CHAPTER 14

Measuring Individuals in a Social Environment

Conceptualizing Dyadic and Group Interaction

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Currently, a controversy is dividing physicists: Do the basic laws of nature operate only at the level of elementary particles (the reductionist position) or also (and differently) at higher levels of matter? If proponents of the former position are correct, then a complete explanation of physics can be achieved by studying the most basic particles in isolation. A similar controversy has long divided researchers in personality and social psychology: Do the basic laws of behavior operate only at the level of the individual person or also (and differently) at higher levels of social interaction? Are dyads and groups somehow more than the sum of their individual constituents? Do they have a level of existence that cannot be defined in individualistic terms? Can we understand human psychology by studying one human at a time?

Let us be candid about what this chapter will accomplish: We do not offer answers to the thorny questions we posed above. Instead, we offer some methodological pointers for thinking about dyadic and group data in ways that help clarify what these questions mean. We explore, through several graphical examples, the interpretational complexities that are part and parcel of any dyadic or group design. Our approach has both a negative agenda—to point out common pitfalls of dyadic analysis—and a positive agenda—to explore the conceptual benefits of marrying theory and methodology in the study of dyads and groups. In particular, we encourage researchers to "think outside the box" when analyzing dyadic data—where the box represents the confines of standard data analytic methods and is defined by the classic assumption of "independent" data points.

There is no doubt that traditional analytic methods encourage a reductionist or individualistic perspective, which has a long and honored tradition in social psychology. Social psychology, at least in the American tradition, has been defined as the study of the individual in a social context. Even though the most common, pervasive, and powerful social contexts are those made up of other people, it is no accident that most of the great demonstrations of the "power of the situation" feature an active individual facing an impassive and inflexible social group. Whether it is the unyielding and unanimously mistaken majority of Asch's conformity studies, the magisterial and unshakable experimenter of Milgram's compliance studies, the forbidding and frightening scientist of Schachter's fear and affiliation studies, or the unconcerned and distracted onlookers of Darley and Latane's bystander intervention studies, the social context—that is, the other people—is constrained to uniformity to provide a controlled experience for the "real" participants in the studies.

There are good reasons for the individualistic approach of classic experiments on the influence of "social" context. The experimental method itself, the manipulation and control of factors that allows the experimenter to draw the cherished causal inference, brings with it some basic ground rules: Individuals within conditions should be treated exactly alike to eliminate confounding and to reduce within-cell error variance. The standard between-subjects analysis of variance, which goes hand in hand with the simple factorial experimental design so beloved by classic social psychologists, requires that each data point has "independent and identically distributed errors" (known as the IID assumption). Each participant in a study is explicitly required to be independent of every other participant except for the common effect of the manipulation. Thus, the very issue of how people combine, interact, and affect each other is stripped away from the classic experimental design in social psychology.

The decision to remove actual group interaction from the standard toolkit of social psychologists was a deliberate and considered one. It marked the end of the ascendancy of the "group dynamics" approach developed by Lewin and his students and colleagues. This change in emphasis and design reflected both statistical and theoretical influences. Group dynamics researchers who had studied actual groups—their interactions and changes over time—became frustrated with the amount of effort required to gain one additional data point, because the independence assumption meant that responses from all members of a group were aggregated or collapsed into a single value (usually the group mean). Furthermore, the main outcome variables of interest shifted from qualities of the group (e.g., group cohesion, norms, intergroup communication, group performance) to qualities of individuals (e.g., anxiety, attitude change, attribution, individual performance). Theories that once focused on the forces that held groups together or led to their disintegration were now adapted to focus on the forces that led to consistency between attitudes and behavior, or between expression and emotion.

One of the social psychologists who influenced this transition was Harold Kelley. He is well known for his contributions to attribution theory, a defining approach to individual social cognition. He also codeveloped an influential and important theory of social interaction called Interdependence Theory. One of the reasons that attribution theory has sparked much more empirical research than interdependence theory is that the study of interdependence cannot be done within the confines of the statistical independence assumption. (A second reason is that some types of interdependence, such as that which might develop in an intimate romantic relationship, are difficult to study within the confines of the 30-minute laboratory experiment.) Remarkably, it is only within the last 10 years that a sizable number of social psychologists have returned to looking at groups as molecules, as entities that are more than a collection of individual atoms. The good news is that this is happening at all. The bad news is that the same statistical limitations that shackled the original group dynamics movement, in particular the statistical independence assumption, are still limiting the conceptualization, design, and analysis of dyads and groups.

In this chapter, we discuss techniques that will help social psychologists move beyond the statistical independence assumption in dyadic and group research designs. We first discuss the common error of creating independence within an intrinsically non-independent data set. Then we consider three analytic models for "breaking apart" individual and group levels of analysis while preserving the basic structure of non-independence. Throughout, the lesson is that an analytic or statistical strategy should reflect theoretical assumptions about the mechanism or model of non-independence. There is no single way to analyze data from dyads or groups. As is always the case, the "right way" to analyze one's data depends on the research question one is asking. The main lesson we hope to convey to the reader is that the researcher must first be mindful of the type of research question being asked because the nature of the research question leads one to different analytic approaches.

NON-INDEPENDENCE AND INTERDEPENDENCE

The independence assumption generally comes in the form of a linear model such as $Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$ where Y_{ij} is the jth dependent variable in the ith condition. This is the standard model for a one-way analysis of variance. The variable *Y* is what is observed. In an experiment, the α_i reflects the shared effect of the manipulation on every member of a given cell or condition. The term μ is the grand mean of the dependent variable, which is a scaling constant that applies to all observations in the study. The ε_{ij} reflects the set of unique influences on an individual that are unshared with the other members in that cell or condition. This "unshared" effect is at the heart of the independence assumption because it is assumed that each of the errors ε_{ij} is independent from the others.

To appreciate how a violation of independence might occur, consider a somewhat contrived example. If three members of one condition are surveyed on a sunny day whereas all others are surveyed on a rainy day (weather is unrelated to the experimental manipulation), a possibility of "shared error" is created that would violate the independence assumption. The violation of independence would make the statistical model written above inappropriate because the resulting *p* value would be incorrect. This is because the three individuals might respond similarly to each other due to their shared sunny environment (even though they experienced it at different times), and not simply because of their shared experimental condition. This violation of independence can be modeled as a correlation between the error terms, so that the error terms would now have a systematic component caused by a shared influence as well as a random unique component. (See Kenny and Judd [1986] for a complete treatment of the effects of a violation of the independence assumption.)

In a non-experimental observational study, the *Y* represents the observed variable, the μ reflects the grand mean of the observed variable, the α_i reflects the shared effect of some fixed value of the predictor variable (say, an individual's rating of political conservatism) on the observed variable, and the ε_{ij} again reflects the set of unique unshared influences on an individual. For example, some respondents might be sampled during the summer and others during the winter, and people's expressed attitudes might vary across the seasons even though their true level of political conservatism does not. Such shared errors violate the traditional regression model just as much as they violate the traditional analysis of variance model closely associated with experiments. As with the case of experiments, such violations of independence could be modeled by allowing for correlated errors.

