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Models of dyadic social interaction

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We discuss the logic of research designs for dyadic interaction and present statistical models with parameters that are tied to psychologically relevant constructs. Building on Karl Pearson's classic nineteenth-century statistical analysis of within-organism similarity, we describe several approaches to indexing dyadic interdependence and provide graphical methods for visualizing dyadic data. We also describe several statistical and conceptual solutions to the 'levels of analytic' problem in analysing dyadic data. These analytic strategies allow the researcher to examine and measure psychological questions of interdependence and social influence. We provide illustrative data from casually interacting and romantic dyads.

Keywords: dyads; statistical analysis; interdependence; research design

1. INTRODUCTION

Social interaction is a fundamental aspect of psychological life for humans, chimpanzees, dolphins and other 'social animals'. In humans, social interaction, especially dyadic social interaction, can have profound effects, promoting both happiness and depression, and possibly even physical well-being and longevity. Ethology, the study of animals in their natural environments, is dominated by the naturalistic observation of social interaction. Social psychology, often defined—at least in the classic American tradition—as the study of the individual in the social context, is finally turning back to the study of natural social interaction. We begin with the story of how and why social psychology turned its back on the study of social interaction, and then describe models of dyadic social interaction that are guiding the field back to studying this central issue.

The most well-known and influential social psychology studies are controlled experiments that demonstrate the power of the social situation to change behaviour in surprising and profound ways. Probably the best-known series of such studies is that conducted by Solomon Asch (1952), which demonstrated that a unanimous group could impose such conformity pressure on an individual as to make the individual report that a long line was relatively short (and vice versa). Second in prominence is the series of studies by Stanley Milgram (1974) which demonstrated that an insistent 'expert' experimenter with the trappings of authority (e.g. a white laboratory coat) could impose such compliance pressure on an individual that the volunteer 'teacher' would give apparently fatal electric shocks to a 'learner' subject. These and a long list of similarly profound experiments illustrate the power of social interaction *without* ever observing any natural contact between the 'interacting' individuals. Whether it is the unyielding and unanimously mistaken majority of the conformity studies of Asch (1952), the magisterial and unshakeable experimenter of the compliance studies of Milgram (1974), the forbidding and frightening scientist of the fear and affiliation studies of Schachter (1959), or the unconcerned and distracted onlookers of the bystander intervention studies of Darley & Latane (1968), the social contexts—that is, the other people—are 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 identically to eliminate confounding and to reduce within-cell error variance.

There is no doubt that these and similar experiments have taught us much about the nature of social influence (most importantly, that an individual's thoughts, feelings and behaviour are powerfully determined by the presence and behaviour of others), and each of these scholars clearly acknowledged the interplay between individual and group in real life. However, the experimental methodology of the individual subject faced with pre-programmed confederates has stifled the study of actual group or dyadic processes. From the perspective of the classic experimental tradition, actual interaction brings with it two undesirable consequences. First, extraneous or uncontrolled variation and covariation are introduced, whereas the goal of the controlled experiment is to maximize the systematic effect relative to the uncontrolled variation. Second, the interaction brings with it the threat of a statistical 'nuisance', the statistical dependence of data across individuals. As the methodologist David Kenny (1994) has noted, this nuisance is actually the 'very stuff' of social interaction, because it indicates that interacting individuals actually affect each other. However, to the social psychology experimenter, this statistical dependence across

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subjects within conditions was devastating because it required moving the level of statistical analysis from the individual to that of the group, and this dramatically reduced the number of units analysed and hence the power of that analysis. Thus, a study of 16 interacting groups, each with five individuals, would not have 80 units or total degrees of freedom to analyse, but only 16.

These methodological challenges helped deter experimentalists from studying actual social interaction. However, a few brave souls were committed to studying relationships such as those between romantic partners, between siblings or between parents and children. Although it was clear that such relationships could not simply be studied by controlled experiments, the individual level of analysis still reigned supreme because of a third problem with conceptualizing and analysing dyadic and group interaction. That is, from disciplines more at home with data from aggregates (in particular, sociology and political science) came warnings of the dangers of making cross-level inferences. Robinson (1950) illustrated the 'ecological fallacy' with the following example: across the 48 US states represented in the 1930 census the correlation between percentage foreign born (i.e. immigrants) and percentage literate was $+0.58$; however, within the states the average correlation between the two dichotomous variables was -0.11. As Freedman (2001) summarizes, 'The ecological correlation suggests a positive correlation between foreign birth and literacy: the foreign born are more likely to be literate ... than the native-born .... The ecological correlation gives the wrong inference. The sign of the correlation [at the aggregate between-state level] is positive because the foreign-born tend to live in states where the native-born are relatively literate' (p. 4027). Freedman also demonstrates that the same patterns of correlation are found today between measures of income and immigration: large and positive between-state correlation and small and negative within-state correlation—primarily because immigrants are attracted to large cities in wealthy areas.

