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Chapter 9

On the Statistics of Interdependence: Treating Dyadic Data with Respect*

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> *"The time has come" the Walrus said,*
> *"to talk of many things:*
> *Of shoes and ships and sealing wax,*
> *of cabbages and kings...*
> (LEWIS CARROLL, *Through the Looking Glass*)

Dyadic relationships form the core element of our social lives. They also form the core unit of study by relationship researchers. Then why (to paraphrase Woody Allen) do so many analyses in this area focus on only one consenting adult at a time? The reason, we suspect, has to do with the rather austere authority figures of our early professional development: statistics professors who conveyed the cherished assumption of independent sampling. However,

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when we collect data in which the sample units do not arrive one at a time, as in the idealized world of independence, but instead arrive two at a time as in the real world of dyadic interdependence, we are faced with a frustrating dilemma. How do we capture the psychology of interdependence with the statistics of independence?

Unfortunately for the development of interpersonal relationships theory, the patterns laid down during the imprinting period of graduate statistics classes tend to dominate the rest of one's professional life. Interdependence in one's data is typically viewed as a nuisance and so dyadic researchers have developed strategies to sweep interdependence under the statistical rug. These strategies include (a) averaging interdependence away by creating a sample of "independent" dyad mean scores, (b) partialling interdependence out and thereby creating a sample of "independent" individual scores, and (c) dropping one dyad member's scores and thus creating a truncated sample of "independent" individual scores. This ritual mutilation of dyadic data comes at a high cost: important information about the similarity or dissimilarity between dyad members is lost.

In this chapter, we review some recent developments in dyadic data analysis that are aimed at making the statistics of interdependence as accessible as the statistics of independence (see Kenny, 1988, for a similar analysis from a slightly different perspective). These techniques give researchers the ability to study interdependence directly; they view interdependence as an opportunity to ask novel research questions, not as a problem to avoid. We focus on correlational and regression methods because these represent the areas of greatest confusion among researchers. The techniques we will describe should help prevent four particular errors of interpretation that haunt dyadic data analysis: the assumed independence error, the deletion error, the cross-level or ecological error, and the levels of analysis error. We first discuss these four common errors in the analysis of dyadic data and then present a general framework that can handle many data analysis issues that occur when subsets of subjects are interdependent.

FOUR COMMON ERRORS

We consider the problems and opportunities of dyadic data analysis in light of a specific example. Stinson and Ickes (1992) had pairs of male students interact in an unstructured "waiting room" situation. These interactions, some between friends and some between strangers, were videotaped and coded on a number of dimensions including the frequency of verbalizations and the frequency of gazes. How should researchers evaluate the strength of the linear relation between speaking and gazing in the context of individuals interacting in dyads? We point out four errors that researchers should avoid when evaluating the linear relation between two variables in the context of dyads.[1]

[1] These errors were not made by Stinson and Ickes, who used these data to answer different research questions than those being addressed here.

First, researchers must avoid the *assumed independence error*, which consists of correlating the $2N$ interdependent data points as if they were independent (where N represents the number of dyads). To do this would invalidate the statistical test of the correlation, which depends primarily on the appropriate sample size (see also Kenny, 1995b). One remedy is to adjust the significance test to take into account the degree and type of interdependence in the sample. This approach is described in more detail later in the chapter.

Second, researchers should not create independent data by throwing out half their sample, an error that we call the *deletion error*. Although in some situations this may not bias the actual correlation obtained, it is a waste of power to drop subjects. The deletion error also prevents the researcher from assessing the type and degree of interdependence in dyads. We view the assessment of interdependence as an opportunity to examine interesting theoretical questions, not as a statistical nuisance that needs to be eliminated.

Third, researchers must avoid the tendency to generalize from one level of aggregation to another, the *cross-level error*. In particular, researchers should not attempt to circumvent the independence problem by creating dyadic averages on each variable and then interpreting the correlation between averages as an index of the correlation for these individuals (Robinson, 1950, 1957). Depending on the degree of interdependence within dyads on each variable, the correlation between dyadic averages can be quite different from the correlation computed for individual scores. This will be discussed in more detail below.

Finally, researchers must avoid a common interpretational fallacy, the *levels of analysis error*. That is, they must avoid interpreting the correlation between dyad means as indicating "dyad-level processes" and similarly avoid interpreting the correlation between individual scores as indicating "individual-level processes". Instead, they must appreciate the fact that both of these correlations contain a *mix* of dyad-level and individual-level information. Separating the dyad-level and individual-level correlations requires an approach that explicitly identifies and models the degree of interdependence within and between variables at each level of analysis.

Identifying common errors is useful only to the extent that sensible alternatives are available. Having pointed out errors to avoid, we now turn to a technique that helps researchers avoid these errors. This technique, the *pairwise method*, is simple to use, produces Pearson-type correlations that are familiar to researchers, and permits relatively straightforward significance tests that adjust for the observed degree of interdependence within the dyads. The primary advantage of the pairwise method, however, is that it offers researchers a general framework in which to think about psychological processes in dyads. Within the pairwise approach, researchers can (a) ask questions at both the dyad level and the individual level simultaneously, (b) use data from both members of the dyad, and (c) test the significance of an observed correlation or regression slope in a manner that appropriately adjusts for the degree of interdependence in the dyad members' responses.

ASSESSING INTERDEPENDENCE ON A SINGLE VARIABLE

In this and the next few sections we deal with the problem of assessing interdependence in a dyad for a single dependent variable (i.e., univariate interdependence). In each case, we illustrate the concepts using data from Stinson and Ickes (1992). In the case of strangers, the dyadic partners were randomly assigned by the experimenter, so we can assume that individuals start off no more similar to their partners than they are to any other person in the sample. However, if interaction leads to interdependence—so that the dyads are no longer simply the "sum of their individual parts"—then interaction should generally lead to individuals becoming more similar to their partners than to the other people in the sample.[2]

There is a fundamental dimension on which both types of dyads in the Stinson and Ickes study (i.e., male friends and male strangers) differ from other kinds of dyads that researchers may study. In some dyads, such as heterosexual couples, the dyad members are *distinguishable* because sex can be used to differentiate the members within the dyads. That is, when computing a correlation, the researcher "knows whose score to put in column X and whose score to put in column Y" by virtue of the individual's sex. In this example, we are using sex as the variable to distinguish the dyad members, but the general point is that in the distinguishable case *some* meaningful variable can be used to distinguish the two dyad members. However, with same-sex platonic friends or homosexual couples, the dyad members are *exchangeable* because they are not readily distinguished on the basis of sex or any other non-arbitrary variable (i.e., the researcher does not know whose score to put in column X and whose score to put in column Y). When the dyad members are distinguishable it is possible for the scores of the members within each category to have different means, different variances, and different covariances. When the dyad members are exchangeable, however, their scores have the same mean, the same variance, and the same distribution because there is no meaningful way to divide them into distinct categories.

How do we assess the degree of interdependence in the distinguishable case? That is, on a single variable how similar are the two distinguishable dyad members? Most readers will realize that the standard interclass, or Pearson product moment correlation, can be used to assess interdependence when the two individuals in each dyad are distinguishable. The interclass correlation assesses "relative similarity"—for example, whether a woman who receives a high score on a variable *relative to other women* tends to be paired with a man

[2] Note that when dyadic sorting is nonrandom, as in the case of heterosexual romantic relationships or male friends as in the Stinson and Ickes (1992) study, this inference is not so straightforward. Similarity within dyads may indicate interdependence arising through interaction, but it may also be an artifact of sorting due to common interests, common abilities, or common status. In such cases, all the statistics presented here will still be appropriate, but their interpretation may be different depending on whether there was random or nonrandom sorting in how the dyads were created.

who receives a high score on that variable *relative to other men*. Because it assesses relative rather than absolute similarity, mean group differences do not affect the interclass correlation. This is an important point because the interclass correlation in this context cannot be interpreted as a measure of absolute similarity, or agreement, between the dyad members (Robinson, 1957).

How do we assess the degree of interdependence in the exchangeable case? In this situation the researcher cannot meaningfully distinguish the dyad members so the interclass correlation cannot be computed. However, it is possible to compute the intraclass correlation. The assumption of equal variance is guaranteed in this case because there is no meaningful way to separate the two members; they are both sampled from the same distribution. In the exchangeable case it is not possible to examine relative similarity but it is possible to examine absolute similarity.

It is also possible to measure absolute similarity in the distinguishable case when it can be assumed that the two groups come from populations with equal variances. The similarity measure is the intraclass correlation with mean differences partialled out. This index of interdependence generally yields a value that is very similar to the interclass correlation, but unlike the interclass correlation it can be used as the basis for the more complex measures that are introduced below.

We have argued that the intraclass correlation and the partial intraclass correlation can be useful in assessing intra-dyadic similarity. There have been several treatments in the literature on computing and testing the intraclass correlation (Haggard, 1958; Kenny, 1988; Kenny & Judd, 1996; Shrout & Fleiss, 1979); these treatments presented the intraclass correlation in the context of analysis of variance (ANOVA). The ANOVA framework does not always make concepts transparent to the researcher who (understandably) tends to be more interested in answering research questions than in learning statistical theory. We present a different framework, a correlational approach based on the pairwise coding of data, that, we hope, makes the relevant concepts more intuitive to the researcher. The advantage of the pairwise approach will become obvious when we generalize the univariate situation to the multivariate case. The complicated analysis problem of multivariate dyadic data will be seen as relatively simple when we apply the techniques developed in the next section. Another benefit of the approach used here is that significance tests are straightforward to derive (which is not necessarily the case in the ANOVA framework).