Non-independence is simply a statistical issue that invokes no assumptions about the cause of the relationship: Are sets of scores correlated beyond the shared effect of being in the same experimental condition or having the same fixed quantity of an explanatory variable? That is, are there subsets of similar scores within an experimental condition or within a level of a predictor variable? The correlation may come about because of third variables (such as the weather or time of year) or from social interaction (perhaps the development of shared norms) or "contagion" between the participants (in the extreme, a "group mind" as postulated by Le Bon, 1897/2001). Typically, in experiments or surveys, non-independence is a nuisance, and we correct for it by adding a new factor or predictor variable to account for shared effects of weather or season or gender of the interviewer; this in effect shifts the shared effect from error (where it is a problem) to the fixed structural model, where it belongs (at least in traditional designs). A violation of independence can seriously influence the conclusions from a statistical test in that the *p* value can be seriously distorted (Kenny & Judd, 1986).

In dyadic and group designs, the "non-independence in the errors" is due to group membership. Two members of the same couple or group are correlated by virtue of the experience of being in the same group. Group membership will create correlated errors in much the same way that we discussed above. However, there is a major difference in connotation that we want to highlight. Usually, the violation of independence is a nuisance that the investigator wants to correct or avoid. However, in the case of dyads and groups, the violation of independence may be the very phenomenon the social psychologist is trying to assess: Are the scores of people within the same dyad or group similar to each other—that is, does the group display a shared culture or outlook or even a personality? To convey this subtle difference, we use the term *interdependence* (rather than non-independence, or violation of independence) to refer to correlated error due to social interaction. The underlying statistical model, however, is the same. The key difference in how we handle interdependence as compared to non-independence is that we will use the nature of the correlated error to test hypotheses specific to the underlying social dynamics (rather than try to "correct" for the correlated error, as is usually done in the case of non-independence).

To be explicit, we again write the linear model and show how it describes interdependence. In symbols, we have $Y_{ij} = \mu + \alpha_i + \varepsilon_{ij}$, where μ reflects the grand mean of the dependent variable and α_i represents the effect of a manipulated variable such as exposing couples to one of two experimental treatments (or the different values of a predictor variable). In much the same way that subjects measured on sunny days versus rainy days can lead to correlated error, group membership can lead to correlated errors ε_{ij} for individuals in the same group. Thus, the group can be conceptualized as a confounding variable. Data from two individuals who are married might be related to each other because the two individuals are married, in addition to being related to each other because the two individuals were exposed to the same experimental treatment (or have similar values on a predictor variable). However, if we are interested in the psychology of social interaction, we do not necessarily want to discard completely (i.e., partial out or correct for) the correlated error structure. As we show below, interesting insight about underlying process can be gleaned by modeling the correlation between the errors. That is, the interdependence of the error terms can tell us quite a bit about the social psychology of interaction among dyad and group members.

THE INTRACLASS CORRELATION

The magnitude of the interdependence present in a variable is indexed by the intraclass correlation (ICC, often denoted r_{xx}). As we will soon see, the ICC is the basic building block of dyadic and group designs. The ICC, which comes in many forms and has several uses (Shrout & Fleiss, 1979), indexes the similarity of scores on the variable in terms of the proportion of shared variance within clusters to the overall variation across all scores. The ICC can be viewed as an index of agreement within or across judges, a building block of Cronbach's alpha indexing the reliability of a multi-item scale, or a measure of effect size for ANOVA models (Haggard, 1958).

In the case of dyadic and group designs, the ICC has a specific meaning because it assesses the degree of agreement within group members. For example, if husbands and wives rate their feeling of security in their relationship (that is, the husband and the wife each rate their own level of security), the data come naturally in pairs due to marriage. This pairing, or clustering, could produce a correlation within the cluster that may differ from the correlation between two individuals who are not married. The ICC provides an index of this correlation. The standard independence assumption is that all observations are independent from each other. The ICC provides a measure of agreement within couple members, so it provides a natural measure of interdependence. The ICC would be a relevant measure if a researcher was interested in testing whether there was agreement between the husband and the wife on their ratings of security in the relationship.

We now consider some special cases of the ICC. If each wife provides a rating that is equal to her husband's, but the ratings differ between couples, then the ICC will be 1 because couples are maximally similar (i.e., all the variance is between couples). If ratings vary within couples just as much as they vary between couples, then the ICC will equal 0 because there is no evidence of similarity or dissimilarity within couples. If ratings vary more within couples than they do between couples, the ICC will be negative, indicating that individuals within groups are more dissimilar than expected by chance. Notice the analogy to the traditional *F* test used in the ANOVA model: When variance is primarily between conditions, the *F* ratio is larger than 1; when variance is primarily within conditions, the *F* ratio is smaller than 1. The development of the ANOVA model by R. A. Fisher at the beginning of the 20th century was in fact a modification of the basic intraclass correlation then in use (Haggard, 1958). The ANOVA approach can be restated in terms of the ICC, but because of its traditional association with experimental methods (particularly factorial experimental methods), the ANOVA approach has become almost synonymous with the independence assumption. Repeated measures, or within-subject, ANOVAs allow a restricted pattern of correlated errors across people or across time, and multivariate (M)ANOVAs allow unrestricted correlations across outcome variables. Thus, specific generalizations of the independence condition are in common use (e.g., a paired *t* test allows correlated error across the two observations from the same person). The task of the social psychologist studying interdependence is to make use of such generalizations in order to answer specific psychological questions (e.g., what is the level of husband/wife agreement?).

The ICC can be used to index non-independence or interdependence across a wide range of applications, from diary studies in which individuals are measured a number of times (time is embedded within individuals, and an individual's scores may be similar across those times) to educational studies in which students within classes share a common environment (students are nested within schools, and the students within a school may be similar) to studies of close relationships in which individuals mutually influence each other. In each of these designs and many others, the presence of non-independence or interdependence provides a challenge and an opportunity. The challenge is to deal with the level-of-analysis problem (e.g., individuals versus classes versus schools), both statistically and conceptually. The opportunity is to go beyond merely acknowledging the degree of non-independence and unpack the meaning of the shared effects. For example, interdependence means that interacting individuals influence each other's outcomes. If a researcher is examining the impact of social interaction, then the degree of interdependence might be the central measure of interest and should be modeled directly rather than treated as a statistical nuisance that needs to be corrected. Such theoretical presumptions guide the way that data must be structured and analyzed.

Throughout the rest of this chapter, we focus on examples of one particular class of designs, observational studies of dyadic interaction, and systematically develop models for conceptualizing different types of dyadic processes. Our modest goal is to end the hegemony of the independence assumption and its atomic perspective and to celebrate the return of the molecular model to social psychology. We hope to provide an intuitive understanding of diverse dyadic models by graphical demonstrations. All the conceptual principles that are presented apply to experimental designs as well, but we expect that the most common application will be to observational designs. We describe three prototypical designs for modeling dyad-level data: the latent dyadic model, the actor-partner model, and the slopes-as-outcomes (HLM) model. Although each model is built upon a common building block (the intraclass correlation), each solves the levels-of-analysis or multilevel problem in a different way, with very different implications for theory building and theory testing.