As Robinson (1950) recognized, the difference between the ecological and individual correlations combines two biases: an aggregation bias whereby the individual-level effect is amplifed by the combination process, and a level-specific confounding whereby the relation at each level is determined by a different set of causal factors. If only the First bias is operating, then the aggregate correlation will be of the same sign as the individual-level correlation, only larger. However, a confounding bias (as in the census examples) can result in the sign of the correlation switching.

The message of Robinson (1950) was that researchers should restrict their inferences to the level at which they collected their data and that they should be sensitive to different causal influences at each level, across and within units. However, in psychology, this warning had the effect of reinforcing the bias towards studying individual behaviour and avoiding the effects of actual social context. Thus, relationship researchers routinely measured only one member of a couple, or if they collected data on both members, they would analyse the data for each sex separately. Why was this so wrong, other than making it impossible to find evidence of social interaction or social influence effects? Consider the cross-state example again. What level of analysis is represented by examining a national census and correlating foreign-born status and literacy *ignoring states*? This 'total' correlation combines the individual (within-state) and ecological (between-state) relationship and tells us nothing about each level of analysis separately. Note that a proper individual-level correlation in the census example was always computed *within-state*. In a dyadic design, the individual-level correlation is not the total correlation across all individuals, but is instead the within-dyad correlation. Thus, whenever effects may operate at both the individual and the dyadic level, no problems are solved by analysing only one individual per dyad. The results will represent a conglomeration of individual and dyadic effects.

In the dyadic case, this can be described by the following identity:

$$r_{xy} = \sqrt{r_{xx'}}r_{\mathrm{d}}\sqrt{r_{yy'}} + \sqrt{(1 - r_{xx'})}r_{\mathrm{i}}\sqrt{(1 - r_{yy'})},$$

where r_{xy} represents the total correlation across individuals, r_{d} represents the corrected dyad-level correlation, r_{i} represents the corrected individual-level correlation, and $r_{xx'}$ and $r_{yy'}$ represent the ICCs or proportion of shared variance on each variable. The 'pieces' of this equation are the building blocks of interdependence theory and are thrown away by the kind of designs that throw away statistical dependence. The ICCs represent the similarity within dyad members, and are the fundamental building blocks for measuring interpersonal influence. We begin with this and build up models for dyadic social interaction.

We consider the problems and opportunities of dyadic data analysis in light of a specific example. Stinson & Ickes (1992) observed pairs of male students interacting 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, gestures and gazes. Note that this is a special situation because the researchers randomly assigned the pairs of strangers. This provides a rare opportunity to examine how interdependence *emerges*. That is, any similarity between individuals within these dyads can be seen as an emergent property of the social interaction. Owing to the random assignment, 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 might lead individuals to become more (a positive ICC) or less (a negative ICC) similar to their partners than to the other people in the sample. When dyadic sorting is non-random, as in the case of heterosexual romantic relationships or male friends as in the Stinson & Ickes (1992) study, this inference is not so straightforward. Similarity within dyads may indicate interdependence arising through interaction, but it may also be an artefact of sorting owing to common interests, common abilities or common status.

A second aspect of the study of Stinson & Ickes (1992) is noteworthy. Dyads made up of male friends or male strangers have members that are (in statistical terms) *exchangeable* because they are not readily distinguished on the basis of sex or any other non-arbitrary variable. When the dyad members are distinguishable it is possible for the scores of the members within each 'type' or category to have different means, different variances and different covariances. For example, if the dyads were made up of a teacher and a learner, the two types of individuals might behave very differently. 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. We do not dwell on this categorization but simply note that the analytic methods are generally more complex in the exchangeable case (Gonzalez & Griffin 2000).

2. ASSESSING INTERDEPENDENCE ON A SINGLE VARIABLE: THE INTRACLASS CORRELATION

In the case of dyadic and group designs, the ICC has a special meaning because it assesses the degree of agreement within group members. For example, if we assess how often two strangers speak, the ICC provides a measure of agreement within dyads, and so it provides a natural measure of interdependence. If each individual vocalizes at a rate that is equal to his dyadic partner's, but different dyads have different mean levels of vocalization, then the ICC will be a perfect 1 because pairs are maximally similar (i.e. all the variance is between couples). If ratings vary within dyads just as much as they vary between dyads, then the ICC will equal 0 because there is no evidence of similarity or dissimilarity across coupled individuals. If ratings vary more within dyads than they do between dyads, the ICC will be negative, indicating that individuals within groups are more dissimilar than expected by chance, that is, individuals within a dyad are behaving in a *complementary* fashion.