The Pairwise Intraclass Correlation as a Measure of Interdependence

Exchangeable Case

A useful measure of intra-dyadic similarity for a single variable is the *pairwise intraclass correlation* (Donner & Koval, 1980; Fisher, 1925). The pairwise intraclass correlation is so named because each possible within-group pair of scores is used to compute the correlation. For example, with individuals Adam and Amos in the first dyad, there are two possible pairings: Adam in column one and Amos in column two; or Amos in column one and Adam in column two. With three exchangeable dyads (Adam and Amos, Bob and Bill, and Colin and Chris) the pairwise set-up consists of the scores on X of Adam, Amos, Bob, Bill, Colin, and Chris in the first column (denoted X') and the scores on X of Amos, Adam, Bill, Bob, Chris, and Colin in the second column (denoted X'). Note that each pairing occurs twice, but in opposite orders (Adam in column one with Amos adjacent in column two, then Amos in column one and Adam adjacent in column two, etc.). Thus with $N = 3$ dyads, each column contains $2N = 6$ scores because each member is represented in both columns. This coding is represented symbolically in Table 9.1. The two columns (i.e., variables X and X') are then correlated using the usual product-moment correlation. This correlation is denoted $r_{xx'}$, is called the *pairwise intraclass correlation*, and is the maximum likelihood estimate of the intraclass correlation. The correlation $r_{xx'}$ indexes the absolute similarity between two exchangeable partners in a dyad. In other words, $r_{xx'}$ is the intraclass correlation of one person's score with his or her partner's score. It is important to point out that the intraclass correlation, unlike the usual Pearson correlation, carries a "variance accounted for" interpretation in the $r_{xx'}$ form, that is, there is no need to square the intraclass correlation (see, e.g., Haggard, 1958).

Table 9.1 Symbolic representation for the pairwise data setup in the exchangeable case. The first subscript represents the dyad and the second subscript represents the individual. Categorization of individuals as 1 or 2 is arbitrary.

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

The correlation $r_{xx'}$ is computed over all $2N$ pairs. However, because the correlation $r_{xx'}$ is based on $2N$ pairs rather than on N dyads, as in the usual case, the test of significance needs to be adjusted, i.e., a researcher cannot use the p-value printed by standard statistical packages. The sample value $r_{xx'}$ can be tested against the null hypothesis that $\rho_{xx'} = 0$ using the asymptotic test[3]

[3] To simplify matters, we have chosen to present large sample asymptotic significance tests throughout this chapter, unless a well-known and easily accessible "small sample" test was available. For most applications of these tests, "large sample" refers to approximately 30–40 (or more) dyads. We also present a null hypothesis testing approach rather than a confidence interval approach because the former is relatively simple in the pairwise domain. Readers interested in the relevant standard errors to compute confidence intervals can consult the more technical papers we cite.

$$Z = r_{xx'}\sqrt{N} \tag{9.1}$$

where N is the number of dyads and Z is normally distributed. The observed Z can be compared to critical values found in standard tables. Thus for applications where the researcher sets the Type I error rate at $\alpha = 0.05$ (two-tailed), the critical value for Z will be 1.96. An observed Z greater than or equal to 1.96 leads to a rejection of the null hypothesis that $\rho_{xx'} = 0$.

The pairwise intraclass correlation indexes the similarity of individuals within dyads, and so is closely related to other methods of estimating the intraclass correlation such as the ANOVA estimator (Fisher, 1925; Haggard, 1958). However, the pairwise method has several important advantages in the present situation. Most important, it is calculated in the same manner as the usual Pearson correlation: the two "reverse-coded" columns are correlated in the usual manner, thus offering ease of computation, flexibility in the use of existing computer packages, and an intuitive link to general correlational methods. As we will show, it also has certain statistical properties that make it ideal to serve as the basis for more complicated statistics of interdependence. Moreover, the same pairwise method used to compute the intraclass correlations within a single variable can be used to compute the "cross-intraclass correlation" across different variables—an important index that is discussed below.

Distinguishable Case

The calculation of the *partial pairwise intraclass correlation* in the distinguishable case follows the same general pattern. However, in the distinguishable case the pairwise correlation model requires one extra piece of information: a grouping code indexing the dyad member. This extra information is needed because each dyad member is distinguishable according to some theoretically meaningful variable, and that information needs to be incorporated into the value of $r_{xx'}$. Therefore, it is necessary to create an extra column of data to partial out mean class differences. This first column (labeled C) consists of binary codes representing the "class" variable, e.g., the sex of the subject. For example, 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, and this pattern would be repeated for each of the N dyads in the sample, yielding $2N$ binary codes.

The second column (labeled X) consists of the scores on the variable of interest corresponding to the class code in column one. So, for example, adjacent to the first "1" in column one (representing the female member of the first dyad) the first woman's score would be placed. Below that, adjacent to the first "2" in column one (representing the male member of the first dyad) the first man's score would be placed. This pattern would then continue for the N dyads in the sample, again 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 in column two is placed his or her partner's score in column three. Again, this pairwise "reversed" column of scores on X is referred to as X'. This coding is represented symbolically in Table 9.2.

The sample estimate of the partial pairwise intraclass correlation is simply the Pearson correlation between X and X' partialling out variable C. The partial pairwise intraclass correlation is denoted $r_{xx'.c}$. This correlation can be computed with standard statistical packages (e.g., the partial correlation routine in either *SAS* or *SPSS*). For completeness we present the formula for the partial correlation

$$r_{xx'.c} = \frac{r_{xx'} - r_{cx}r_{cx'}}{\sqrt{(1 - r_{cx}^2)(1 - r_{cx'}^2)}}$$

Table 9.2 Symbolic representation for the pairwise data setup in the distinguishable case. 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.

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

The sample value $r_{xx'.c}$ can be tested against the null hypothesis that $\rho_{xx'.c} = 0$ using the large sample, asymptotic test

$$Z = r_{xx'.c}\sqrt{N}$$

where Z is normally distributed and can be compared to critical values found in standard tables. Note that the equality of variance assumption applies in the distinguishable case. For instance, the population variance for the men on variable X is assumed to be equivalent to the population variance for the women on variable X. Standard tests for the equality of two dependent variances can be used to determine if this assumption is valid (e.g., Kenny, 1979). See Gonzalez and Griffin (1998b) for advice about dealing with situations where the between-group variances are different.

Examples of the Pairwise Intraclass Correlation

In this section we present examples of the pairwise intraclass and partial pairwise intraclass correlations.

Exchangeable Case: Pairwise Intraclass Correlation

From the Stinson and Ickes data, we selected three variables on which to measure dyadic interdependence: gazes, verbalization, and gesture. Our example focuses on the 24 dyads of same-sex strangers. Each variable was coded in the pairwise fashion, creating a total of six columns of data for the three variables (e.g., the $2N$ gaze scores in column one, and the $2N$ gaze scores in reversed order in column two and so on). The resulting value of $r_{xx'}$ for the frequency of gazes was 0.57; for the frequency of verbalizations, 0.84; and for the frequency of gestures, 0.23 (i.e., 57%, 84%, and 23% of the variance in each variable, respectively, was shared between dyad members). These values of $r_{xx'}$ suggest that dyad members were quite similar on the frequency of their gazes and the frequency of their verbalizations, but it appears that the similarity between dyad members in the frequency of their gestures was low.

A direct application of Equation (9.1) yields significance tests for these three sample $r_{xx'}$ values against the null hypothesis that $\rho_{xx'} = 0$. In this example there were $N = 24$ dyads (thus 48 individuals). The corresponding values of Z were 4.12 for gaze, 2.79 for verbalization, and 1.11 for gestures. Thus, using a two-tailed $\alpha = 0.05$, the dyadic similarity was significantly different from zero for gaze and verbalization, but not for gestures.

Distinguishable Case: Partial Pairwise Intraclass Correlation

Consider the following example from a study of distinguishable dyads. Sandra Murray (1995) collected self-evaluations and partner-evaluations from both members of 163 heterosexual couples who were dating exclusively. A comparison of the men's and women's variances on these two variables revealed that, in each case, the between-group differences were very small (i.e., the men and women had approximately equal variance), justifying the use of pooled variances in the partial pairwise intraclass correlation. The partial pairwise correlation for self-evaluations was 0.218, which is statistically significant ($Z = 0.218\sqrt{163} = 2.78$) and the partial pairwise correlation for partner-evaluations was 0.365, also significant ($Z = 4.65$). Thus the partners resembled each other on each of the two variables. It is interesting to note that the interclass correlation between self-evaluation and partner-evaluation was 0.46, and the interclass correlation for the women was 0.55, which was not statistically significant ($Z = 1.08$).

Now that we have introduced the pairwise method of computing the intraclass correlation in the dyadic case, we will use this technique as a building block for more complicated correlational methods. In the remainder of the chapter we present methods for examining dyadic correlations between two variables, methods for separating individual and dyadic effects, and methods for testing actor–partner effects in dyadic research. We take each topic in turn.

OVERALL CORRELATION AND THE CROSS-INTRACLASS CORRELATION

Consider the situation where the researcher has two variables, X and Y, measured on each member of the dyad. For instance, suppose a trust scale and a satisfaction with relationship scale are given to each member of N dyads. There are two natural questions the researcher might ask: Is an individual's trust associated with his or her satisfaction? and is an individual's trust associated with his or her partner's satisfaction?

To answer these questions, the researcher might compute two Pearson correlations over all individuals: (a) a correlation between X and Y, which we call the *overall within-partner correlation* (e.g., individual's trust correlated with satisfaction), and (b) a correlation between an individual's X and his or her partner's Y, which we call the *cross-intraclass correlation* (e.g., individual's trust correlated with partner's satisfaction). The values of these two correlations serve as estimates of the underlying linear association. Unfortunately, the standard tests of significance for these two correlations will generally be incorrect. They commit the assumed independence error because the standard test assumes that there are $2N$ independent subjects, yet the data may not obey independence. This violation of independence can have a dramatic effect on the result of a significance test (e.g., Kenny & Judd, 1986).