The latent dyadic model places the main causal forces giving rise to shared behavior or attitudes at the level of latent or underlying dyadic effects. An example of a research question that can be tackled by the latent dyadic model is "What is the dyadic-level correlation between a couple's rating of security in the relationship and a couple's level of intimacy?" The actor-partner model places the main causal forces giving rise to individual behavior as acting between individuals. An example of a research question that can be addressed by the actor-partner model is "Which is a stronger predictor of the husband's rating of intimacy—his rating of security or his wife's rating of security?" These two models require the same type of data to be collected: Ratings on each variable are collected from each member of the couple. The slopes-as-outcome model emphasizes causal forces acting between levels, and for dyads this model requires a more complicated data collection where data from each member of the couple are collected over multiple times (as in a diary study). An example of a research question that can be tackled by the slopes-as-outcome model is "Does the level of security as rated by the couple members moderate how conflict in the relationship today predicts an individual's feeling of intimacy with the partner on the next day?" Note how these three models are not simply different statistical frameworks that are available for the data analyst; they imply different underlying causal structures and thus permit different conclusions to be made from one's data. (Note, however, that the plausibility of these conclusions depends on the plausibility of the assumed causal structure.)

Before we turn to our three focal models, we mention a hybrid model that combines a classic experimental approach with actual social interaction. Kenny's Social Relations Model (Kenny & La Voie, 1984) brings the logic of factorial composition to interpersonal interaction by systematically pairing different interaction partners (a "round robin design") and measuring the outcome. This approach, which can be seen as a rare marriage of social and personality psychology, is not reviewed below because it solves the non-independence problem by design (the experimenter's control over the sequence of interaction partners) rather than by analysis, per se. In fact, in a full round robin or factorial design, the experimenter can reduce the ICC to zero. Our interest in this chapter is in focusing on the special case where group membership comes "as is" (e.g., a husband and a wife, and one generally cannot pair each husband with all wives!).

The application to experiments involving dyadic interaction is similar to the observational case. Indeed, if husband and wives are brought into the lab and placed into experimental conditions, the analytical options remain the same as with observational studies. An experimental setting may introduce new types of designs (such as a female confederate who interacts with all participants in the study), and these design changes do have implications for data analysis. For instance, even though the experiment might involve dyadic interaction between the confederate and each participant, the confederate usually does not provide data (usually only the participant in the dyad is the subject of the study and provides data). In such cases interdependence, while it may be occurring between the confederate and the research participant, would not be present in the data. Once again, the devil is in the details, and different experimental designs may call for variations in how to handle dyadic or group interdependence.

GRAPHICAL REPRESENTATION OF THE INTRACLASS CORRELATION

The intraclass correlation is one of the oldest, as well as one of the most versatile, statistics. The original computation method for the intraclass correlation proposed by Karl Pearson (1901) was quite intuitive. He focused on the similarity of all possible pairwise combinations of the members from within the same group. Imagine that the researcher is studying roommates who live in three-bedroom apartments, so there are three individuals living in each apartment. Each roommate provides a rating of satisfaction with the living situation. The following comparisons are possible for each score: Roommate 1 is compared to Roommate 2, Roommate 1 is compared to Roommate 3, and Roommate 2 is compared to Roommate 3. Originally, this pairwise intraclass correlation was computed using a special way of coding data, which we describe below. Although other methods of computation have been developed, the method we present is identical to the maximum likelihood estimate of the ICC seen in hierarchical linear modeling programs (when groups have equal size). This equivalence is nice because the relatively simple pairwise approach helps illustrate the more complicated maximum likelihood estimate that is generated from statistics packages, which may not be easy to understand.

Consider a simple example of five male homosexual couples where each member of the couple provides a rating of his own level of intimacy in the relationship. Let's say that the scores on this dependent variable were (1, 2), (3, 4), (4, 4), (5, 4), and (2, 3). The two members of a given couple are denoted within a set of parentheses. We could enter

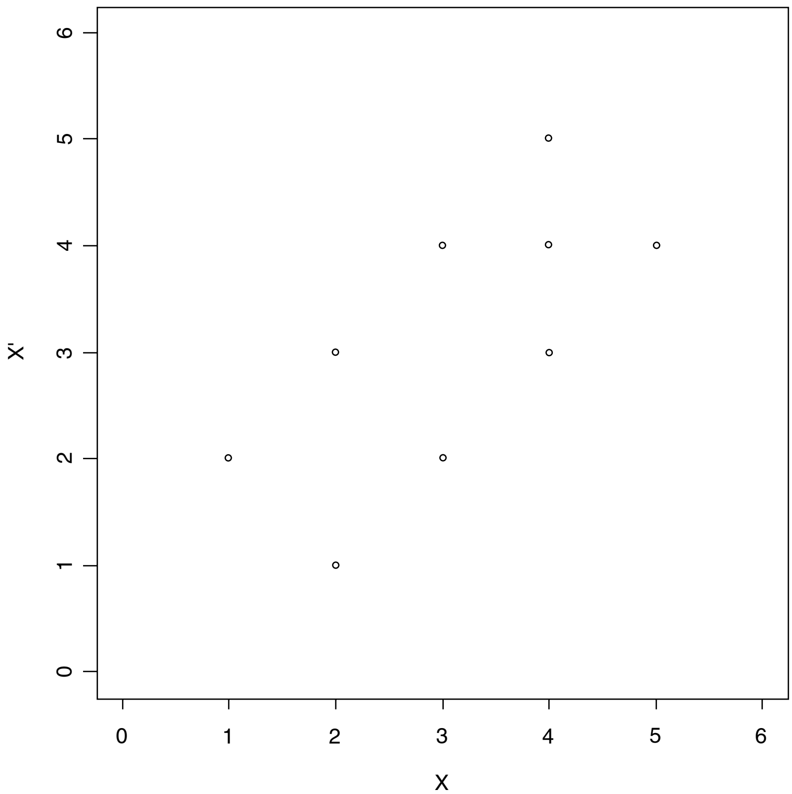

Figure 14.1 Graphical Illustration of the Pairwise Coding Using Data for Five Homosexual Couples on a Single Dependent Variable

these 10 data points in one long column—1, 2, 3, 4, 4, 4, 5, 4, 2, 3—along with an associated column of codes that tell us of which dyad the individual was a member. The pairwise approach involves re-entering the same data but in a different order, an order that switches the two individuals within the same dyad. So, for these data the second column would be 2, 1, 4, 3, 4, 4, 4, 5, 3, and 2. To understand how this coding works, it is helpful to plot these data, calling the first column *X* and the second column of reordered data *X′* (see Figure 14.1).

This plot appears to show a positive correlation between the two columns, but actually it shows more. If we connect the two points of the same dyad with a line segment, we see some structure around the identity line. It is this very structure that is the violation of the independence assumption and provides information about the degree of interdependence. These data are not randomly scattered on the plane; instead, points are joined as pairs according to dyadic structure—group membership defines an association between pairs of points. Figure 14.2 shows the same points displayed with the additional structure.