The ICC can be used to index non-independence or interdependence across a wide range of applications, from diary studies where 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 where 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 where 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. Clearly, if a researcher is examining the impact of social interaction, then the degree of interdependence might be a central phenomenon of interest, and should be modelled directly rather than treated as a statistical nuisance that needs to be corrected.

The ICC is one of the oldest, as well as one of the most versatile, statistics. The original computational method for the ICC was proposed by Karl Pearson (1901). He was searching for an index of similarity in plants for use in genetic research. For example, early genetics researchers could have studied whether the pea blossoms on a particular plant tended to be of a similar size. Pearson (1901) proposed a method for listing all the measurements of interest across all plants and tagging those that came from

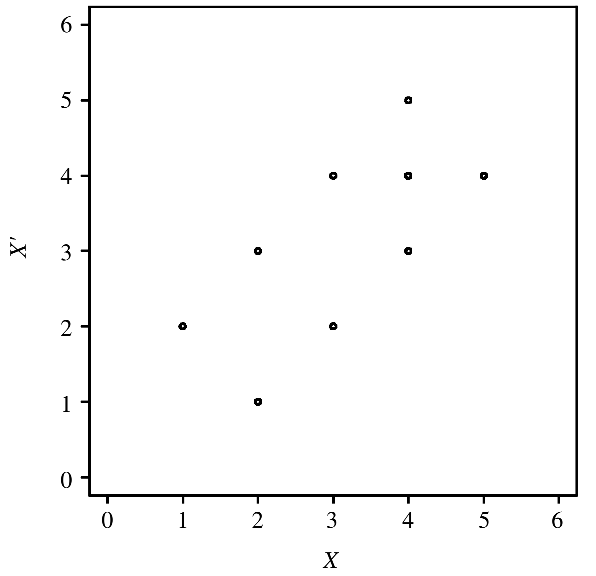

Figure 1. Demonstration of pairwise coding—points only.

'within' the same plant. He focused on the similarity of all possible pairwise combinations of the blossoms within a plant. Imagine there are three blossoms on the first plant: 1 is compared to 2, 1 is compared to 3 and 2 is compared to 3. If they are all the same size—but different from the overall mean across all plants—that adds up to evidence for within-plant similarity.

Originally, this pairwise ICC was computed using a special way of coding data, although other methods of computation have been developed for this maximum-likelihood estimate of the ICC. Consider a simple example of the frequency of vocalization in the members of five male dyads. Let us say that the scores on this dependent variable were (1,2), (3,4), (4,4), (5,4) and (2,3). Each member of the same couple is denoted within parentheses. We could enter these ten 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, 5, 4, 3 and 2. To understand how this coding actually codes the level of agreement within dyads, it is helpful to plot these data, calling the first column X and the second column of reordered data X' (see figure 1).

This plot appears to show a positive correlation between the two columns regardless of dyadic membership, but actually it shows more. If we connect the two points from the same dyad with a line segment, we see some structure around the identity line. It is this very structure that is the experimental 'nuisance', the violation of statistical independence: these data are not randomly scattered on the plane, instead points are coupled according to dyadic structure. Here are the same points displayed with the additional structure highlighted (see figure 2).

This second plot shows that the two members of each dyad tended to share a tendency to vocalize, as the behaviour of the two members in four of the five couples differed by only one point. Note that perfect agreement corresponds to a point on the identity line, as seen in the dyad

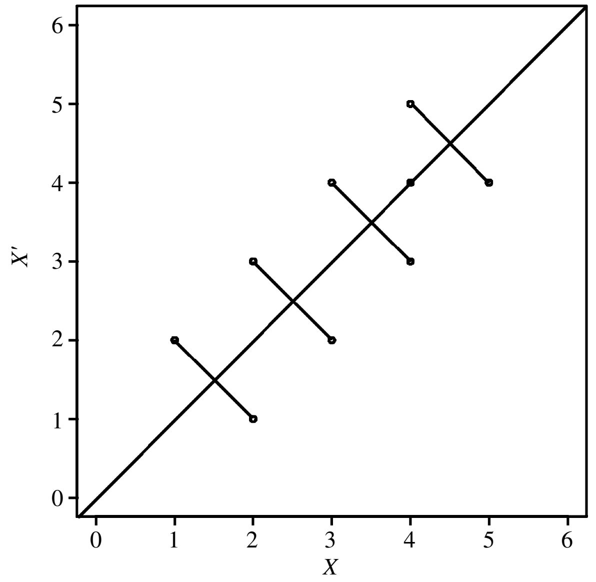

Figure 2. Demonstration of pairwise coding—points and dyad indicator.