Pairwise Approach for the Exchangeable Case

Fortunately, a straightforward solution for the test of significance for both the overall correlation and the cross-intraclass correlation can be found by using a generalization of the pairwise approach developed in the previous section. We first consider the case for exchangeable dyad members and then the case for distinguishable dyad members. The pairwise coding is done on each variable X and Y separately. That is, the $2N$ scores for X, the $2N$ scores for X that have been "reversed coded" (denoted X', as previously shown in Table 9.1), the $2N$ scores for Y, and the $2N$ scores for Y' are entered into four columns. This creates a total of four variables, X, X', Y, and Y', which are shown symbolically in Table 9.3. In this framework there are six possible correlations, which are depicted in Figure 9.1. Figure 9.1 shows that the pairwise intraclass correlations for X and Y are given by $r_{xx'}$ and $r_{yy'}$, respectively; the overall within-partner correlation is given by r_{xy}; and the cross-intraclass correlation is given by $r_{xy'}$. Note that in this framework $r_{xy'} = r_{x'y}$ and $r_{xy} = r_{x'y'}$.

Table 9.3 Symbolic representation for the pairwise data setup for two variables in the exchangeable case. The first subscript represents the dyad and the second subscript represents the individual. Categorization of individuals as 1 or 2 is arbitrary.

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

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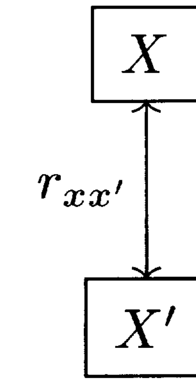

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ad and the second subscript
1 or 2 is arbitrary.

Variable			
X	X'	Y	Y'
X_{31}	X_{32}	Y_{31}	Y_{32}
X_{32}	X_{31}	Y_{32}	Y_{31}
X_{41}	X_{42}	Y_{41}	Y_{42}
X_{42}	X_{41}	Y_{42}	Y_{41}

With the four basic correlations found in Figure 9.1 it is possible to compute tests of significance for r_{xy} and $r_{xy'}$ that take into account the degree of interdependence. For details regarding the derivation of these tests and supporting simulations see Griffin and Gonzalez (1995). Under the null hypothesis that $\rho_{xy} = 0$, the approximate large-sample variance of r_{xy} is $1/N^*_1$, where

$$N^*_1 = \frac{2N}{1 + r_{xx'}r_{yy'} + r^2_{xy'}}$$

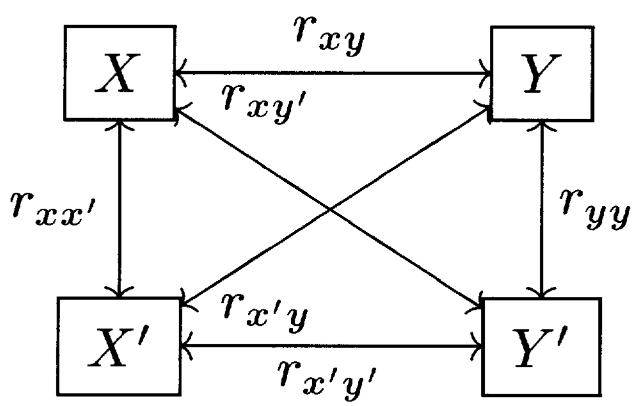

Figure 9.1 All possible pariwise correlations between variables X, Y, and their corresponding "reverse codes".

Thus the overall correlation r_{xy} can be tested using a Z test where

$$Z = r_{xy'}\sqrt{N^*_1} \tag{9.2}$$

Intuitively, N^*_1 can be thought of as the "effective sample size" for r_{xy} adjusted for dependent observations (see Rosner, 1982, and Eliasziw & Donner, 1991, for the development of this intuition).

The formula for the effective sample size N^*_1 illustrates that a common practice used by some researchers may be flawed. Some researchers follow the practice of first testing the intraclass correlations, and if both intraclass correlations are close to zero, proceeding as though the data were independent. The problem with this practice is that there is another source of dependence relevant to the standard error of r_{xy}: the cross-intraclass correlation $r_{xy'}$. Only when all three sources of dependence are zero can the data be treated as independent. The Z test in Equation (9.2) is useful because it can be applied regardless of the values for the three sources of interdependence.

The correlation between an individual's score on variable X and his or her dyad partner's score on variable Y (i.e., the variable Y') is the cross-intraclass correlation. The cross-intraclass correlation $r_{xy'}$ assesses the strength of the relationship between two variables measured on different dyadic partners. Under the null hypothesis that $\rho_{xy'} = 0$, the asymptotic variance of $r_{xy'}$ is $1/N^*_2$, where

$$N^*_2 = \frac{2N}{1 + r_{xx'}r_{yy'} + r^2_{xy}}.$$

The cross-intraclass correlation $r_{xy'}$ can be tested using a Z test, where

$$Z = r_{xy'}\sqrt{N^*_2}$$

Like N^*_1, N^*_2 can be thought of as the "effective sample size" for $r_{xy'}$ adjusted for dependent observations. Again, we see that the test of significance is influenced by sources of interdependence as measured by the two intraclass correlations and the overall within-partner correlation.

An Example of the Exchangeable Case

Consider the 24 same-sex, stranger dyads studied by Stinson and Ickes. Researchers might be interested in the following questions. Over all individuals, were the three variables (frequency of gazes, frequency of verbalizations, and frequency of gestures) significantly related to each other? Examination of the boxed values in Table 9.4 reveals that all three overall correlations are positive and moderately large: the overall correlation between verbalization frequency and gaze frequency was 0.386, the overall correlation between verbalization frequency and gesture frequency was 0.449, and the overall correlation between gaze frequency and gesture frequency was 0.474. Recall that the significance test of the overall correlation r_{xy} depends on the effective sample size N^*_1. Between verbalizations and gazes,

$$N^*_1 = \frac{48}{1 + (0.841)(0.570) + 0.471^2} = 28.22;$$

between verbalizations and gestures $N^*_1 = 33.81$; and between gazes and gestures $N^*_1 = 38.88$. The resulting significance tests were $Z = 0.386\sqrt{28.22} = 2.05$, $p < 0.05$; $Z = 2.61$, $p < 0.05$; and $Z = 2.96$, $p < 0.05$, respectively. All three overall correlations were significantly positive.

We now turn to the assessment of the cross-intraclass correlation $r_{xy'}$. Is an individual's score on one variable related to his partner's score on a second variable? The cross-intraclass correlation $r_{xy'}$ between verbalizations and gazes was 0.471. The effective sample size was

$$N^*_2 = \frac{48}{1 + (0.841)(0.570) + 0.386^2} = 29.48;$$

and the resulting Z was $0.471\sqrt{29.48} = 2.56$, $p < 0.05$. The correlation $r_{xy'}$ between verbalization frequency and gesture frequency was 0.479. Testing $r_{xy'}$ against its standard error (with $N^*_2 = 34.49$) yielded an observed $Z = 2.82$, $p <$

Table 9.4 Pairwise correla
(Stinson & Ickes, 1992).

	Verb
Verb	1.000
Verb'	**0.841**
Gaze	0.386
Gaze'	0.471
Gest	0.449
Gest'	0.479

Pairwise intraclass correlations a
Frequency of gazes. Gest = Frequ
Notes: Boxed values are the ove

0.01. Similarly, the cross-in
gesture frequency was 0.32
35.46) yielded an observed
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Pairwise Approach fo

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subscript to denote that va
ard formula for the partia
$r_{xy.c}$ is computed accordin

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$r_{xy'}$

Table 9.4 Pairwise correlation matrix for randomly sampled, same-sex strangers (Stinson & Ickes, 1992).

	Verb	Verb'	Gaze	Gaze'	Gest	Gest'
Verb	1.000					
Verb'	**0.841**	1.000				
Gaze	0.386	0.471	1.000			
Gaze'	0.471	0.386	**0.570**	1.000		
Gest	0.449	0.479	0.476	0.325	1.000	
Gest'	0.479	0.449	0.325	0.474	**0.226**	1.000

Pairwise intraclass correlations are typed in bold. Verb = Frequency of verbalizations. Gaze = Frequency of gazes. Gest = Frequency of gestures.
Notes: Boxed values are the overall r_{xy} correlations.

0.01. Similarly, the cross-intraclass correlation $r_{xy'}$ between gaze frequency and gesture frequency was 0.325. Testing $r_{xy'}$ against its standard error (with $N^*_2 = 35.46$) yielded an observed $Z = 1.94$, $p = 0.053$. The significant, positive values for $r_{xy'}$ indicate that individuals who speak frequently are associated with partners (in this case strangers) who gaze and gesture frequently; individuals who gaze frequently are moderately associated with partners who gesture frequently.