Figure 14.2 shows that the two members of each dyad tended to agree, and as the data show, the members in four of the five couples differed by one point on this scale. Thus, pairs within dyads tend to be similar, but there is quite a bit of variation across dyads, as indicated by the line segments intersecting the identity line at different places. Perfect agreement corresponds to a point on the

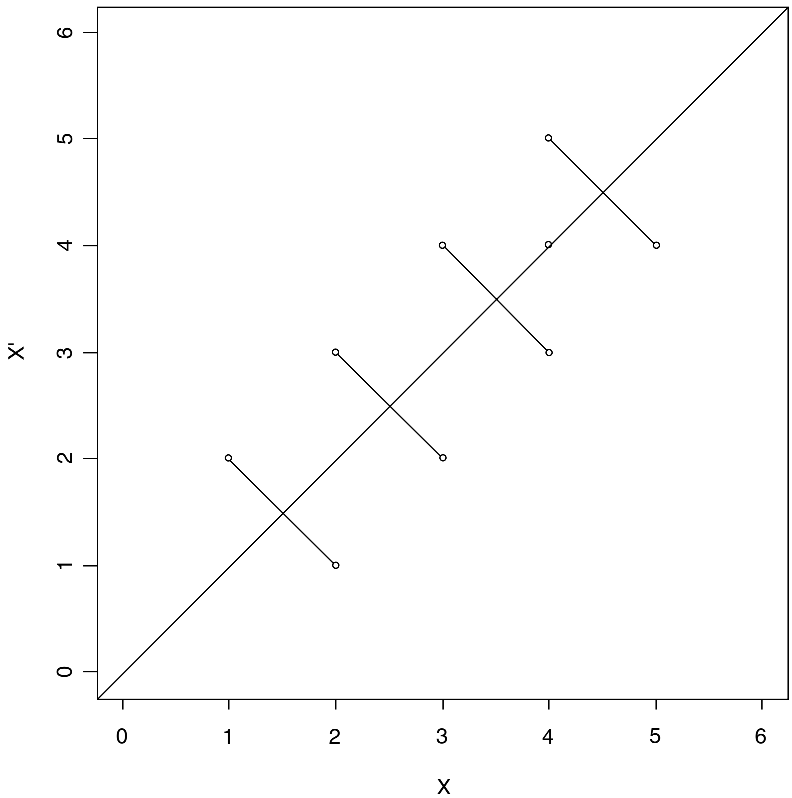

Figure 14.2 The Data From Figure 14.1, With Line Segments Connecting Points for Members of the Same Couple

identity line, as seen in the couple that had the score (4, 4). It turns out that the traditional Pearson correlation between these two variables (i.e., variables that have been "pairwise" or double coded) provides the pairwise ICC, which is the maximum likelihood estimator. In this example, the intraclass correlation is relatively high at 0.706, suggesting a high level of within-dyad agreement.

A different example shows what the plot would look like when there is little similarity within dyads. Consider the data (1, 5), (2, 5), (3, 1), (4, 1), and (5, 3). Again, string these data into one long column, *X*, create a second column that contains the recoded pairwise data *X*´, examine the plot, and compute the Pearson correlation between the two columns *X* and *X*´. As one would expect with these data, Figure 14.3 reveals relatively little agreement within dyads; instead, there is a type of dissimilarity such that when one member of the couple scored relatively high (i.e., above the mean), the other member scored relatively low, indicating some sort of complementarity within the couple. Indeed, the plot shows that the pairs of points are not close to the identity line (which would have signified agreement); the Pearson correlation between *X* and *X*´ is –0.615.

These plotted examples used data for which dyad members are indistinguishable, or exchangeable, in the sense that we have no theoretical reason to distinguish one person from another. Other examples of exchangeable dyads are same-sex twins, members of a work group, and members of a jury (except

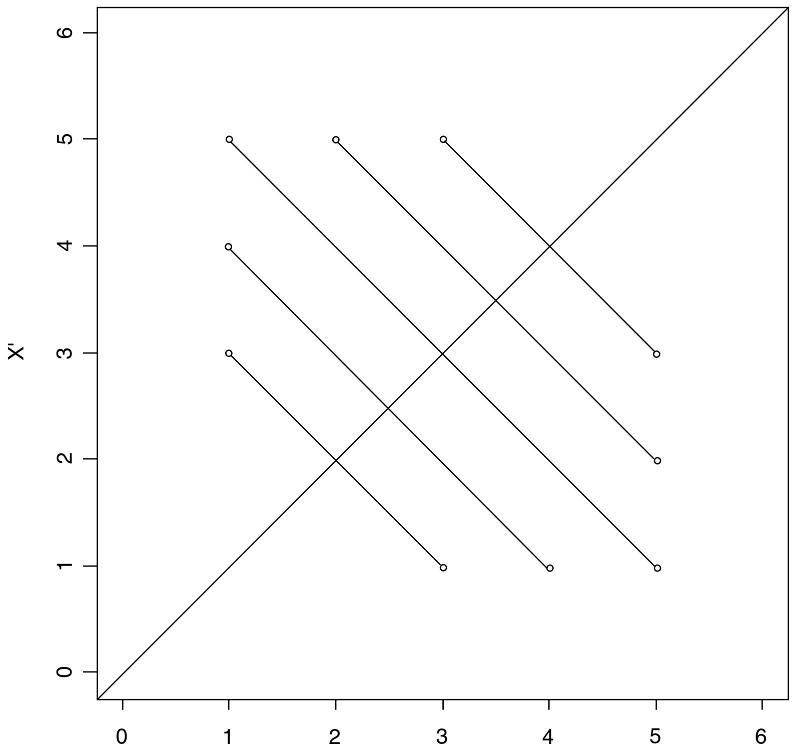

Figure 14.3 A Second Example of the Pairwise Coding Illustrating Little Within-Couple Agreement

for possibly the foreperson). A reader may think of ways of making the individuals distinguishable, such as coding the older same-sex twin, or the seniority of each member of the work group, or the chair each juror took at the deliberation table. Although each of these additional variables provides a means in principle for distinguishing the members of a group, our use of the term "exchangeable" refers more to the underlying theoretical variable of interest.

A more familiar type of dyad is where members are distinguishable by some theoretically meaningful variable; examples include heterosexual couples where sex is the distinguishing variable, a landlord/tenant pair, and a medical team of a doctor and an aide. Distinguishable dyads have the key characteristic that it is appropriate to place data from all members of one "type" under one column in the data file and members of the other type in a second column, and compute a regular Pearson correlation. In exchangeable dyads, this is not possible because it is not clear "who should be in Column 1 and who should be in Column 2." The pairwise ICC in the distinguishable case provides different information from the regular Pearson coefficient because the ICC indexes absolute rather than relative similarity. The computation involves a slight modification to the procedure used in the exchangeable case. Rather than taking the Pearson correlation between X and X' as in the exchangeable case to compute the pairwise ICC, one computes a partial correlation between X and X' controlling for the distinguishing variable (e.g., including a single dummy code for gender). (See Gonzalez and Griffin [1999] for details.)

The data coding for the pairwise approach can be extended to groups of larger size, but it becomes somewhat tedious because the coding must include all possible pairs of group members. For example, if Amos, Bram, and Carl (A, B, C) make up a triad, column *X* would need six rows to do the pairwise coding: using first letters of their names, we would enter data from A, A, B, B, C, C. In column *X*′ we place the pairwise coding where each partner is listed adjacent to each member (but excluding self pairings). Thus, column *X*′ would be B, C, A, C, A, B, which lines up against column *X* to include all possible pairwise codes; in this case and any time there are equal numbers within each group, the Pearson correlation of columns *X* and *X*′ provides the maximum likelihood estimator of the ICC (the same estimate of the ICC that would result from a hierarchical linear modeling program using maximum likelihood). Elsewhere we discuss simple computational formulae for the pairwise ICC in groups and explain the difference between the pairwise ICC and the ANOVA-based ICC (Gonzalez & Griffin, 2001). Throughout the remainder of this chapter, we focus on dyads because our goal is to convey the basic ideas. Although the basic ideas scale naturally from dyads to larger groups, readers interested in groups larger than dyads should consult our other papers for specific details (e.g., Gonzalez & Griffin, 2001).