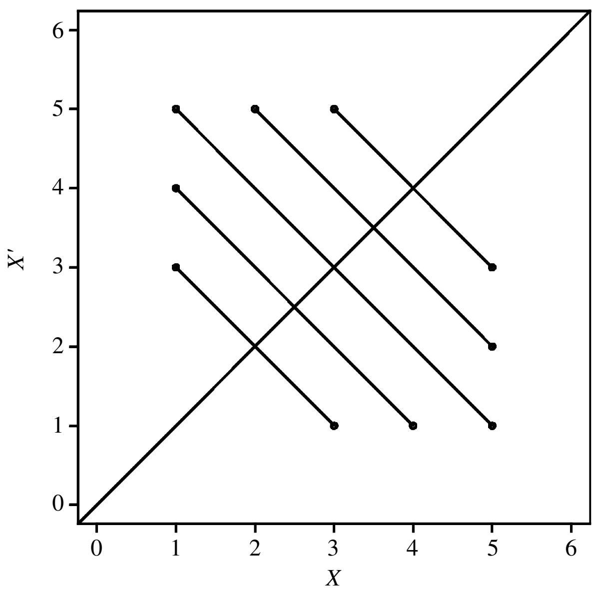

Figure 3. Demonstration of pairwise coding—relatively low agreement.

scoring (4,4). Importantly, not only do pairs within dyads tend to be similar but there is quite a bit of variation across dyads. It turns out that the traditional Pearson product-moment correlation between these two variables (i.e. variables that have been 'pairwise' or double coded, X and X' in our nomenclature) provides the pairwise or Pearson ICC. In this example, the intraclass is relatively high at 0.706, suggesting a high level of within-dyad agreement.

Consider the data plotted in figure 3, demonstrating a lack of similarity within dyads. This plots the data (1,5), (2,5), (3,1), (4,1) and (5,3). Again, string these data into one long column, create a second column that contains the re-coded pairwise data, examine the plot and compute the Pearson correlation between the two columns. As one would expect with these data, there is relatively little agreement within dyads but instead there is marked dissimilarity in 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 process of complementarity. Indeed, the plots show that the pairs of points are not close to the identity line (which would have signified agreement) and the Pearson correlation between X and X' is -0.615.

From the data of Stinson & Ickes (1992), we selected three variables on which to measure dyadic interdependence: gazes, verbalizations and gestures. 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 1, and the $2N$ gaze scores in reversed order in column 2, and so on). The corresponding 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. Recall our argument about the role of random assignment in allowing inferences about emergent properties in dyads. Clearly, individuals allocated to dyads started out with varying norms of how much to gaze at their partner. There was no reason for individuals within groups to show such concordance in amount of gazing unless something like a group norm emerged spontaneously in these waiting-room interactions. When dyads are sorted more naturalistically, then sorting may occur based on the similarity of any number of variables. Then, the standard of proof for identifying emergent norms is much higher, and such inferences may require a multivariate form of dyadic similarity as captured in the dyad-level correlation described in the next section.

Figure 4 presents two intraclass plots displaying actual data from another variable collected by Stinson & Ickes (1992): frequency of smiles and laughter. This variable shows an interesting difference in interdependence between dyads made up of strangers and dyads made up of friends. Strangers share 72% of the variance in smiles and laughter (intuitively, if one member of the dyad smiles, so does the other). However, the data from 24 dyads of best friends reveal the percentage of shared variance is lower (intuitively, there was less matching of smiles in laughter in the dyads of best friends than in the dyads of strangers). This difference in agreement complements the more traditional analysis of the mean, which shows that the best friends smiled and laughed more on average than did the strangers. The agreement analysis provides additional information about the degree of (in)dependence between the two individuals on this variable.