Pairwise Approach for the Distinguishable Case

The computational setup for the overall within-partner and the cross-intraclass correlations in the distinguishable case parallels the setup in the exchangeable case. As with the pairwise intraclass correlation, the distinguishable case is treated differently than the exchangeable case only in terms of the coding variable that is partialled out. The basic data arrangement is shown in Table 9.5, which is similar to Table 9.3 for the exchangeable case except for the extra column representing the categorization of individuals within the dyad. The coding variable C is partialled from all correlations. Figure 9.2 shows the possible correlations between the four variables, using a ".c" in the subscript to denote that variable C has been partialled out. Again, the standard formula for the partial correlation is used. The partial overall correlation $r_{xy.c}$ is computed according to the formula

$$r_{xy.c} = \frac{r_{xy} - r_{cx}r_{cy}}{\sqrt{(1 - r_{cx}^2)(1 - r^2_{cy})}} \tag{9.3}$$

and the partial cross intraclass correlation $r_{xy'c}$ is computed as

$$r_{xy'.c} = \frac{r_{xy'} - r_{cx}r_{cy'}}{\sqrt{(1 - r_{cx}^2)(1 - r^2_{cx}{}')}} \tag{9.4}$$

Table 9.5 Symbolic representation for the pairwise data setup for two variables in the distinguishable case. 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. The primes denote the reverse coding described in the text.

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

Once data have been arranged as in Table 9.5, these partial correlations can be computed in standard statistical packages such as *SAS* or *SPSS*. The partial pairwise intraclass correlations for X and Y are denoted by $r_{xx'.c}$ and $r_{yy'.c}$, respectively; the partial overall correlation is denoted by $r_{xy.c}$; and the partial cross-intraclass correlation is denoted by $r_{xy'.c}$

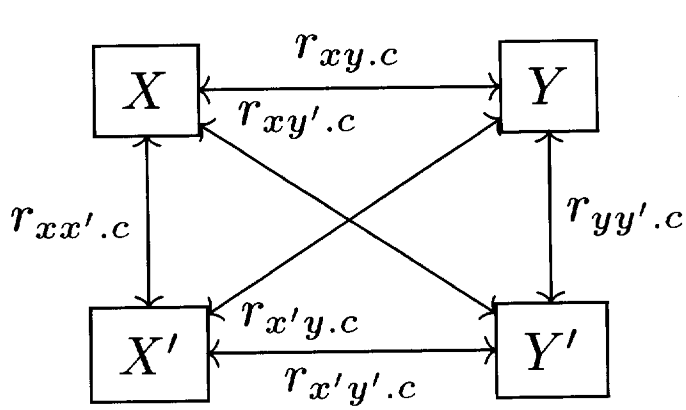

Figure 9.2 All possible pairwise correlations between X, Y, and their corresponding "reverse codes" in the distinguishable case. Variable C has been partialled out from all correlations.

Unlike the exchangeable case, there are three assumptions that need to be checked before proceeding: (a) equality of variance between the two classes on each variable (e.g., the variance for men on X needs to equal the variance for women on X; the variance for men on Y needs to equal the variance for women on Y), (b) equality of covariances between the two variables across classes (e.g., the covariance between X and Y for men needs to equal the covariance between X and Y for women), and (c) equality of cross covariances between the two variables (e.g., the covariance between the women's X and the men's Y needs to equal the covariance between the men's X and the women's Y). The reason these assumptions were not made in the exchangeable case was because the individuals could not be meaningfully separated into two classes (e.g., men vs women). However, in the distinguishable case the individuals can be separated into two classes; consequently, the equivalence of the variance and covariances must be checked before the data from the two groups are pooled for the partial overall and partial cross-intraclass correlations. Recall that the equality-of-variance assumption was also made for the partial pairwise intraclass case. Gonzalez and Griffin (in press) discuss the details for testing these assumptions. In general, when these assumptions are met the computation of the relevant correlations will be more efficient and the corresponding tests more powerful compared to the usual strategy of analyzing data of each class separately. There are also substantive reasons for making these assumptions (see Griffin & Gonzalez, in press).

Given the four basic correlations found in Figure 9.2 it is possible to compute tests of significance for $r_{xy.c}$ and $r_{xy'.c}$ that take into account the degree of interdependence. For details regarding the derivation of these tests, supporting simulations, and a discussion of how to perform the tests using standard structural equations modeling programs, see Gonzalez and Griffin (in press). Under the null hypothesis that $\rho_{xy.c} = 0$, the approximate large-sample variance of $r_{xy.c}$ is $1/N^*_1$, where

$$N^*_1 = \frac{2N}{1 + r_{xx'.c}r_{yy'.c} + r^2_{xy'c}} \tag{9.5}$$

Thus the partial overall correlation $r_{xy.c}$ can be tested using a Z test where

$$Z = r_{xy'c}\sqrt{N^*_1}$$

The partial cross-intraclass correlation assesses the strength of the relationship between two variables measured on different dyadic partners partialling out mean differences between the two partners. Under the null hypothesis that $\rho_{xy'.c} = 0$, the asymptotic variance of $r_{xy'.c}$ is $1/N^*_2$, where

$$N^*_2 = \frac{2N}{1 + r_{xx'.c}r_{yy'.c} + r^2_{xy.c}} \tag{9.6}$$

The partial cross-intraclass correlation $r_{xy'.c}$ can be tested using a Z test, where

$$Z = r_{xy'.c}\sqrt{N^*_2}$$

An Example of the Distinguishable Case

Recall that Murray (1995) found that for the 163 couples the correlation between self- and partner-evaluations for the men was 0.46, and the correlation between the same two variables was 0.55 for the women, which was not statistically significantly. The correlation between the women's self-evaluation and the men's partner-evaluation was 0.37, and the correlation between the men's self-evaluation and the women's partner-evaluation was 0.41. Further, the variances for the men were similar to the variances for the women (on each variable). Thus, the necessary conditions for computing the overall partial and cross-intraclass correlation are met for these data.

The partial overall correlation (with sex partialled out) between self-evaluations and partner-evaluations was 0.501. That is, controlling for sex differences, it appears that each individual's self-evaluations was strongly related to his or her evaluation of the partner. This result, along with the previously-reported partial intraclass correlations of 0.218 for self-evaluations and 0.364 for partner-evaluations, gives

$$N^*_1 = \frac{163 * 2}{1 + 0.218 * 0.364 + 0.392^2} = 264.39,$$

a straightforward application of Equation (9.5). The Z-value for this overall correlation was $0.501\sqrt{264.39} = 8.15$, $p < 0.001$.

The partial cross-intraclass correlation between one person's self-evaluations and the other's partner was 0.392. That is, controlling for sex differences, it appears that an individual's self-evaluation was moderately correlated to his or her partner's evaluation of the individual. The partial cross-intraclass correlation can be tested using the effective sample size given by substituting sample size N, the two partial pairwise intraclass correlations, and the partial overall correlation into Equation(9.6), which for this sample was 244.30. The Z-value for this sample $r_{xy'.c}$ was $0.392\sqrt{244.30} = 6.13$, $p < 0.001$.

A LATENT VARIABLE MODEL FOR SEPARATING INDIVIDUAL AND DYADIC EFFECTS

We now apply the pairwise framework to address the levels of analysis problem present in dyad research. A researcher studying dyads can ask questions at either the level of the individual, the level of the dyad, or both (Kenny & La Voie, (1985). To make this issue concrete we refer to the Stinson and Ickes (1992) study. A researcher can ask the question: Do *individuals* who gesture more also verbalize more? A researcher can also ask the question: Are *dyads* where both individuals gesture more also the dyads where both individuals verbalize more? The two questions differ in their level of analysis: individuals or dyads.

Both levels of analysis can be informative, and focusing on only one level is wasteful of information that might theoretically be interesting. Further, it is possible to find situations in which the direction of the relationship between two variables differs in sign across the two levels. For instance, imagine that trust and satisfaction scales are taken from married couples. Each partner answers both scales so there are a total of four observations per couple: two trust scores and two satisfaction scores. It is plausible that the relationship between trust and satisfaction at the dyad-level is positive (more trusting dyads are more satisfied with the relationship) whereas at the individual-level the relationship could be negative (the individual within a dyad who is relatively more trusting could be relatively less satisfied because his or her trust is not reciprocated). Thus, it is possible to find correlations in different directions (positive or negative) at different levels of analysis. Such patterns are interesting both in terms of theory development and theory testing because a complete understanding of dyadic interaction must address both levels of analysis.

The problem of separating the individual-level analysis from the dyad-level analysis has bothered methodologists for a long time. Robinson (1950) pointed out that the correlation between two aggregated variables (e.g., mean educational attainment and mean income correlated *across* states) is not equivalent to the correlation between the same two variables measured on individuals (e.g., educational attainment and average income *within* a state). In sociology, the cross-level error, or the erroneous generalization from one level to another, is termed the "ecological correlation fallacy" (Hauser, 1974; Robinson, 1950). The need for statistical techniques that permit analysis at different levels ("multi-level analysis") has led to a cottage industry of different viewpoints and statistical programs (see Bock, 1989; Bryk & Raudenbush, 1992; Goldstein, 1987; Goldstein & McDonald, 1988; Kreft, de Leeuw, & van der Leeden, 1994).

In this section we show how different levels of analysis can be incorporated into the pairwise approach. Our own work has been greatly influenced by Kenny and La Voie (1985), who proposed a group correlation model to decompose individual-level and group-level effects. Kenny and La Voie derived their group correlation model in the context of ANOVA. We present the pairwise version of Kenny and La Voie's group correlation model. We call it the *pairwise latent variable model*. The ingredients for this model again depend on whether the dyad members are exchangeable or distinguishable.

Pairwise Latent Variable Model for the Exchangeable Case

Figure 9.3 shows a simple latent variable model for the exchangeable dyadic design. In this model, each measured variable is coded in a pairwise fashion so that the variables X and X' (and, by the same logic, Y and Y') are identical except for order. The variance of a given observed variable is assumed to result from two different latent (not measured) sources: a dyadic component representing the portion of that variable that is shared between dyadic partners and an individual component representing the portion of that variable that is unshared or unique.

As Figure 9.3 illustrates, there are two levels at which the variables can be related. The shared dyadic variance of X and Y can be related through the dyadic correlation r_d. The unique individual variance of X and Y can be related through the individual-level correlation r_i. The model depicted in Figure 9.3 permits simultaneous estimation and testing of r_d and r_i.