INDIVIDUAL AND GROUP EFFECTS: ONE IS NOT ENOUGH

We now move to the case of two variables, say level of intimacy and degree of commitment to the relationship. Research questions in social psychological research usually involve multiple variables, so we need to extend the measure of interdependence presented above to handle more than one dependent variable. We present an example to show why it is useful, even necessary, to consider effects both at the level of the individual and at the level of the group. That is, we can ask whether two variables are related at the dyadic level and also whether the same two variables are related at the individual level. Does a couple's joint level of commitment correlate with the couple's joint intimacy rating? Does the wife's rating of commitment correlate with her intimacy rating, and does that correlation differ from the husband's correlation between the same two variables? Asking research questions at multiple levels (dyadic and individual) creates opportunities for new theory testing. We now illustrate this distinction with some examples.

Let's make up a simple example with five homosexual couples (i.e., five exchangeable dyads). The scores for the five dyads on level of intimacy are as before, with the example showing high agreement: (1, 2), (3, 4), (4, 4), (5, 4), and (2, 3). The scores for degree of commitment also show high agreement (pairwise ICC = .834): (5, 5), (2, 1), (3, 3), (3, 2), and (4, 5). Let's call these two variables *X* and *Y*, respectively, and we will also create the pairwise coded version of these variables *X*′ and *Y*′. The two pairwise plots for level of intimacy and degree of commitment are presented in Figure 14.4. Next to each line segment depicting a dyad, we place a number corresponding to which dyad it is; for example, on intimacy the point (3, 3) corresponds to Dyad 3 in our hypothetical data set.

Although both plots show a relatively high level of dyad-agreement (positive correlation within variables—meaning the lines perpendicular to the identity line are relatively "short" compared to the variation along the identity line), it is instructive to compare the dyad numbers listed in the intimacy plot with the dyad numbers listed in the commitment plot. At a higher level of analysis, there appears to be a negative correlation between the placement of these dyad numbers across variables: When both dyad members are low

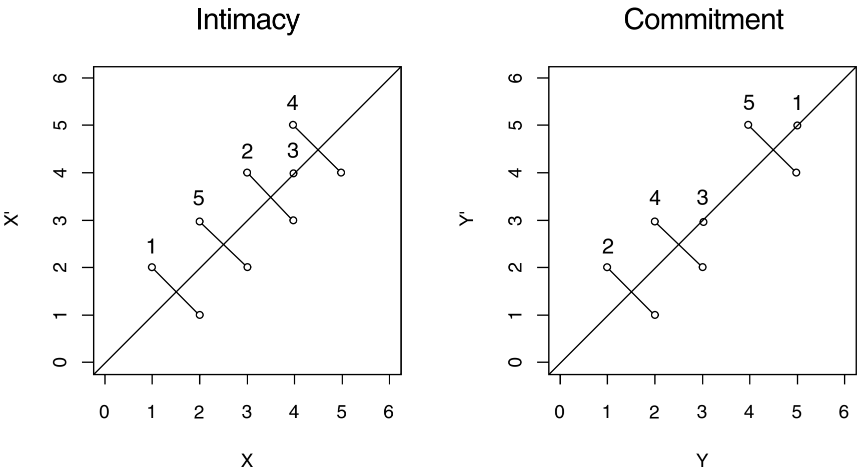

Figure 14.4 Pairwise Plot for Two Dependent Variables With Dyad Number Next to Each Line Segment

on intimacy, such as Dyad 1, both dyad members tend to be high on commitment.

How can we capture this dyad-level relationship between joint standing on one variable and joint standing on a second variable? We need what is called the dyad-level correlation, which is obtained in two steps: calculating the cross-partner, cross-variable correlation and then correcting this correlation by the degree of within-dyad similarity on each variable. The cross-partner, cross-variable correlation can be visualized using a variation of the pairwise ICC plot where we place each *individual*'s intimacy score on one axis and the *partner's* commitment score on the other axis, as shown in Figure 14.5. In other words, it is a cross-variable pairwise intraclass correlation.

The Pearson correlation between an individual's intimacy and the partner's commitment is –.656, which captures in a raw-score sense the negative relationship between the relative ordering of dyads on the intimacy pairwise ICC and the commitment pairwise ICC plots we showed earlier. The negative correlation can be seen by looking at the 10 points in the plot (ignoring the line segments connecting dyad members). These 10 points show a negative correlation between an individual's intimacy and the partner's commitment. To see the negative correlation, note that the scatterplot of points moves from the northwest corner to the southeast corner of the scatterplot. The line segments provide further information because they identify the pairs of points that belong to the same dyad—again giving a visual measure of the within-dyad similarity on each variable.

The key conclusions from this plot are (a) that when individual-level relations are stripped out of the data (by examining across-partner relations) there is a strong negative correlation, and (b) the dyads appear to be similar on both intimacy and commitment.

These two conclusions are jointly modeled in the dyad-level correlation that captures the relation between the two variables at the level of dyadic latent variables. To move to the latent or true-score level, the correlation between X and Y' is adjusted by a denominator that is made up of the product of the ICCs of each; this dyad-level correlation

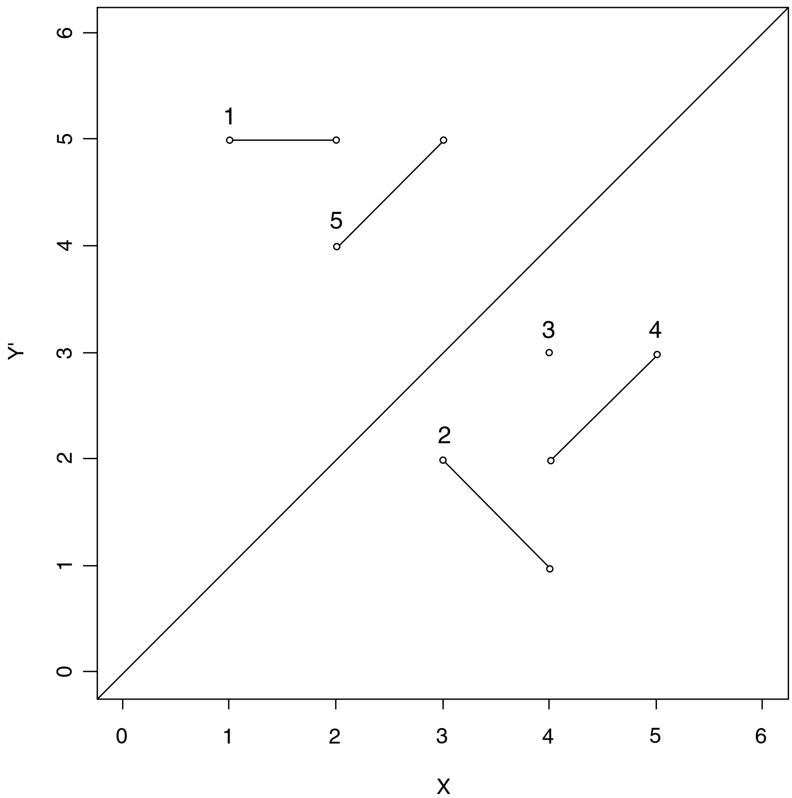

Figure 14.5 Pairwise Plot of Variable *X* Against Variable *Y´*

measures whether the type of dyadic similarity on one variable—for example, when both members of a given couple are high—relates to the type of dyadic similarity on the other—for example, when both members are low (see Griffin & Gonzalez, 1995, and Gonzalez & Griffin, 2002, for details). Such a latent variable correlation also can be interpreted as the correlation between the "true" dyad-level scores on each variable—scores that have been purged of the unique individual-level effect of each dyad member.