3. THREE STATISTICAL MODELS

Building on the ICC as the fundamental building block of measures of interpersonal influence, we develop models for conceptualizing different types of dyadic processes. We describe three prototypical designs for modelling 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

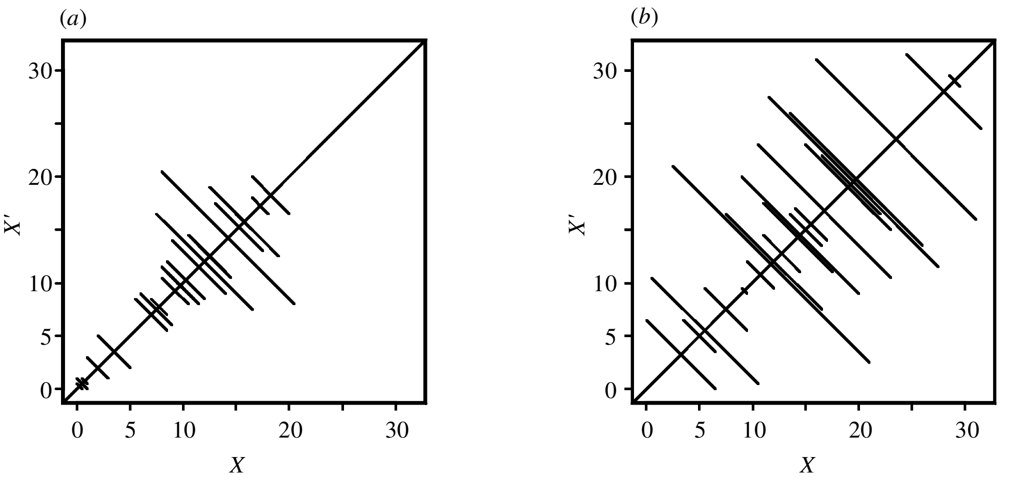

Figure 4. Comparing two types of dyads: the laughter of (*a*) strangers ($r_{xx'} = 0.72$) and (*b*) friends ($r_{xx'} = 0.4$).

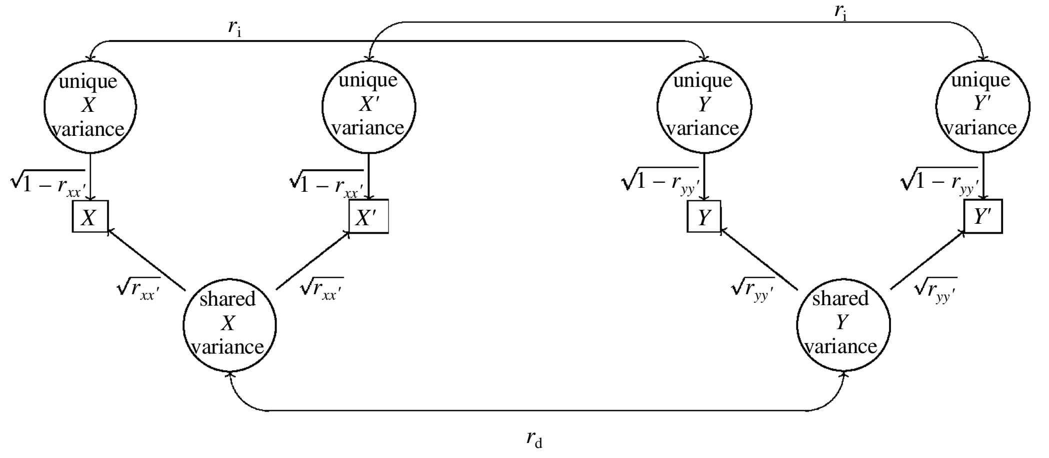

Figure 5. The latent variable model.

block, the ICC, each solves the levels of analysis or multilevel problem in a different way, with very different implications for theory building and theory testing.

Consider each model in relation to the study of dyads of Stinson & Ickes (1992). The latent dyadic model (figure 5) places the main causal forces giving rise to shared behaviour or attitudes at the level of latent or underlying dyadic effects. This model is consistent with such notions as a 'group mind' or a 'dyadic personality'. This model requires substantial dyadic similarity on both variables as a given behaviour is modelled as the combination of an underlying emergent dyadic effect that is shared by the dyadic members and an individual effect that is unique to one of the members. The emergent effects on each variable are then related to yield an estimate of the dyad-level correlation: an example of a research question that can be tackled by the latent dyadic model is 'What is the dyad-level correlation between a dyad's tendency to gaze and a dyad's tendency to talk?' We return to this example and explore it more thoroughly in the following paragraphs.