The individual-level correlation, r_i, and the latent dyad-level correlation, r_d, can be computed as follows:

$$r_i = \frac{r_{xy} - r_{xy'}}{\sqrt{1 - r_{xx'}}\sqrt{1 - r_{yy'}}} \tag{9.7}$$

and

$$r_d = \frac{r_{xy'}}{\sqrt{r_{xx'}}\sqrt{r_{yy'}}}. \tag{9.8}$$

Note that both r_i and r_d are computed from the four basic correlations shown in Figure 9.1. The numerator of the individual-level correlation r_i is the difference between the observed correlation r_{xy}, which combines dyad-level and individual-level effects, and the cross-intraclass correlation $r_{xy'}$, which contains only dyad-level effects. Thus r_i is a measure of the individual-level relation uncontaminated by dyad-level effects. The numerator of the dyad-level correlation r_d is simply the pairwise cross-intraclass correlation $r_{xy'}$, and in this model corresponds to the direct measure of the dyad-level relations. The denominators, too, are conceptually straightforward: they correct the scale of the correlations for the fact that only "part" of each observed variable is being correlated. When the individual components of variables X and Y are correlated, the denominator adjusts for the proportions of variance in the observed X and Y that correspond to the *non-shared* effects ($\sqrt{1 - r_{xx'}}$ and $\sqrt{1 - r_{yy'}}$, respectively). Similarly, when the *dyadic* components of the variables X and Y are correlated, the denominator adjusts for the proportions of variance in the observed X and Y that correspond to the shared dyadic effects ($\sqrt{r_{xx'}}$ and $\sqrt{r_{yy'}}$, respectively). Note that r_d can be interpreted as $r_{xy'}$ that has been disattenuated (i.e., divided by the intraclass correlations representing the proportion of dyadic variance). The pairwise latent variable model is equivalent to the maximum likelihood group-level correlation suggested by Gollob (1991).

Testing the Underlying Correlations r_i and r_d in the Exchangeable Case

For the special case of dyads, r_i can be computed by Equation (9.7) or equivalently by correlating the deviation scores on X and on Y. That is, the dyad mean on X is subtracted from each X score and the dyad mean on Y is subtracted from each Y score, then the $2N$ deviations on X are correlated with the $2N$ deviations on Y. For dyads, Equation (9.7) and the deviation method yield identical values for r_i, which can be tested using the usual Pearson correlation table (or the associated t-test formula) with $N - 1$ degrees of freedom (Kenny & La Voie, 1985).

Note that when either of the intraclass correlations $r_{xx'}$ or $r_{yy'}$ (or both) are small, r_d will tend be large and may even exceed 1.0. Because the dyadic model is based on the assumption of dyadic similarity, the model should only be tested when *both* intraclass correlations are significantly positive. In general, the practice of restricting the application of this model to cases when both intraclass correlations are significantly positive should reduce the occurrence of out-of-bounds values for r_d. A significance test for r_d is reported in Griffin and Gonzalez (1995). Interestingly, the p-value associated with r_d is identical to the p-value associated with $r_{xy'}$. Therefore, when both intraclass correlations are significant, implying significant dyad-level variance in both X and Y, we recommend interpreting $r_{xy'}$ as the raw-score version of r_d (i.e., r_d is the disattenuated version of $r_{xy'}$).

The Mean-Level Correlation

It may appear that the correlation between the means of each dyad on the two variables should yield an estimate of the dyad-level correlation. Contrary to this intuition, the "mean-level" correlation (which we denote r_m) reflects both individual and dyad-level effects and can best be thought of as a "total" correlation. The mean-level correlation r_m should not be used as an index of dyad-level relations because it can be significantly positive or negative even when $r_d = 0$. According to the model in Figure 9.3, a positive dyad-level correlation exists only when the tendency of *both* dyad members to be high on X is matched by the tendency of *both* dyad members to be high on Y. However, this is only one of several circumstances that can lead to a positive value of r_m, indicating that a high *average* value on X is matched with a high *average* value on Y. For example, a positive mean-level correlation will result when the tendency of one member to be extremely high on X is matched with the tendency of that member to be extremely high on Y—regardless of the score of his or her dyadic partner on either variable. See Griffin and Gonzalez (1995) for a more systematic treatment of r_m.

An Example of the Exchangeable Case

We continue using the Stinson and Ickes (1992) data to illustrate the exchangeable case. Having determined that there was dyad-level variance—as indexed by the pairwise intraclass correlation—in at least two of the three variables of interest, we calculate and test r_d and r_i. In the case of verbalizations and gazes,

$$r_d = \frac{0.471}{\sqrt{(0.841)(0.570)}} = 0.680.$$

The observed Z- and p-value for r_d was identical to that found for $r_{xy'}$ (i.e., $Z = 2.56$, $p < 0.01$). The latent dyad-level correlation (r_d) between gaze frequency and gesture frequency was 0.906, $Z = 1.94$, $p = 0.052$, just shy of statistical significance. The dyad-level correlation (r_d) between verbalization frequency and gesture frequency was 1.10, which is "out of bounds". Such

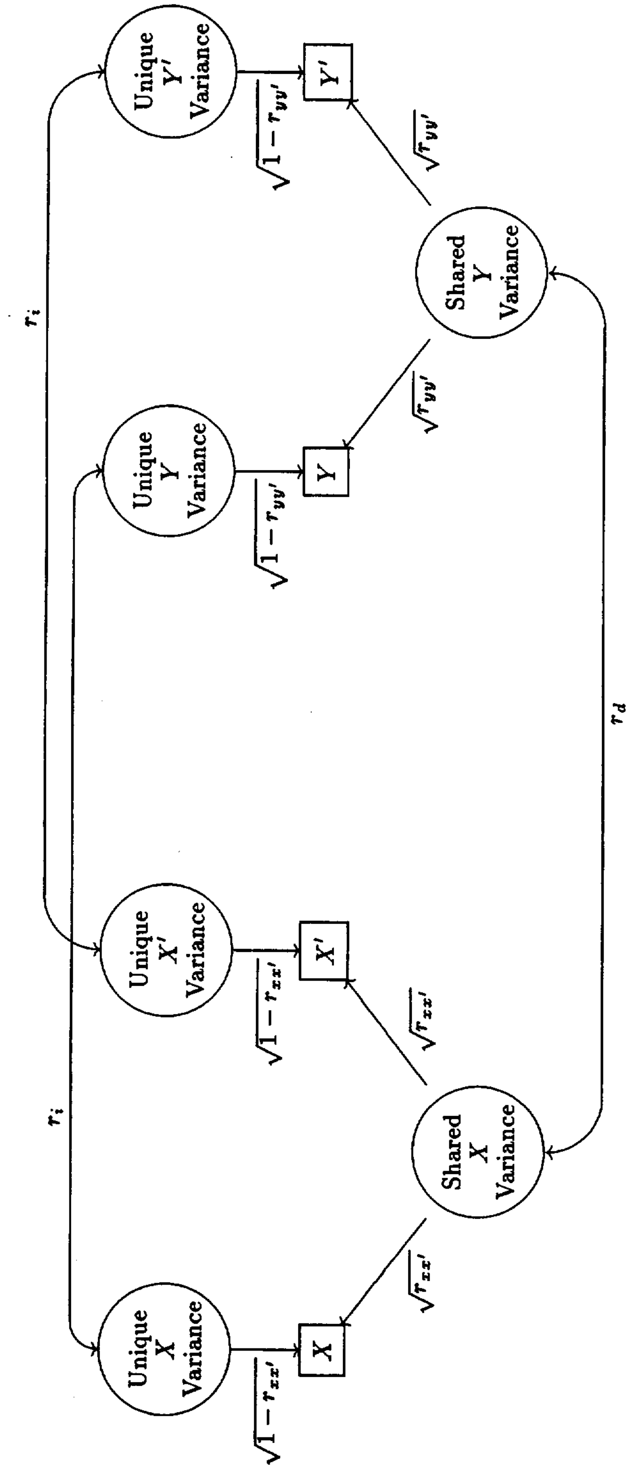

Figure 9.3 A latent variable model separating individual-level (unique) and dyad-level (shared) effects.

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out-of-bounds values are most likely to occur when the intraclass correlation for one or both of the variables is marginal or non-significant (as in the case of gestures). In sum, the significant, positive values of r_d (and $r_{xy'}$) indicate that dyads in which both members gaze frequently are also dyads in which both members speak to each other frequently and gesture to each other frequently.

Were the three variables related at the level of *individuals* within dyads? The computation of the individual-level correlation, r_i, between verbalizations and gazes is straightforward:

$$\frac{r_{xy} - r_{xy'}}{\sqrt{1 - r_{xx'}}\sqrt{1 - r_{yy'}}} = \frac{0.386 - 0.471}{\sqrt{(1 - 0.841)(1 - 0.570)}} = -0.325.$$

In contrast to the positive dyad-level correlation between verbalization and gaze (0.680), the individual-level correlation is negative. That is, the dyad member who speaks *more* often tends to be the dyad member who looks at the other *less* often. This negative individual-level correlation emerges despite the fact that dyads in which there is frequent speaking also tend to be dyads in which there is frequent gazing. However, the individual-level correlation is also only marginally significant ($p < 0.010$),

$$\begin{aligned} t_{N-1} &= \frac{r_i\sqrt{N-1}}{\sqrt{1 - r^2_i}} \\ &= \frac{-0.325\sqrt{23}}{\sqrt{1 - 0.325^2}} \\ &= 1.65. \end{aligned}$$

Note that this significance test relies on the usual formula for testing a correlation, except that in this case the degrees of freedom are $N - 1$ (rather than $N - 2$). The individual-level correlations for the other pairs of variables were relatively small and nonsignificant. For verbalizations and gestures $r_i = -0.086$, and for gestures and gazes $r_i = 0.258$. All three values of r_i were markedly discrepant from the corresponding values of r_d and $r_{xy'}$, underlining the importance of separating the dyad-level and individual-level relations.