This is one possible solution to the levels-of-analysis problem: Shared variance within a dyad is treated as a dyadic effect and related to create a dyadic-level correlation or regression; unshared variance is treated as an individual effect and related to create an individual-level correlation or regression (as we describe below). Note, however, that such a model is first and foremost a theoretical choice that implies that there is some underlying and unobserved group-level construct (dyadic personality? shared environment? group mind?) that gives rise to the observed similarity. This is an important point because it shows how the choice of one's statistical model reflects one's underlying theoretical model. Practically, this theoretical choice translates into a requirement that the ICC for each variable must be high, or at least marginally significant (Kenny & La Voie, 1985), which signals the presence of shared within-group variance.

This formulation extends the simple case of the ICC on one variable to cases with two or more dependent variables. There are four key correlations in the two variable case: the ICC for variable *X*, the ICC for variable *Y*, the dyad-level correlation described above, and an individual-level (within-dyad) correlation. To make a connection with the simple ICC on one dependent variable that we presented earlier, we now consider two linear equations, one for each variable, and show how to depict the four relevant correlations.

$$\begin{array}{l} X_{ij} = \mu_x + \alpha_i + \varepsilon_{ij} \\ \qquad\qquad\;\; \Updownarrow_{r_d} \; \Updownarrow_{r_i} \\ Y_{ij} = \mu_y + \alpha_i + \varepsilon_{ij} \end{array}$$

The first equation yields the ICC for variable *X*, and the second equation the ICC for variable *Y*, as we saw before in the single-variable case. The α_is are random-effect terms that index dyad membership, and the μs reflect the grand means of each of the two variables. The additions in the two-variable case are the two vertical arrows that connect terms across the two equations. The arrow labeled r_d depicts the dyad-level correlation, which is a correlation between the group level effects α_i; the arrow labeled r_i depicts the individual-level correlation, which is a correlation between the εs. An intuition for the two correlations is that each represents a "unique" relation controlling for the other. In other words, the dyad-level correlation controls for the individual effect, and the individual-level correlation controls for the dyad-level effect (see Kenny & La Voie, 1985). For details of how to estimate this model using the pairwise approach, see Griffin and Gonzalez (1995). In the distinguishable case, this latent variable model can be implemented using standard structural equation modeling (SEM) programs (Gonzalez & Griffin, 1999).

Although this is not a standard HLM model (discussed below), even with exchangeable dyads the model can be instantiated in HLM as a special case of multivariate outcomes, where both variables *X* and *Y* are treated as outcome variables. For details on how to implement this model in the context of an HLM program, see Gonzalez and Griffin (2002). Under maximum likelihood estimation and when all the groups have the same number of members, the parameters estimated in HLM are identical to the parameters estimated with the pairwise approach (e.g., Griffin & Gonzalez, 1995). The individual-level correlation is also identical to the "average within-dyad" partial correlation one would estimate if dyad was entered as a grouping or dummy code (i.e., controlling for the variability of group means), a procedure that can be implemented easily in multiple regression (Cohen & Cohen, 1983). However, a complete analysis of one's dyadic data should do more than examine the individual-level variance. As we have been arguing in this chapter, there is useful psychological information in the group-level variances and covariances. The latent variable model permits a decomposition of individual- and group-level effects so that both types of effects may be examined simultaneously.

The Use of Dyad Means as Indicators of Shared Variance

The reader may ask, "Why not use the dyad mean as an index of 'dyad-level score' and then correlate the dyad means? What is the value added in running this complicated latent variable model? Is it not the case that if we compute the dyad means for intimacy and the dyad means for commitment, and then correlate the two sets of means, that we can get an estimate of the group level correlation?" Indeed, in the hypothetical example presented earlier, we observed a value of –.80

as the correlation between the two sets of group means, which at least in terms of sign is consistent with the information from the graphical representation we presented.

However, there is a major problem with using dyad means as a measure of dyadic effect because the mean aggregates across both individual-level and dyad-level processes. The correlation between dyad means consists of multiple components, and some of these components do not reflect dyad-level processes. It is possible that the correlation between the dyad means could be negative even when the actual dyad-level correlation is positive. Indeed, there are many possible ways in which the correlation of dyad means can be misleading (see Griffin & Gonzalez, 1995). Thus, a correlation between dyad means cannot be interpreted meaningfully in the context of this model except as an "aggregate," or combination, of both dyadic and individual effects.

The plots presented above show why it is inappropriate to discard one of the dyad members, which is a common simplifying strategy among some data analysts who study dyads. There is information in the degree of similarity or shared variance within a dyad that is conceptually meaningful. To discard such information is to ignore potentially interesting findings about social behavior. Most important, examining individuals "outside the group context" provides little information about what part of the apparently "individual" behavior is shared and what is unique.

INFLUENCE AND INTERACTION: A MODEL OF INTERDEPENDENCE

The latent variable model of dyadic influence implies that dyadic influence flows from a shared dyadic construct to each individual's behavior. However, the same data can be analyzed under the assumptions that the influence flows from individual to individual (without latent variable constructs), and that an individual's outcome is created by his or her own qualities (the "actor effect") plus the qualities of the partner (the "partner effect"). (See Figure 14.6 for a graphical depiction.) Although the parameters of the "actor-partner" model are in fact algebraic transformations of those given by the latent variable model, the focus and interpretation of the parameters are quite different, with the actor-partner model fitting Kelley's interdependence model where all forces are between individuals. In the actor-partner model, there is no underlying dyadic effect giving rise to observed similarity; similarity on X is simply unexplained (i.e., correlated predictor variables), whereas similarity on Y is generated by the actor and partner predictor variables plus correlated (unexplained) residuals. Note that the actor-partner model does not directly model group processes in terms of relationship parameters that are related to similarity (as does the latent variable model presented earlier). Instead, the actor-partner model merely "corrects" for the fact that individuals are nested within dyads or groups, and it models relationship parameters in terms of regression coefficients that can be interpreted in terms of an actor's influence on the self and the partner's influence on the self.