The actor–partner model (figure 6) models the causal forces entirely at the level of individuals: in particular, is an actor's behaviour primarily a function of his own qualities or the qualities of his partner? Here, interdependence as assessed by the ICCs is not an indicator of some underlying shared force or emergent dyadic property but is simply a statistical artefact to be corrected. This model does not require dyadic similarity on either variable, but can accommodate any degree of similarity or dissimilarity. An example of a research question that can be addressed by the actor–partner model is 'is an actor's tendency to gaze at his partner primarily determined by his own level of vocalization or his partner's level of vocalization?' A phenomenon that is significantly affected by partner effects demonstrates social influence.

The slopes-as-outcomes (also known as HLM) model emphasizes causal forces acting between levels. Like the actor–partner model, the HLM model corrects for interdependence but does not require it or model it directly. The key assumption is that structure 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 outcome points) and a set of slopes (representing the within-group relation between predictors and the outcome). 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. When significant 'random' variation exists among the within-unit parameter values, the analyst searches for 'cross-level interactions', higher-level group factors that predict variations in the within-unit parameter of interest. Note that

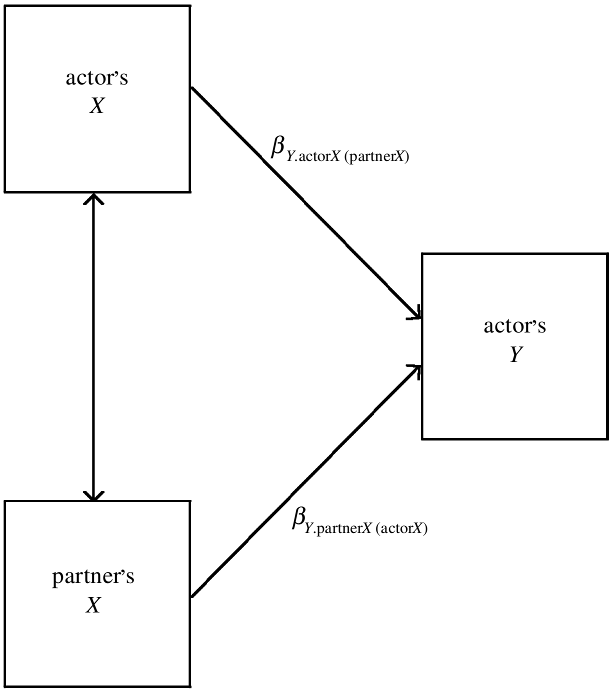

Figure 6. The actor–partner model.

this model is not appropriate for the data of Stinson & Ickes (1992) because the dyad members were randomly assigned (thus there are no higher-level variables associated with dyads) and because there are not enough observations to permit within-dyad regressions to be estimated.

Let us consider an HLM model that builds on the actor–partner model of figure 6 and is based on the actual model of Murray *et al.* (2002). They examined how individuals (nested in married couples) responded to daily conflicts with their partners. Reports of conflict from each partner on day t were used to predict reported feelings of intimacy on day $t+1$. Each individual within each couple filled out a set of daily diaries for 21 days. Thus, it was possible to model each actor's intimacy as a function of an average level (an intercept) and slope coefficients for the actor's prior report of conflict and the partner's prior report of conflict. These within-dyad processes (the relative magnitude and direction of the actor and partner coefficients) were then related to higher-level variables, such as the duration and quality of the relationship.

Before we delve more deeply into our three focal models, we mention a hybrid model that combines a classic experimental approach with actual social interaction. The 'social relations model' of Kenny (1994) 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 here 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.

The notion of a dyad-level correlation or even of emergent behaviour is not easy to communicate. We build up these intuitions with graphical examples. Let us make up a simple example with five all-male dyads such as those studied by Stinson & Ickes (1992), i.e. five exchangeable dyads. The scores for the five dyads on level of vocalization are as before with the example showing high agreement: (1,2), (3,4), (4,4), (5,4) and (2,3). The scores for gazing also show high agreement (pairwise ICC = 0.834): (5,5), (2,1), (3,3), (3,2) and (4,5). Let us 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 vocalization and gaze frequency are presented in figure 7. Next to each line segment depicting a dyad, we place a number corresponding to which dyad it is, for example, on vocalization frequency the point (4,4) corresponds to dyad 3 in our hypothetical dataset.

Both of these 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 with the variation along the identity line); it is also instructive to compare the dyad numbers listed in the vocalization plot with the dyad numbers listed in the gaze plot. At the dyadic 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 on vocalization such as dyad 1, both dyad members tend to be high on gazes. This dyad-level relationship between joint standing on one variable and joint standing on a second variable is the dyadic or dyad-level correlation. Another way to visualize this is to plot what Pearson (1901) called the cross-ICC or $r_{xy'}$, in this case the relation between standing on vocalization frequency (variable X) and standing on gaze frequency (variable Y'), as shown in figure 8.