Recall that all three overall correlations were moderate and positive. However, the overall correlation represents a combination of underlying dyadic and individual-level correlations. A more detailed picture of the social interactions that occurred in this study emerges when the two levels are decomposed. Verbalizations and gazes were negatively correlated at the individual level, but positively correlated at the dyad level. Verbalizations and gestures were unrelated at the individual level, but positively correlated at the dyad level. Finally, gazes and gestures were positively correlated at both the individual and dyadic levels.

Pairwise Latent Variable Model for the Distinguishable Case

The pairwise latent variable model for the distinguishable case is similar to the model for the exchangeable case except that the "class" or grouping variable C needs to be partialled out of the four variables X, X', Y, and Y. Thus the corresponding model is identical to the model depicted in Figure 9.3 for the exchangeable case except that all observed correlations are partial correlations (with the grouping variable C being the control variable). In this section we simply sketch the pairwise latent variable model for the distinguishable case and refer interested readers to Gonzalez and Griffin (in press) for more detail.

The formula for the partial individual-level correlation r_i can be expressed in terms of the observed partial correlations given in Figure 9.2

$$r_i = \frac{r_{xy.c} - r_{xy'.c}}{\sqrt{1 - r_{xx'.c}}\sqrt{1 - r_{yy'.c}}}$$

Note that because the individual-level correlation r_i uses the correlations $r_{xy.c}$ and $r_{xy'.c}$ in its computation, the assumptions needed for computing the partial overall and partial cross-intraclass correlations apply to r_i as well. The implication of these assumptions is that the individual-level relationship is required to be the same for each level of the category variable (e.g., r_i for husbands equals r_i for wives).

The sample r_i can be tested against the null value of 0 using the standard t-test for a correlation. In the distinguishable case, the test has $N - 2$ degrees of freedom (one degree of freedom less than the r_i for the exchangeable case because the binary class variable C is used in the distinguishable case). For the Murray data sample, r_i between the self-evaluation and the partner's evaluation was 0.155, yielding an observed $t = 2.00$, $p < 0.05$.

The partial dyad-level correlation r_d can be expressed in terms of the observed correlations given in Figure 9.2

$$r_d = \frac{r_{xy'.c}}{\sqrt{r_{xx'.c}}\sqrt{r_{yy'.c}}}. \tag{9.9}$$

Again, the estimation of r_d for the pairwise model requires an assumption that the partial cross-intraclass correlations are equal to each level of the class variable. For instance, the population correlation between the husband's self-evaluation and the wife's partner-evaluation is assumed to equal the population correlation between the wife's self-evaluation and the husband's partner-evaluation. If this assumption is plausible given the sample data, then the partial cross-intraclass correlation can be used as the raw-score version of the dyad-level correlations (i.e., not disattenuated by the partial intraclass correlations). If this assumption appears to be violated, then a more general model can be estimated using a structural equations approach (see Gonzalez & Griffin, in press).

For the Murray data, the equality of cross-partner correlations appears to hold ($r_{xy'.c} = 0.41$ for the men and $r_{xy}{'}_{.c} = 0.37$ for the women; the difference was not statistically significant). Also, recall that the partial intraclass correlations for self-evaluation was 0.22 and for partner-evaluation was 0.364. Even though both of these values are statistically different from zero, they are still relatively small and we anticipate that this could produce an out-of-bounds value for r_d. The dyad-level correlation r_d for the Murray data turned out to be out-of-bounds, $r_d = 1.39$, making it difficult to interpret as a correlation. Fortunately, because the partial intraclass correlations were significant we can interpret $r_{xy'.c}$ as the raw-score estimate of r_d (i.e., the dyad-level correlation that has not been disattenuated by the partial intraclass correlations), which was 0.392. The Z test for this sample $r_{xy'.c}$ was 6.13, as we saw before. Thus, the Murray et al data suggest that self-evaluation and partner-evaluation are positively correlated at both the individual-level and the couple-level.

STRUCTURAL MODELS IN DYADIC RESEARCH

Researchers often wish to go beyond calculating the strength of linear relation between variables. Most commonly, they wish to go beyond the correlational index and estimate parameters in a structural model in which one or more independent variables determine the value of a dependent variable. There are a number of ways that this can be accomplished with dyadic data. We will briefly outline a few of these models, focusing on examples of their use rather than on detailed computational descriptions.

Regression Models for Dyadic-Level and Individual-Level Effects

The correlational methods for separating dyadic- and individual-level effects presented above can be extended to cases with multiple predictor variables. Although such analyses are straightforward for the individual level of analysis, the extensions to the dyadic level is more complex. The individual-level analysis is relatively simple because the interdependence between dyadic partners has been "partialled out" of the individual-level correlations, and so the individual-level correlations can be entered as input to standard multiple regression routines or structural equation modeling programs, allowing complete estimation and significance testing through the standard programs. The dyad-level correlations, in contrast, measure only interdependent information and therefore violate the independence assumption that is essential to standard regression routines. Thus, even though the dyad-level correlations can also be entered as input to multiple regression routines, the resulting significance tests are not appropriate.

Consider again the results of Stinson and Ickes' (1992) study. In our earlier analysis of the dyad-level and individual-level correlations, we assessed whether the three relevant variables were interrelated at the dyadic level of analysis, at the individual level of analysis, or at both levels of analysis. As an extension of these correlational analyses, we have formulated a psychological model illustrated in Figure 9.4. This path diagram implies that gesture frequency and gaze frequency are both predictors of verbalization frequency. For a possible psychological theory that relates those three variables, see

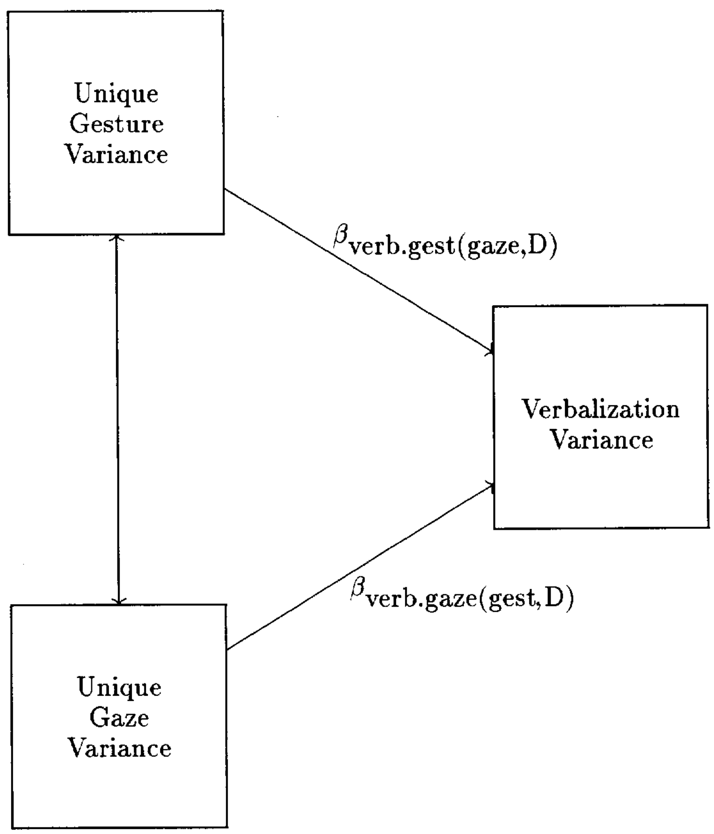


Figure 9.4 Representation for the regression between individual-level effects. All input correlations are the individual-level r_i's. The variable D represents a set of N-dummy codes. We follow the standard notation in the regression literature: the variable to the left of the dot is the dependent variable, the variable(s) to the right of the dot are the predictors, and the variable(s) in the parentheses are variables that have been controlled for, i.e., entered in a previous step.

Duncan and Fiske (1977). Because the goal in this chapter is to illustrate the application of several statistical models, we do not provide psychological motivation for the particular examples we selected.

This multiple regression model must be estimated separately for the two levels of analysis. Turning first to the individual level, we know that the individual-level correlation between the two predictors (gestures and gazes) is 0.258. This remains unchanged in the regression model and, because it is rather small, we will expect little change between the zero-order correlations and the standardized partial regression coefficient. When the three individual-level correlations (and the appropriate *N*, see below) are entered into a multiple regression program that accepts correlations as input (such as the REGRESSION command in *SPSS*; see Table 9.6 for example code), we find that the standardized coefficient for predicting verbalizations from gazes is –0.324 (virtually identical to the individual-level correlation). The coefficient for predicting verbalizations from gestures is –0.002, again virtually the same as the comparable individual-level correlation. These two standardized regression coefficients are denoted $\beta_{\text{verb.gaze(gest)}}$ and $\beta_{\text{verb.gest(gaze)}}$, respectively.

For this individual-level analysis, the appropriate significance test depends on the number of subjects. However, because the individual-level correlations are actually derived from one score for each dyad, the appropriate *N* to enter into the multiple regression routine is the number of dyads, *not* the number of subjects. In this case, the correct "sample size" to enter in the multiple regression routine is 24. At this sample size, neither coefficient is significant, although the regression coefficient for gazes is marginal ($t = 1.52$, $p < 0.15$). A method equivalent to that described here is to create $N - 1$ dummy codes that represent the dyads, and run the regression of verbalization on the dummy codes, the gesture variable, and the gaze variable. The dummy codes will account for the sum of squares due dyads.