How should one choose between the actor-partner model or the latent variable model? Because the two models are transformations of each other (i.e., identical goodness-of-fit estimates, and the parameters of one model can be mapped one-to-one to parameters in the other model when certain equality constraints are placed on parameters), the choice is not a statistical one. Rather, the choice should be based on what the investigator wants to highlight in the data. If the investigator wishes to highlight how similarity within group on one variable correlates or predicts similarity within group on another variable,

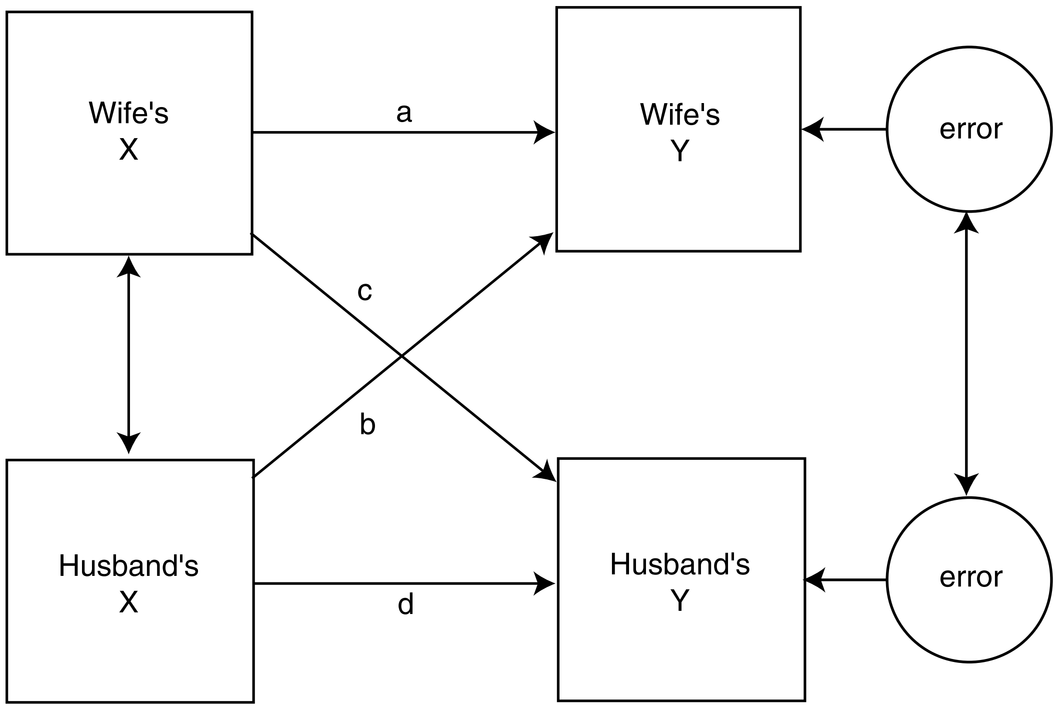

Figure 14.6 The Actor-Partner Model

then the latent variable model would be appropriate. If the investigator wishes to highlight how predictors measured on the self and other relate to outcomes for the self and other, then the actor-partner model would be appropriate because it corrects for interdependence.

When the members of couples or dyads are distinguishable (e.g., mixed-sex romantic couples), it is straightforward to estimate the models implied by the actor-partner model using structural equation modeling (Gonzalez & Griffin, 1999). One benefit of using a structural equations modeling approach is that the software allows for straightforward testing of equality constraints (e.g., one can test whether the wife's influence on the husband is different from the husband's influence on the wife). However, when the members are exchangeable, standard methods are inappropriate, and even hierarchical linear modeling programs take some coaxing to fit the model (Campbell & Kashy, 2002). In the exchangeable case, the pairwise coding approach we introduced above provides appropriate maximum likelihood estimates of the actor, partner, and interaction parameters when the pairwise columns are analyzed with standard multiple regression programs. However, special standard errors must be used to test the parameters because of the presence of interdependence (Gonzalez & Griffin, 2001). In particular, the special standard errors adjust for the non-independence on both *X* and *Y*; when the intraclass correlations on *X* and *Y* are 0, then the tests automatically simplify to usual standard errors for the regression model.

Thibaut and Kelly (1959) presented a specific theoretical model of interdependence involving three components: how an actor influences his or her own behavior, how the partner influences the actor's behavior, and how the actions of the pair as a joint entity influence the actor's behavior. This theoretical framework can be translated into a more general actor-partner model that includes an interaction term as well as the two main effects (one for actor and one for partner). This more general actor-partner model presents a point of departure from the latent variable model because, with the inclusion of the interaction term, the two models are no longer statistically indistinguishable. The details of this more general model still need to be developed, with statistical testing procedures requiring proof and simulation. Kenny (1996) provided some initial proposals on how to operationalize the interaction term. These advances provide an interesting example of how developments in statistical theory are being motivated by particular theoretical problems in social psychology.

HIERARCHICAL LINEAR MODELING: SAME OLD STORY OR A NEW PERSPECTIVE?

Most readers will be aware that there is a new "toolbox" for thinking about nested or multilevel data that has been developed in educational studies. Research on classroom performance led to emergence of a new standard approach, used when individuals are nested within dyads, or pupils are nested within classrooms, or workers are nested within organizations. These new programs (including HLM for Hierarchical Linear Models and MLNwin for Multi-Level models) automatically adjust in their own way for the levels of analysis displayed in the plots we presented above. The standard hierarchical linear models invoke theoretical assumptions about how to divide up and use within-group shared variance. The key assumption is that interdependence within groups, or individuals across time, can be captured in a within-unit regression model described by an intercept (representing the elevation of the set of outcomes points) and a set of slopes (representing the relation between predictors and the outcomes). These within-unit intercepts and slopes are then described in terms of a "fixed" component that is common to all units and a "random" component that consists of the variability among the units. A significant random component of a slope or intercept means that there is meaningful systematic variation between the units on that parameter. When significant "random" variation exists among the within-unit parameter values, the analyst searches for "cross-level interactions": higher-level factors (e.g., the average SES of the school) that predict variations in the within-unit parameter of interest (e.g., the relation between incoming GPA and graduation test scores).

Consider a multilevel analysis carried out by Murray, Bellavia, Rose, and Griffin (2003) examining how individuals (nested in married couples) responded to daily conflicts with their partners. The authors hypothesized that conflicts on a given day could give rise to individuals feeling more or less intimate with their partners the next day, and the direction and magnitude of this cross-day relationship would be moderated by the individual's level of felt security in the relationship. Each individual within each couple filled out a set of daily diaries for 21 days. Clearly, a number of different sources of non-independence exist in these data. First, there are multiple observations across time from each individual (generally, we will treat this within-individual level as "Level 1" and

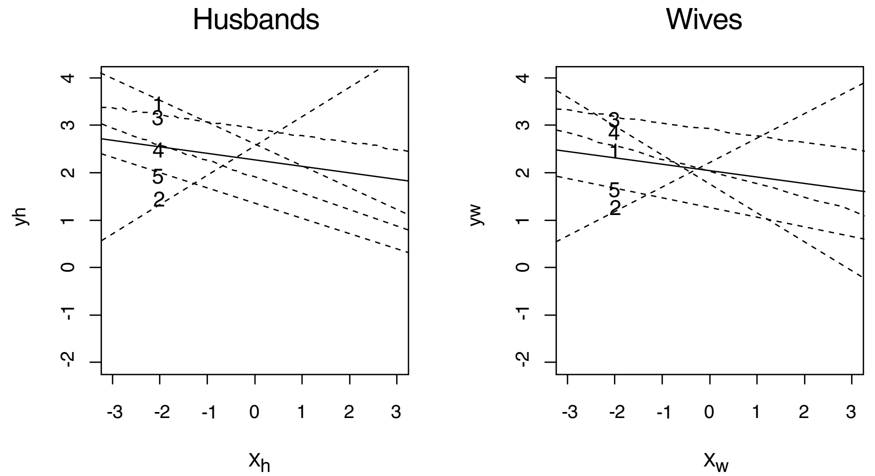

Figure 14.7 Graphical Depiction of the Slopes-as-Outcomes Model

model the slopes and intercepts from this level in terms of predictors from higher levels, e.g., from the individual or couple level). Second, at each point there are observations from matched husbands and wives that may or may not correspond or be similar. Third, the slopes and intercepts that are computed within each individual at Level 1 may be similar within couples. In a typical slopes-as-outcomes model with dyadic data, the first and third types of non-independence are modeled and the second is not.