In figure 8, the Pearson correlation between an individual's vocalization and the partner's gaze, the cross-ICC, is -0.656. The negative correlation can be seen by looking at the 10 points in the plot (ignoring the line segments connecting dyad members). 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 considerable within-dyad similarity on each variable. The key conclusions from this plot are:

(i) that when individual-level relations are stripped out of the data (by examining across-partner relations) there is a strong negative correlation; and
(ii) the dyads appear to be similar on both vocalization and gaze.

These two conclusions are jointly modelled in the dyad-level correlation that captures the relation between the two variables at the level of dyadic latent variables. 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 the analysis problem: shared variance within a dyad is treated as a dyadic effect and related across variables to create a dyad-level correlation or regression; unshared variance is treated as an individual effect and related across variables to create an individual-

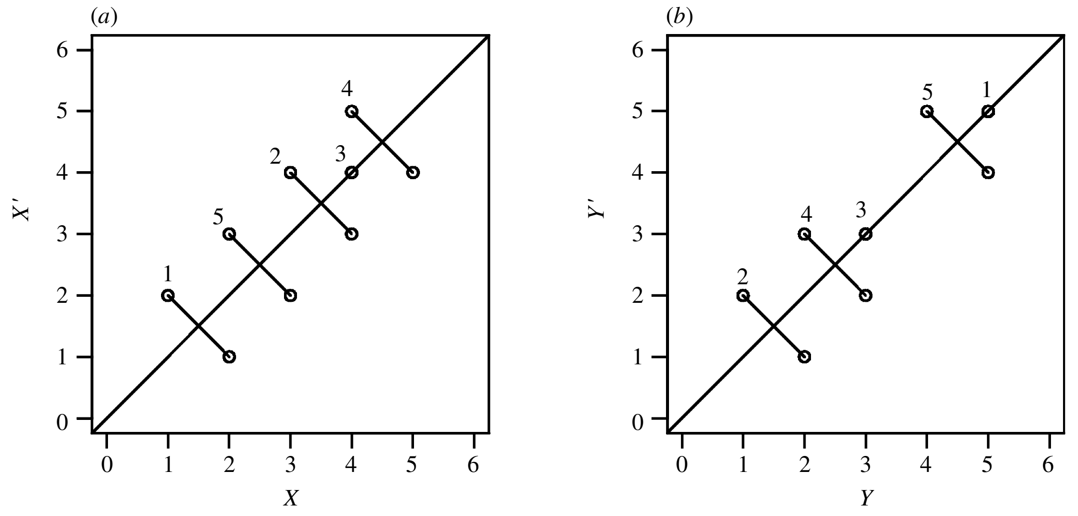

Figure 7. Pairwise plots for two variables: (*a*) vocalization and (*b*) gazing. Numbers in the figure refer to couple identification numbers.

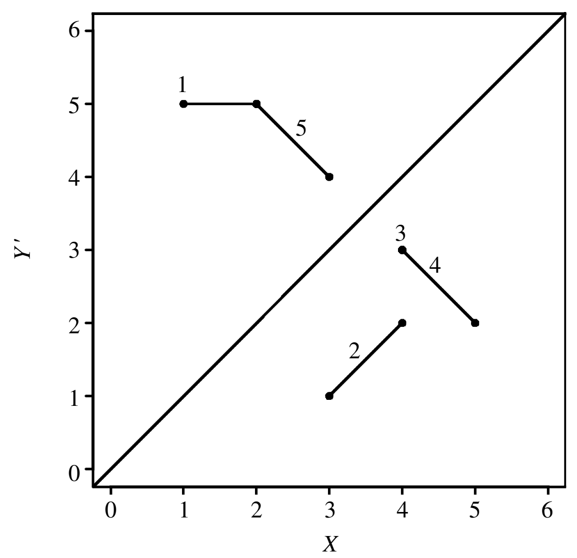

Figure 8. Cross variable pairwise plot. Numbers in the figure refer to couple identification numbers.

level correlation or regression (as we describe in the following paragraphs). Note, however, that such as 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. Alternatively, this model also helps define and give substance to fuzzy concepts such as dyadic personality: it is a coherent network of dyad-level relationships among variables.