The analysis is more complicated for the dyad-level portion of the analysis because of the sample size problem caused by interdependence. That is, each dyadic correlation is based on a different "effective sample size" depending on the degree of dyadic interdependence in the two relevant variables. Two possible, but inexact, solutions to this problem come to mind. First, because each dyadic correlation will be associated with an effective sample size of at least *N*, the number of dyads, this could be entered into the program as a conservative estimate of sample size. Second, one could use the smallest effective sample size associated with any of the dyad-level correlations in the model. In our example, we will use the second strategy, entering the smallest effective sample size, 29.5 (rounded down to 29), and the three cross-intraclass correlations into the *SPSS* multiple regression routine. All possible cross-intraclass correlations between the relevant variables (i.e., the raw-score index of the dyad-level correlations) are submitted as input to the regression procedure. In this case, the cross-intraclass correlation between the predictors is again moderate, 0.325, indicating that the standardized coefficients will not be much different than the corresponding zero-order correlations. In fact,

Table 9.6 Example SPSS code for executing the regression model described in the text. The input correlations are the individual-level correlations r_i between all possible pairs of gestures, gaze, and verbilization frequency.

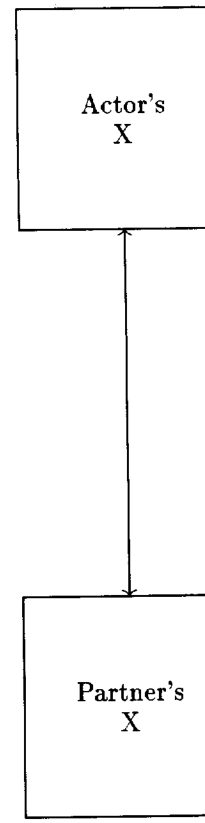
```
matrix data variable=gest gaze verb
  /contents=corr
  /n=24.
begin data
  1
   .258  1
  -.086  -.325  1
end data.
regression matrix in (*)
  /noorigin
  /dependent=verb
  /method=enter gest gaze.
```

both standardized regression coefficients remain significant when the two predictors are entered together. The coefficient for gestures is somewhat reduced (0.364, $p < 0.05$, compared to the cross-intraclass correlation of 0.479), as is the coefficient for gazes (0.352, $p < 0.05$, compared to 0.471).

This approach can be used for either exchangeable or distinguishable dyads. In addition, for distinguishable dyads one may use structural equation modeling, which will yield significance tests in the distinguishable case for a more direct approach. In such a case, the covariance matrix is entered directly into a structural equation modeling program such as *LISREL* or *EQS*, following the general procedures outlined in Gonzalez and Griffin (in press). Note again that it is not appropriate to enter the pre-computed dyadic correlations into a structural equation modeling program.

A Regression Model for Separating Actor and Partner Effects

Earlier we noted that the overall correlation in a dyadic design can be decomposed into underlying correlations representing the dyadic-level and individual-level relations. It is these correlations that were entered into the multiple regression models discussed in the preceding section. However, this



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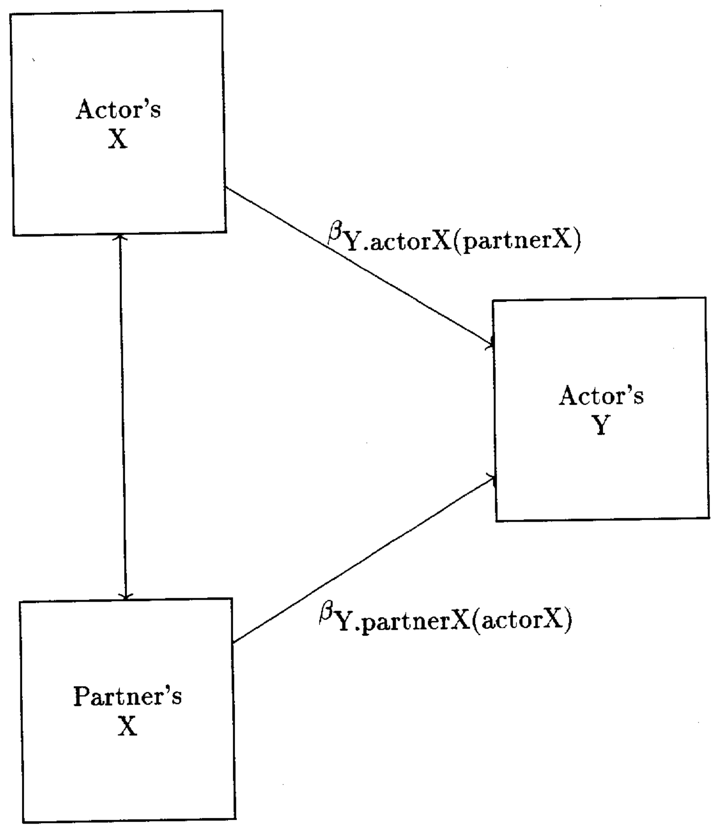

Figure 9.5 Representation of the actor–partner regression model.

particular decomposition is only one of a number of possible models that can be applied in this situation. Another useful way to model the social interaction within a dyad is as a combination of two paths linking X and Y: an actor effect, which represents the extent to which a dyad member's (the "actor") standing on variable X determines that actor's standing on variable Y, and a partner effect, which represents the extent to which the partner's standing on X determines the actor's standing on Y. We now turn to an example of an actor-partner model.

In the Stinson and Ickes example, we might ask: "What predicts an individual's verbalization frequency?" An individual actor's speech frequency might be caused by the joint effect of the individual's own gazes and his or her partner's gazes. Following the structural model illustrated in Figure 9.5 leads to the interpretation of the (semi-partial) pairwise r_{xy} as the "actor correlation" and the (semi-partial) pairwise $r_{xy'}$ as the "partner correlation". To obtain the actor and partner effects in the exchangeable case, it is necessary to partial out the shared component of the actor and partner variance—which means partialling out $r_{xx'}$, the pairwise intraclass correlation on X. The comparison of this model (depicted in Figure 9.5) with the decomposition presented earlier in this chapter (Figure 9.3) illustrates the importance of a theoretical model in guiding and formulating how an analysis should be conducted. Under different models the same correlations r_{xy} and $r_{xy'}$ carry different interpretations.

The actor–partner regression model (introduced in its most general form by Kenny, 1995a) can be estimated with the pairwise method. The dependent variable of interest (Y) is simply regressed on the X and X' columns, using a standard regression program on the pairwise data setup we have used throughout this chapter (where each column contains $2N$ data points). Either the raw regression coefficients or the standardized regression coefficients can be read from the program output and tested for significance (see Griffin & Gonzalez, 1998). Like the tests for the pairwise model given earlier, the significance tests for the actor and partner regression coefficients are made up of the four pairwise correlations: $r_{xx'}$, $r_{yy'}$, r_{xy}, and $r_{xy'}$. We will not go through the computational details here, but simply present examples and discuss their interpretation. Technical details as well as a generalized model that includes an interaction term that permits estimation of the Thibaut and Kelley (1959) concepts of reflexive control, fate control, and behavioral contrast are given in Griffin and Gonzalez (1998).

It is instructive to express these raw-score regression coefficients in terms of pairwise correlations. The actor regression coefficient is given by

$$\frac{s_y\,(r_{xy} - r_{xy'}r_{xx'})}{s_x\,(1 - r^2_{xx'})} \tag{9.10}$$

where s_y and s_x are the standard deviations of the criterion variable and the predictor variable, respectively. This formula produces a value that is identical to the coefficient produced by standard regression programs. The regression coefficient for the partner effect has the same form with the role of r_{xy} and $r_{xy'}$ interchanged. Under the null hypothesis that the population $\beta = 0$, the variance for the actor regression slope is

$$V\,(\beta_{\text{actor}}) = \frac{s^2_y\,(r^2_{xy'}r^2_{xx'} - r_{xx'}r_{yy'} + 1 - r^2_{xy'})}{2N\,s^2_x\,(1 - r^2_{xx'})} \tag{9.11}$$

The test of significance for the actor effect is computed with a Z test using $\beta/\sqrt{V_{(\beta)}}$. The test for the partner effect is analogous, except that r_{xy} appears in Equation (9.11) in place of $r_{xy'}$.

For the Stinson and Ickes' data that we have been using throughout this chapter, the actor correlation r_{xy} between gaze and verbalization was 0.386. In the context of the model shown in Figure 9.5, the standardized regression coefficient was 0.173 (Z = 0.97). This standardized regression coefficient is interpreted as the influence on an actor's frequency of verbalization given one standard deviation change on the actor's frequency of gaze, holding constant the partner's frequency of gaze. In this case, the actor effect was not statistically significant. Similarly, the partner correlation $r_{xy'}$ between gaze and verbalization was 0.471. The standardized regression coefficient was 0.372 (Z = 2.09). In other words, the influence on the actor's frequency of verbalization given one standard deviation change on the partner's frequency of gaze, holding constant the actor's frequency of gaze, was statistically significant. The partner's gaze frequency was a more powerful predictor of the actor's verbalization frequency than the actor's own gaze frequency. For one possible theoretical analysis of these results see Duncan and Fiske (1977).

A more complicated form of the actor–partner regression model is used for analyzing data from distinguishable dyads because when there are two different types of dyad members it is usually of interest to examine whether the actor effects and the partner effects vary across the two types of individuals. For example, consider the model presented in Figure 9.6, adapted from the study by Murray, Holmes, and Griffin (1996a) of married couples. In this model, a woman's image of her partner is determined by two causes: her own self-image (the "projection" path labeled "a", which is an actor effect) and her partner's self-reported self-image (the "matching" path labeled "b", which is a partner effect). A man's image of his partner is similarly determined by an actor effect "d" and a partner effect "c".