To illustrate the slopes-as-outcomes approach, data from five dyads are plotted in Figure 14.7. Each dotted line represents a best-fitting line for the 20 daily points where today's feeling of intimacy is predicted by the amount of conflict experienced yesterday. The *X* variable (amount of conflict yesterday) has been centered so that the 0 point corresponds to the mean level for that individual. In such a transformed model, the Level 1 or within-individual across-time intercept reflects how intimate one partner feels the day after an average amount of conflict. The Level 1 slope reflects reactivity: how much one's level of intimacy today depends on the amount of conflict experienced yesterday. The solid line refers to the best-fitting line (defined by slope and intercept) across all individuals—this is the fixed effect. There is a small but nonsignificant negative slope between conflict and intimacy for men and women. The average level of intimacy, the elevation of the fixed line, is virtually identical for men and women. The focus of the slopes-as-outcomes model, however, is on the variability of the individual lines around the fixed line.

Consider the partners from Marriage 2 (the number next to each regression line refers to couple number). In this small subsample of men and women, they are the only ones who show a positive slope between yesterday's conflict and today's feelings of intimacy. This illustrates both the covariation between partners (essentially the ICC between partner's Level 1 coefficients) and the as-yet-unexplained variability of the slopes and intercepts. This variability is then explained in terms of higher-level factors (e.g., individual- or couple-level factors) that cause some individuals or couples to be more reactive than others, or for some to react positively and others to react negatively. In accord with Murray et al.'s (2003) hypothesis, individuals with high levels of felt security responded to higher levels of conflict than average by drawing closer to their partners, whereas those with low levels of felt security responded to higher than average conflict days by drawing away from their partners.

In this model, romantic partners are treated as parallel multivariate measures so that interdependence is modeled (i.e., accounted for in the model) but is not the focus. The focus, instead, is on explaining or predicting the Level 1 slopes and intercepts by higher-level factors. However, the Level 1 slopes can include across-partner (within-level) interdependence directly at Level 1, for example, by examining whether a man's report of conflict on a given day predicted his wife's report of conflict. Both the multivariate outcome model and the cross-partner analysis just described are limited to cases where the dyad members are distinguishable. It is a challenge to extend the same models to the exchangeable case.

Despite the power and elegance of the "slopes-as-outcomes" model, it is designed to answer one particular kind of question: What group-level factors predict the elevation and slope of within-group relations? As such, it does a fine job of identifying the individual effect in context. However, this standard multilevel model does not deal with all the research questions stated above. Instead, it focuses primarily on how the pattern of relations at Level 1 depends on the values of the higher-level units. Also, the multilevel framework can get very complicated when one allows for non-independence due to time, interdependence within a variable (the ICC), and interdependence across multiple dependent variables (such as in the latent dyadic model). Specific implementation of HLM models are beyond the scope of this chapter. We refer the reader to book-length treatments such as Raudenbush and Byrk (2002) and Snijders and Boskers (1999), where details such as centering of variables, definition of latent variables, and various implementation details are described. For a discussion of centering in HLM models, see Hoffman and Gavin (1998).

MORALS

In most chapters such as this, a major goal is to highlight a hot new analytic technique available to the researcher. As such, one would expect us to showcase HLM as the new kid on the scene and expect us to convince readers to use it in their analyses. However, our approach has been to present HLM as a statistical framework that provides a direct way to estimate parameters of interest under a particular model, the slopes-as-outcomes model. We did not offer HLM as the "correct" way to analyze one's data. We hope that the reader has extracted some lessons from this chapter beyond the simple awareness of how to use the hottest new technique currently available. Our goals were (a) to show that there are deeper ways of thinking about the degree of interdependence among interacting individuals and (b) to provide some intuitions about how to think about violations of independence, why it might present a problem for standard statistical tests, and why interdependence provides an opportunity for researchers interested in studying interacting individuals. The violation of independence suggests that interacting individuals are not "isolated." As such, interdependence is a signal that the very phenomenon researchers are seeking—people influencing each other—is present in one's data.

We presented three different theoretical models. Each of these models provides a different way to think about one's data and highlights different features. The latent variable model places similarity at the forefront; it models similarity directly within dyads both within a variable and across multiple variables. It answers individual-level questions such as "What is the correlation between an individual's rating of commitment and the same individual's rating of intimacy?" as well as group-level questions such as "Are couples in which both individuals are high on commitment also the couples in which both individuals are high on intimacy?" The actor-partner model places interpersonal influence at the forefront; it models interdependence across variables and corrects for interdependence within variables. It answers questions such as "Which variable is a better predictor of her intimacy rating: his commitment to the relationship or her commitment rating?" The slopes-as-outcomes model places individual processes at the forefront; it models these processes (often over time) as a function of other variables (which can be variables from the individual actor or the partner, or can be a unit variable such as number of children). It answers questions such as "Does the level of commitment each partner feels moderate how today's intimacy in the relationship predicts tomorrow's level of intimacy?"

Which model is correct? Which model should I use on my data? Unfortunately, these are not questions that can be answered with simulation or mathematical reasoning. It turns out that all the models presented here (as well as others presented by Kenny, 1996) are in some sense correct. In fact, some statistical programs can be used to estimate all three models. For example, an HLM program can be used to estimate the latent variable model (Gonzalez & Griffin, 2002; Griffin & Gonzalez, 1995). But special tricks are needed because the latent variable model is in a sense "multivariate" and HLM programs are designed primarily for univariate regressions (that is, the slopes-as-outcomes framework needs to be "tweaked" to estimate the parameters of the latent variable model). Another example is that an SEM program, which is used to estimate the latent variable model (with dyad and individuals as latent variables), also can be used to estimate the regression-based actor-partner model (Gonzalez & Griffin, 2001).

Our point is that the particular statistical program one uses is not the real issue, because with a little bit of work it is possible to make a program estimate the necessary parameters. One should not use HLM merely because it is what other researchers in one's area are using. We encourage researchers to ask themselves the critical question, "Which model is most appropriate for the information I want to extract from my data?" The answer to this question determines how to proceed with specific analytic techniques. The different models we presented have (superficially) different ways of handling the non-independence that results from group membership. Which method is right for you depends mostly on the theoretical question you want to answer.

This answer may not be satisfying to people who want to know which technique to use to analyze a data set in front of them. But we believe that without knowing the underlying theoretical framework that motivated the research question, it would be inappropriate to make a blanket recommendation. Instead, we offered the pairwise approach as a tutorial method to illustrate several issues surrounding interdependence and offered three conceptual frameworks against which various psychological research questions can be modeled. As David Kenny has said, interdependence is the "very stuff" of relationships. Once one understands how to measure interdependence, then there is an immediate realization that the way to handle interdependence depends on the underlying model one has in mind. A general statistical framework that can be guided by theory and mold itself to the specific needs of a researcher is the best analytic tool that anyone could wish for.

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