We continue using the Stinson & Ickes (1992) data to illustrate the exchangeable case. Having determined that there was dyad-level variance—as indexed by the pairwise ICC—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, $r_d = 0.680$. The observed Z and p values for r_d were $Z = 2.56$, $p < 0.01$. The latent dyad-level correlation (r_d) between gaze frequency and gesture frequency was 0.906, $Z = 1.94$, $p = 0.052$. The dyad-level correlation (r_d) between verbalization frequency and gesture frequency was 1.10, which is 'out of bounds'. Such out-of-bounds values are most likely to occur when the ICC 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 -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. The individual-level correlations for the other pairs of variables were relatively small and non-significant. 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 relationships.

Note that all three overall correlations (across all individuals ignoring dyadic membership) 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.

The latent variable model of dyadic influence implies that dyadic influence flows from a shared dyadic construct to each individual's behaviour. However, the same data

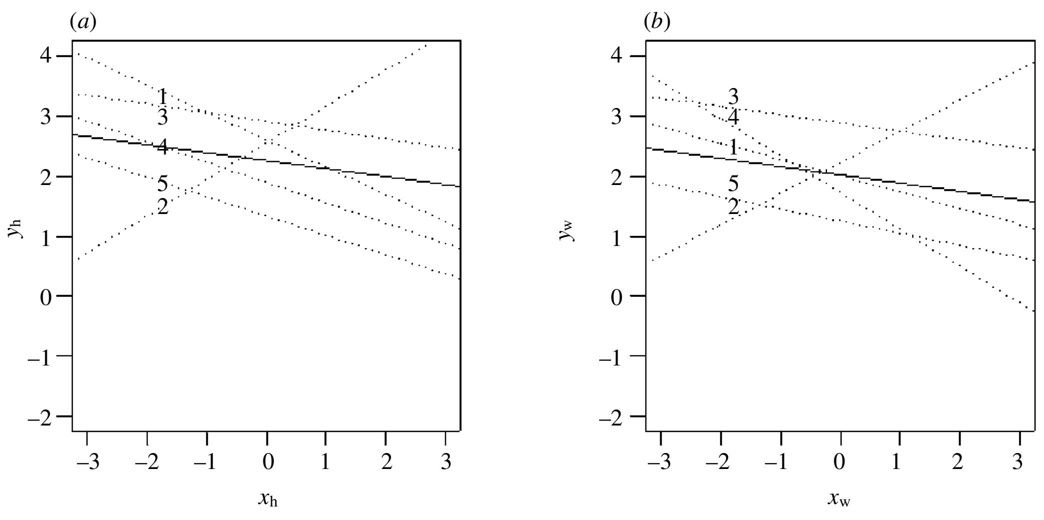

Figure 9. Example from the slopes-as-outcomes model. (*a*) Husbands and (*b*) wives. Numbers in the figure refer to couple identification numbers.

can be analysed under the assumption 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'). In the actor–partner model, there is no underlying dyadic effect giving rise to observed similarity; similarity on X is simply an unexplained correlation (the ICC) to be modelled but not explained by multiple regression methods.

For the data of Stinson & Ickes (1992) 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 6, the standardized regression coefficient was 0.173 ($Z = 0.97$)—thus, stripping this coefficient of its shared variance (by partialling out the ICC) substantially reduced its predictive power. 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 & Fiske (1977). Note again how the purpose of this model is to apportion relative predictive power between characteristics of the actor and of the partner.

To illustrate the slopes-as-outcomes approach, data from five dyads are plotted in figure 9. We look only at the actor effects. 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 (Murray *et al.* 2002). The X variable (amount of conflict yesterday) has been centred 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 defines the best-fitting line (defined by the 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 famed line, is virtually identical for men and women. But the focus of the slopes-as-outcomes model is on explaining the variability of the individual lines around the fixed line, not the degree of similarity across partners.

Consider the partners from marriage 2 (the number next to each regression line refers to couple number). In this small sub-sample 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 so-far 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 the hypothesis of Murray *et al.* (2002), 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 modelled (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.

4. FUTURE DIRECTIONS

We have briefly sketched some methods and models for capturing the social part of social interaction. Some of these methods are rather simple, even simplistic, but they still serve to direct attention to some key measures of similarity and influence that have been too long ignored in social psychology. The same basic issues can be modelled at any level of complexity, as demonstrated by Gottman *et al.* (2003) who use general systems theory to model the behaviour of married couples. But simple or complex, it is high time that social psychological models begin to focus on—and not hide from—the statistics of interdependence.

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GLOSSARY

HLM: hierarchical linear model

ICC: intraclass correlation