In such a model it is of central interest to test whether the actor (projection) paths are equal across sexes, or whether the partner (matching) paths are equal across sexes. This can be most easily done using structural equation modeling, as in the Murray et al. study, where the fit of the model under equality constraints is compared to the model where the constraints are not imposed. If both the actor and the partner effects are equal across the two classes, then "a" and "d" can be pooled and "b" and "c" can be pooled. In a simple model such as this, the pooled structural equation model is essentially equivalent to carrying out the pairwise regression model adjusted for distinguishable dyads because there the parameters are also averaged across the two types of people. The structural modeling approach can be extended to estimate much more complex models, as illustrated in the Murray et al. study.

In the Murray et al. example, the tests revealed that both the actor and partner effects were equal across husbands and wives. Furthermore, both the actor and partner effects were highly significant and almost equal in magnitude (standardized regression coefficients = 0.315 and 0.304, respectively).

The actor–partner regressions are interpreted quite differently than the regressions based on the dyadic- or individual-level correlations. The actor–partner models are simple regressions, and are used to answer whether an actor's score on an outcome variable is determined by that actor's score

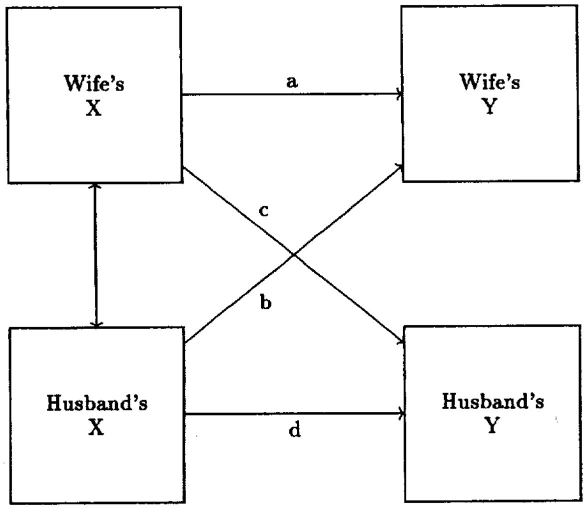

Figure 9.6 Representation of the actor–partner regression model for testing differences in regression coefficients between two classes.

on a predictor variable or by his or her partner's score on the predictor variable. These models provide estimates and significance tests that are corrected for interdependence, but they do not specifically model the interdependence itself. The dyadic-level regressions, in contrast, can be bivariate or multiple regressions, but they explicitly model the interdependence within dyads and answer questions at a different level of analysis. Finally, the individual-level regressions may be bivariate or multiple regressions, and they answer whether the unique or unshared qualities of an individual on the outcome variable are determined by some combination of his or her unique qualities on the predictor variables.

EXCHANGEABLE AND DISTINGUISHABLE DYADS IN THE SAME DESIGN: A SPECIAL ACTOR–PARTNER EFFECT

A special case of the actor–partner model is the Kraemer–Jacklin method (Kraemer & Jacklin, 1979). As Kenny (1995) has pointed out, this is a model for analyzing "mixed" dyads. This is applicable when some dyads are made up of distinguishable members and others are made up of exchangeable members. The classic use of the Kraemer–Jacklin method is to examine whether sex differences in mixed-sex dyads arise from direct (actor) effects or indirect (partner) effects. For example, are men in heterosexual couples more aggressive than their partners because they are men (the actor effect) or because they are paired with women (the partner effect)? In the terminology used by Kenny (1995), is the effect of sex on aggression due to an actor effect or a partner effect? This question cannot be answered in a design where all the dyads contain both men and women—instead it requires a mixed design where some dyads contain a man and a woman, some contain two men, and some contain two women. This design allows the researcher to separate the effect of being a man from the effect of being paired with a woman. Mendoza and Graziano (1982) presented an extension of the Kraemer–Jacklin model to multivariate data. This method uses contrasts to test the hypotheses of the model.

The basic Kraemer–Jacklin design can also be handled by the pairwise regression model. In the classic balanced design (using sex differences as an example), k dyads are male–male, k dyads are female–female, and $2k$ dyads are mixed sex, where $k = \frac{1}{4}N$ (other divisions are possible, but this offers the greatest power because it yields an orthogonal test of the actor and partner hypotheses, see Kenny, 1995). One column codes the sex of the subject and a second column codes the sex of the partner. Two more columns of data are used to code the dependent variable, one coding the outcome variable for the subject and the other coding the outcome variable for the partner.

In the original Kraemer and Jacklin example, there were 12 male–male, 12 female–female, and 21 mixed dyads. The outcome variable was the frequency of offering one's partner a toy. In the columns representing subject sex and partner sex, it is convenient to code boys -1 and girls +1 (although the codes could be reversed without loss of generality). When the outcome variable is regressed upon these two pairwise variables, the actor effect is simply the partial regression coefficient for the subject sex column and the partner effect is the partial regression coefficient for the partner sex column. Again, these coefficients are tested by a formula based on the four pairwise correlations $r_{xx'}$, $r_{yy'}$, r_{xy}, and $r_{xy'}$ Griffin & Gonzalez, 1998). In a perfectly balanced design, such as the one described in the preceding paragraph, the actor and partner effects are orthogonal, so that $r_{xx'} = 0$. This restriction simplifies the hypothesis testing phase. However, in the original Kraemer and Jacklin study, the design was not orthogonal because there are 21 rather than 24 mixed dyads.

In this example, the unstandardized coefficient for the actor effect is one-half the mean difference between toy offers made by girls versus boys. The partner effect represents one-half the mean difference between toy offers made to girls versus boys. (Actually, the means are slightly adjusted for the fact that this was an unbalanced design but the principle is the same). The raw-score coefficients in this case are 0.29 for the actor effect, indicating that girls were more likely to offer toys, and 0.48 for the actor effect, indicating that girls were more likely to be offered toys. Both of these values are identical to the estimates from the original method proposed by Kraemer and Jacklin, which involves a much more tedious method of estimation. The Z tests for the two effects were 1.1 (nonsignificant) and 1.80 (marginally significant), both very similar to the values obtained by the original method. For more details about the pairwise formulation of the Kraemer and Jacklin method, along with derivations and supporting simulations, see Griffin and Gonzalez (1998).

CONCLUSION

"But wait a bit", the Oysters cried,
"before we have our chat.
For some of us are out of breath
and all of us are fat."
(Lewis Carroll, *Through the Looking Glass*)

We have given several examples of research questions that can be answered using the pairwise approach. Our approach differs from those that have been suggested by others. The usual approach to dealing with interdependence has been to define new statistics for a variety of special cases. Some of these statistics have not been readily accessible and have been difficult to implement. In contrast, our approach is to alter the way the data are arranged in the data matrix and then use well-known estimators (such as the Pearson correlation, the partial correlation, correction for disattenuation, regression slopes). The pairwise approach is relatively easy to implement and, as demonstrated here, fairly general in the range of possible research questions that it permits.

However, statistics should not be used in a vacuum. The use of statistics in research should be guided by the substantive theory relevant to the particular domain, the measurement concerns, and the design issues (Gonzalez, 1995). The pairwise technique provides one piece of the puzzle. The other pieces, equally as important, are also necessary for full advancement of a research area. For instance, researchers should develop paradigms that permit interdependence to emerge (see, for example, the paradigm described by Ickes, Robertson, Tooke, & Teng, 1986; Ickes, 1990). Then, armed with statistics for interdependence, relationship researchers can ask new research questions, develop new theory, grapple with measurement issues, and construct new paradigms and research designs. Our own interest in studying the statistics of interdependence grew out of an eagerness to return to research questions that were important during the early stages of our field, which in our opinion have not been adequately resolved.

One of the central phenomena of interest in the history of social psychology was the nature and character of the "group mind". At the turn of the century, French sociologists such as Tarde and Le Bon were fascinated by the difference between the irrational crowd and the rational individual. To them, the crowd was an entity in itself, something more than the sum of its individual parts. However, the phenomenology of the crowd was not amenable to controlled, experimental research and soon dropped out of favor as a topic for research. Later in the 1930s and 1940s, the group again became the focus of an influential school of researchers in social psychology: the Group Dynamics researchers. Once again, however, this group-based approach to social psychology was soon left behind, in part because of statistical design considerations. In particular, the

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realization that statistical dependency among group members' scores made the analysis of group data more complicated than individual data led to the virtual abandonment of experimental group research in favor of the use of confederates, paper-and-pencil descriptions, audiotapes, and similar individual-focused methods (Steiner, 1974, 1986).

It is our contention that with the introduction of conceptually and computationally straightforward techniques for assessing and separating group- and individual-level effects, we can return to the classic questions that fascinated earlier generations. Some of these questions have been addressed in recent years because of the availability of models developed by David Kenny and his colleagues (Kenny, 1995a, 1996; Kenny & La Voie, 1984, 1985; see Kenny & Albright, 1987, for an applied example). Our own work on the pairwise framework has been greatly influenced by the models of Kenny and his colleagues. We can imagine few questions more central to social psychology than those pertaining to when—or whether—groups act as more than the sum of their parts. A good place to start addressing these questions is with the simplest possible group structure: the dyad. (We are currently generalizing the pairwise method presented here to groups of arbitrary size; Gonzalez & Griffin, 1998a) We hope that the techniques presented in this chapter for dyadic data will provide tools that will be useful in asking and answering theoretical questions about dyads and the individuals that comprise them.

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