample values of $r_d > 1$ occurred, and they were excluded from the summary table. The last column of Table 4 shows the number of model-consistent samples (i.e., 500 − the number of discarded samples). Note that when the population intraclass correlations are high (in this simulation, .75) all samples were model-consistent even when $N = 30$.

Instructions to Estimate the SEM Model in Figure 2

We present EQS syntax and guidelines for the package AMOS to estimate the two models described in the text. We first give instructions for estimating r_{xy} and $r_{xy'}$, and then give instructions for estimating r_i and r_d. All relevant correlations will appear in

Table 5. *Bias and effective Type I error rates for the overall within-partner correlation* r_{xy}

			Pairwise	SEM
$\rho_{xx'} = \rho_{yy'}$	$\rho_{xy'}$	Average Estimate	Type I Error	Type I Error
−.5	−.5	−.006	.046	.068
−.5	0	.006	.060	.088
−.5	.5	−.003	.046	.064
0	−.5	−.006	.040	.064
0	0	.000	.050	.064
0	.5	.000	.040	.046
.5	−.5	−.002	.058	.082
.5	0	.007	.054	.072
.5	.5	−.001	.042	.058

Note: Number of dyads in the simulation was 30. Details of the simulation are provided in the text.

the section of the program output giving "standardized" estimates. Note that the two models test identical constraints (e.g., yield identical χ^2 values), and the parameters in one model can be transformed into the parameters in the other model using the equations presented in the text.

The first EQS syntax provides estimates of r_{xy} and $r_{xy'}$. As displayed in Figure 1, this model does not contain latent variables, so we need to create latent variables that are identical to the observed variables. This allows us to place the necessary equality restrictions required by the model. For example, by equating a latent variable to the wife's trust score and a different latent variable to the husband's trust score, one can set the variance of those two latent variables equal to each other, thus providing a way to test whether the observed variance for the wife's trust is equal to the observed variance of the husband's trust.

In the SEM package AMOS, the model in Figure 1 is a little more straightforward to implement. One simply draws Figure 1 directly into AMOS, assigns names to each of the six paths (making sure that paths that are assumed equal receive identical names), and gives names to the variances of each of the four observed variables so that they can be estimated (again, making sure to assign the same name for variances that are assumed to be equal).

The second EQS syntax provides estimates of r_i and r_d with the restriction that the two r_i's are equal to each other. This provides parameter estimates that are identical to those from the pairwise model. As mentioned in the text, the SEM framework has the advantage that it can estimate a model that permits different r_i's for each individual. To perform this more relaxed test, simply delete the line "(E3,E1) = (E4,E2);". The model in Figure 2 can also be implemented in AMOS. One simply draws the model, assigns names to each path, making sure that paths that are assumed to be equal are assigned identical names, and fixes the variances of the latent variables to 1.

```
/TITLE
 MODEL IN FIGURE 1: ESTIMATING rxy and rxy'
 Lines beginning with ! are comments
/SPECIFICATIONS
 VARIABLES = 4; CASES = 98;
 METHODS = ML;
 MATRIX = COV;
/LABELS
 V1 = Wife Trust; V2 = Husband Trust;
 V3 = Wife Conflict; V4 = Husband Conflict;
```

```
/EQUATIONS
 V1 = 1 F1 ; !latent variables without
 V2 = 1 F2 ; !error are defined,
 V3 = 1 F3 ; !indicators are fixed to 1
 V4 = 1 F4 ;
/VARIANCES
 F1 = 1*; !latent variances are free
 F2 = 1*;
 F3 = 1*;
 F4 = 1*;
/COVARIANCES
 F2, F1 = .5*; !all six possible covariances
 F3, F1 = .5*; !are free
 F4, F1 = .5*;
 F3, F2 = .5*;
 F4, F2 = .5*;
 F4, F3 = .5*;
/CONSTRAINTS
 (F1, F1) = (F2, F2); !latent X variances equal
 (F3, F3) = (F4, F4); !latent Y variances equal
 (F3, F1) = (F4, F2); !pooled cov(X,Y)
 (F4, F1) = (F3, F2); !pooled cov(X,Yprime)
/MATRIX
 1.351
 0.440 1.743
-0.857 - 0.365 2.421
-0.443 - 0.438 1.025 2.006
/PRINT
 COVARIANCE = YES;
/END
```

```
/TITLE
 MODEL IN FIGURE 2 WITH INDIVIDUAL COVARIANCES SET EQUAL
 Lines beginning with ! are comments
/SPECIFICATIONS
 VARIABLES = 4; CASES = 98;
 METHODS = ML;
 MATRIX = COV;
/LABELS
 V1 = Wife Trust; V2 = Husband Trust;
 V3 = Wife Conflict; V4 = Husband Conflict;
 F1 = Latent Dyad Trust; F2 = Latent Dyad Conflict;
 E1 = Err Wife Trust; E2 = Err Hus Trust;
 E3 = Err Wife Con; E4 = Err Hus Con;
/EQUATIONS
 V1 = 1* F1 + 1* E1 ;
 V2 = 1* F1 + 1* E2 ;
 V3 = 1* F2 + 1* E3 ;
 V4 = 1* F2 + 1* E4 ;
```

```
/VARIANCES
 F1 = 1; !latent and error variances all fixed to 1
 F2 = 1;
 E1 = 1;
 E2 = 1;
 E3 = 1;
 E4 = 1;
/COVARIANCES
 F2, F1 = .5*; !estimate dyad level cov(X,Y)
 E3, E1 = .5*; !estimate individual level cov
 E4, E2 = .5*; !estimate individual level cov
/CONSTRAINTS
 (E3,E1) = (E4,E2); !set two cov(X,Y)'s equal
 (V1,E1) = (V2,E2); !constrain error variances within
 (V3,E3) = (V4,E4); ! variable to be equal
 (V1,F1) = (V2,F1); !constrain indicators within
 (V3,F2) = (V4,F2); ! variable to be equal
/MATRIX
 1.351
 .440 1.743
-.857 - .365 2.421
-.443 - .438 1.025 2.006
/PRINT
 COVARIANCE = YES;
/END
```